Cognitive Control in Cognitive Dynamic Systems: A New Way of Thinking Inspired by The Brain

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Abstract

Briefly, main purpose of the paper is fourfold:

a) Cognitive perception, which consists of two functional blocks: improved sparse-coding under the influence of perceptual attention for extracting relevant information from the observables and ignoring irrelevant information, followed by a Bayesian algorithm for state estimation.
b) Entropic state of the perceptor, which provides feedback information to the controller.
c) Cognitive control, which also consists of two functional blocks: executive learning algorithm computed by processing the entropic state, followed by predictive planning to set the stage for policy to act on the environment, thereby establishing the global perception-action cycle.
d) Experimental results for exploiting the perceptual as well as executive attention in a co-operative manner, which is aimed at the first demonstration of risk control in the presence of a severe disturbance in the environment.

Keywords: Cognition. Cognitive Dynamic Systems. Cognitive perception. Cognitive Control. Perceptual attention. Executive attention. Predictive planning. Pre-adaptation.

I. Introduction

The human brain is a powerful information processing machine, for which there is no equal when it comes to two challenging issues: perception of the environment (world) and action on the environment.

The idea of *cognitive dynamic systems*, first described in [1] and then expanded in more detail in [2], is inspired by the brain. It is therefore not surprising that by embracing cognitive dynamic systems, we have outperformed traditional entities by orders of magnitude as reported in [3] on cognitive radar and [4] on cognitive control.

As depicted in the block diagram of Fig. 1, a cognitive dynamic system in its basic form consists of two dominant physical parts: the *perceptor* on the right-hand side of the figure and the *controller* on the left-hand side. The system operates in a *self-organized and synchronized manner* by building on basic principles of cognitive neuroscience [5]. The principles are briefly described as follows:

1) **Perception-action cycle**. The cycle begins with the perceptor processing the incoming environmental observables, followed by *feedback information* about the environment sent to the controller by the perceptor to set the stage for the controller to act on the environment. This action naturally produces changes in the environmental observables, which, in turn, sets the stage for a second perception-action cycle, and so it goes on. This distinctive cyclic behaviour of cognitive dynamic systems is continued until we reach a point where further *information gain* about the environment is too small to be of practical value, assuming that the environment is stationary. The perception-action cycle, just described, is said to be of a *global* kind, in that it embodies the environment within itself.
2) **Memory.** There are two parts of memory: *perceptual memory* and *executive memory*. The function of perceptual memory is basically to solve the *source-separation problem*, which is achieved by extracting *relevant* information form the environmental observables that is retained and ignoring irrelevant information; this problem is resolved by having to continually learn from the observables on a cyclic basis. Simply put, function of the perceptor is that of modelling the behaviour of the observables, followed by Bayesian state estimation. As for the executive memory, its function is also to continually learn from feedback information sent to the controller by the perceptor, so as to provide the initiatitive for action on the environment.
3) **Attention.** There are also two kinds to attention: *perceptual attention* and *executive attention*. Both of them rely on *local* perception-action cycles for their respective impacts on cognitive functions carried out in perceptual memory and executive memory, with improved overall performance as the end result.
4) **Intelligence.** Unlike the preceding cognitive functions, intelligence does not occupy a physical place of its own in the block diagram of Fig. 1; its presence only manifests itself in an algorithmic sense distributed throughout the system. Most importantly, it builds on the perception-action cycle, then memory and attention, with the result that intelligence is the most powerful of them all. Nevertheless, we may say that intelligence plays the key role in *decision-making* for action taken by the controller on the environment.

The rest of the paper is organized as follows: Section II is devoted to cognitive perception. Section III addresses the important issue of entropic state of the perceptor. Cognitive

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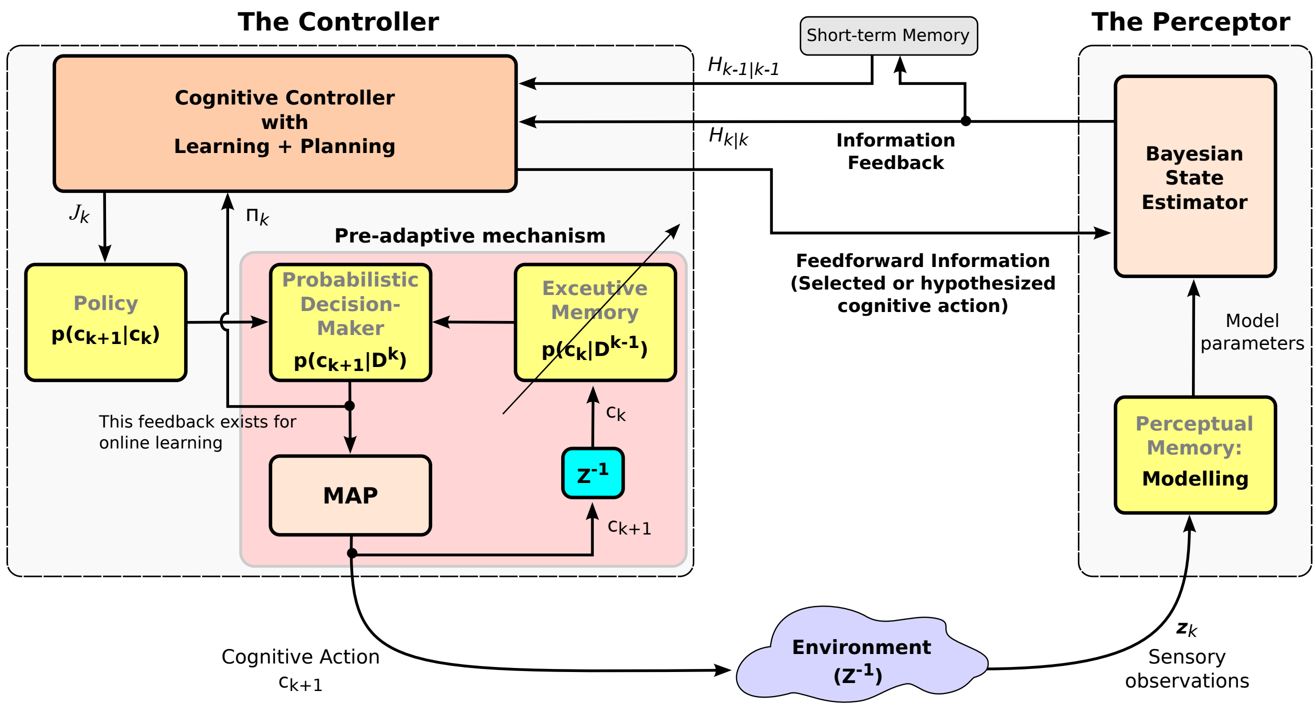

Fig. 1: Block diagram of a basic cognitive dynamic system. Notes: "MAP" stands for the *maximum a posteriori probability* rule, and Z^{-1} denotes global cyclic delay at both places in the diagram.

control is discussed in Section IV. An experiment, demonstrating the importance of perceptual as well as executive attention, is presented in Section V, with risk control in mind. Finally, Section VI summarizes the topics covered in the paper and related issues.

II. Cognitive Perceptor

A. Sparse Coding

When it comes to address the cognitive function of perception, *sparse coding* rooted in neuroscience, plays a key role. In a multilayer perceptor (not shown in Fig. 1), we find that at its top layer, the *relevant features* that represent the observables are easy to recognize, becoming easer as we go up the hierarchy higher. Solution of the sparse-coding problem rests on the following two components [6]:

- A *neural code* is introduced to define the feature vector that represents the observables.
- A *dictionary*, denoted by a rectangular matrix, is also introduced for the purpose of generating elements (e.g., Gabor wavelets) that are *non-orthogonal* with respect to each other; elements of the dictionary are updated from one global cycle to the next.

Unfortunately, because of the unavoidable presence of additive noise in the observables, the sparse-coding problem, operating on its own, is ill-posed in the Hadamard sense [7]. Particularly so when the signal-to-noise ratio is low. For the code to become well-posed, three conditions must be satisfied:

1) a solution to the problem exists;
2) the solution is unique;
3) most importantly, the unique solution is stable.

In its basic form, sparse-coding violates condition 1 because, by definition, it is under-determined. To satisfy conditions 1 and 2, the typical approach has been to invoke *Tikhonov's regularization theory* [8]. But, regularization by itself may not be good enough to satisfy condition 3, that is stability.

To resolve the issue of source separation (i.e., separating relevant features from irrelevant ones) in the perceptor of a cognitive dynamic system, strong arguments were made in [6] for the following statement:

> For the sparse-coding algorithm to be well-posed, there would have to be sufficient information in the observables, subject to the provision that the signal-to-noise ratio is not too low.

Herein, there is an increasing correspondence between predictive-coding formulation of information filtering and the adaptive response to fluctuations in the signal-to-noise ratio. Recently, it has been proposed that attention can be understood as optimizing the precision (i.e., inverse variance) associated with noise [9]. Practically, this proposition involves the use of precision weighted prediction errors, rather than precession encoded by the Kalman filter gain matrix. If, now, we associate signal-to-noise ratio with precision, there is a clear link between perceptual attention and perceptual inference, in which we have greater confidence. Furthermore, the Fisher information is the conditional precision (inverse variance) under linear and Gaussian assumptions. Accordingly, we may view the notion of inverse covariance or precision as an integral part of information filtering. Recognizing that Bayesian information is an inherent characteristic of cognitive perception and information filtering is a special case of Bayesian filtering, we may therefore introduce the following principle [6]:

> The performance of sparse-coding is improved under the influence of perceptual attention through the use of information filtering in a Bayesian sense.

This principle is justified on two accounts:

1) Since the ultimate objective of sparse-coding is to resolve the source-separation problem, the problem may be viewed as one of "decision-making."
2) In light of the basic principles of cognition discussed in Section I, we recall two facts: intelligence is distributed throughout the cognitive dynamic system (including the perceptor), and decision-making builds on attention.

It follows therefore that perceptual attention is indeed responsible for improving the performance of sparse-coding, which is a *new principle* in itself.

B. State Estimation

The relevant information extracted from the observables by the improved sparse-coding algorithm is itself defined by the relevant feature vector (i.e., set of wavelets) selected from the sparse-coding dictionary. Thus, these wavelets (model parameters) constitute the information fed to the Bayesian filter, whose function is that of estimating the *state* of the environment. The Bayesian filter could be linear, exemplified by the *Kalman filter* [10], or nonlinear exemplified by the *Cubature Kalman filter* [11], depending on the application of interest. In any event, the perceptor includes a second functional block, *state estimator*, as depicted in Fig. 1.

III. The Two-state Model

A. The Entropic State of the Perceptor

Examining the block diagram of Fig. 1, we may readily make two statements:

1) The perceptor sees the environment *directly*, which makes it possible for the perceptor to extract the relevant information about the environment from the observables.
2) On the other hand, the controller senses the environment *indirectly* via the perceptor.

Accordingly, for the controller to function properly (i.e., without having to burden Bellman's curse of dimensionality problem), the perceptor must have a "state" of its own. The key question is: How is this new state to be defined?

To address this crucial issue, we first recognize that regardless of how much effort is put into optimizing the state estimation computed by the Bayesian estimator, there will always be *state-estimation errors*. These errors are attributed to unavoidable imperfection in the perceptor as well as imperfection in modelling the state of the environment. The state-estimation errors so produced provide the basis for defining *feedback information* to be delivered to the controller by the perceptor. Recognizing that the cognitive dynamic system is essentially an information-processing machine, we look to the *Shannon entropy* [12] for a new measure that defines the state of the perceptor, hence the following statements:

- The entropic state provides the measure for the state of the perceptor.
- The more perfect the design of the perceptor is, the smaller will the entropic state be.
- No matter what we do, the entropic state will always be greater than zero.

Thus, the entropic state provides the needed feedback information for the controller from one global cycle to the next; hence, the cognitive dynamic system assumes the form of a *closed-loop feedback system*, which, in turn, makes the perception-action cycle a practical reality in a continuous manner.

B. The Two-state Model: Mathematical Formalism

The two-state model is an essential element in deriving the cognitive control algorithm, to be discussed in the next section. By definition, the two-state model embodies two states:

- The first one is the traditional *target state*, pertaining to a target of interest in the environment.
- The second one is the *entropic state* of the perceptor, discussed in part A of this section.

Mathematically, the two-state model of the cognitive dynamic system is described as follows:

1) State-space model of the environment, which embodies the following pair of equations:

$$\begin{cases} \text{Process equation:} & \mathbf{x}_{k+1} = \mathbf{f}(\mathbf{x}_k) + \mathbf{v}_k \\ \text{Measurement equation:} & \mathbf{z}_k = \mathbf{h}(\mathbf{x}_k) + \mathbf{w}_k \end{cases} \quad (1)$$

   where $\mathbf{x}_k \in \mathbb{R}^n$, $\mathbf{z}_k \in \mathbb{R}^m$ are the state and measurement (observable) vectors at cycle k, respectively; $\mathbf{f}$ is a vector-valued transition function, and $\mathbf{h}$ is another vector-valued function that maps the target state-space to the measurement space; both $\mathbf{f}$ and $\mathbf{h}$ are assumed to be Lipschitz continuous[1]; $\mathbf{v}_k$ denotes an additive process noise that acts as the driving force, evolving state $\mathbf{x}_k$ at cycle k to the updated state $\mathbf{x}_{k+1}$ at cycle $k+1$; finally $\mathbf{w}_k$ is the additive measurement noise.
2) Entropic state model of the perceptor, which is formally defined by the following:

$$\text{Entropic-state equation:} \quad H_k = \phi(p(\mathbf{x}_k|\mathbf{z}_k)) \quad (2)$$

   The H_k is the entropic state at cycle k in accordance with the state posterior $p(\mathbf{x}_k|\mathbf{z}_k)$ in the Bayesian sense, which is computed in the perceptor. As such, H_k is the state of the perceptor, and ϕ is a quantitative measure, that is, Shannon's entropy.

IV. Cognitive Control

In a sense, cognitive control may be viewed as the overarching function of a cognitive dynamic system on account of the function it performs in the system. To be more specific, we may define the function of cognitive control as follows [14]:

[1]In order to guarantee the existence and uniqueness of the solution to (1), both $f(\cdot)$ and $h(\cdot)$ are assumed to be Lipschitz continuous [13]; i.e., there exists $\lambda > 0$ such that $||f(x_2) - f(x_1)|| \leq \lambda ||x_2 - x_1||$ for all x_1 and x_2, with $||.||$ denoting the Euclidian norm, and likewise for $h(\cdot)$.

> To control the entropic state (i.e., state of the perceptor), the target's estimated state is expected to continue to be reliable across time.

As mentioned previously, the entropic state plays the role of feedback information, which couples the cognitive controller to the cognitive perceptor, as indicated in Fig. 1.

To elaborate more, cognitive control involves two processes: (a) executive learning and (b) predictive planning, whose combined aim is the formation of *policy*, for which we offer the following definition:

> Policy is the probability distribution of cognitive actions performed on the environment at the next cycle $k+1$, conditioned on the cognitive action selected at the current cycle k.

Formally, we may now write [4]:

$$\pi_k(c, c') = \mathbb{P}[c_{k+1} = c' | c_k = c]; \quad \text{with } c, c' \in \mathcal{C},$$

where $\pi_k(c, c')$ denotes the *cognitive policy* at cycle k, $\mathcal{C}$ is the *cognitive action-space*, c and c' are two cognitive actions, and $\mathbb{P}$ is a probability measure.

Naturally, the policy should pertain to the long-term value of cognitive actions, for the formulation of which we introduce the notion of *rewards*, defined as follows:

> Let $\Delta_1 H_k$ denote the *incremental deviation* in the entropic state from the preceding cycle $k-1$ to the current cycle k; hence, the formula:
>
> $$\Delta_1 H_k = H_{k-1} - H_k \tag{3}$$
>
> which may assume a positive or negative value. If $H_{k-1} > H_k$, then the incremental deviation is positive, on the other hand, if $H_k > H_{k-1}$, then the deviation will be negative.

We may therefore go one step further by introducing the *entropic reward*, denoted by r_k; it is formally defined at cycle k as follows [4]:

$$r_k = g_k(|H_k|, \Delta_1 H_k), \tag{4}$$

where g is a generic scalar-valued operator, which must retain the algebraic sign of $\Delta_1 H_k$. For example, the entropic reward may assume the following simple expression:

$$r_k = \frac{\Delta_1 H_k}{|H_k|} \tag{5}$$

In accordance with the condition imposed on r_k in (4), the reward at cycle k can assume a positive or negative value, which is clearly apparent in the example defined in (5). When the r_k assumes a negative value, it indicates "punishment." It should also be noted that in light of the defining equation (3), there must be a *short-term memory*, as indicated in the block diagram of Fig. 1.

A. Executive Learning in Cognitive Control

We are now formally ready to define a *value-to-go function*, denoted by $J(c)$ for the cognitive controller as follows [4]:

$$J(c) = \mathbb{E}^{\pi}[r_{k+1} + \gamma r_{k+2} + \gamma^2 r_{k+3} + ... \mid c_k = c] \tag{6}$$

where $\gamma \in [0, 1)$ denotes a *discount factor* that continually decreases the effect of future actions, and $\mathbb{E}^{\pi}$ denotes the expected value operator for which the expected value is calculated using the policy distribution π_k. It is important to note that the function $J(c)$ defined in (6) is *stateless*.

Let $\mathcal{R}(c) = \mathbb{E}^{\pi}[r_{k+1} | c_k = c]$ denote the expected immediate reward at cycle $k+1$ for the currently selected action c at cycle k. It can then be proven that the value-to-go function defined in (6) satisfies the following recursion [4]:

$$J(c) = \mathcal{R}(c) + \gamma \Sigma_{c'} \pi_k(c, c') J(c') \tag{7}$$

In order to have a *recursive algorithm*, we my express the recursion of equation (7) in the following *update* format:

$$J(c) \leftarrow \mathcal{R}(c) + \gamma \Sigma_{c'} \pi_k(c, c') J(c') \tag{8}$$

With learning algorithms in mind as it is typical in neural computation [7], we may introduce a *learning parameter* denoted by $\alpha > 0$, on the basis of which (8) may be formulated as follows:

$$J(c) \leftarrow J(c) + \alpha[\mathcal{R}(c) + \gamma \Sigma_{c'} \pi_k(c, c') J(c') - J(c)] \tag{9}$$

where the value-to-go function is now updated form one cycle to the next. The update in (9) is called the *executive learning algorithm*.

To summarize, this new algorithm in cognitive control has been derived by exploiting two basic ideas rooted in cognitive dynamic systems:

1) The *cyclic directed information flow*, which moves from one cycle of to the next under the first principle; the perception-action cycle.
2) The entropic state, which resides in the perceptor under the two-state model.

B. Predictive Planning in Cognitive Control

As already mentioned in this section, the executive learning algorithm is based on the influence of a selected action on the perceptor via the environment in each global perception-action cycle. This influence manifests itself in the entropic state of that global cycle. In addition to the executive learning process, the cognitive controller may also benefit from utilizing successive predictions of future entropic states. It is therefore desirable that another learning process similar to the executive learning algorithm be considered, but this time for the predicted entropic states pertaining to some *hypothesized actions*:

> In this second learning process, the value-to-go function based on *predicted* values of the entropic reward is called *planning*.

In other words, planning constitutes the second intrinsic process of learning in cognitive control.

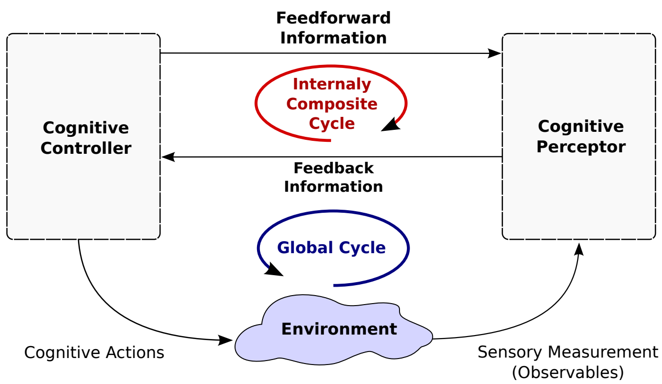

Fig. 2: Block-diagram illustrating the combined presence of feedback information as well as feedforward information links, the combined use of which makes the controller and the perceptor reciprocally coupled.

With predictive planning in mind, it follows that a feedforward link is also required in the design of the cognitive dynamic system, which is depicted in Fig. 2, but in a much clearer manner than it is in Fig. 1. The result of adding this feedforward link is an *internally composite cycle*, which bypasses the environment and permits the prediction of future rewards[2]. The feedforward information in each internally composite cycle is therefore a hypothesized future action, which is to be selected for a planning stage. Using this hypothesized action, the corresponding entropic state will then be computed in the perceptor, and with it, the planning process is initiated.

The complete algorithm for cognitive control that involves the combined use of executive learning and predictive planning was presented in [4]. In the current paper, the algorithm in [4] is expanded by using perceptual as well executive attention, to be discussed in the next section.

V. Risk Control: First Experimental Results

A. The Ideal Strategy for Risk Control

In the course of time operating in a relatively "stationary" environment, at each global perception-action cycle there will be two entirely different sets of action to consider:

a) **Short-term potential actions**, which are selected from the action library under the policy exercised by the cognitive controller.
b) **Long-term experiences acquired from the past**, which will have been stored in the executive memory of the *pre-adaptation mechanism* [15], which is depicted inside the controller in Fig. 1.

When, however unexpectedly, a disturbance occurs in the environment, particularly if it is severe, the cognitive dynamic system is "alerted" as a whole on two complementary accounts in an integrated manner:

i) Under the influence of the perceptual attention, the improved sparse-coding algorithm in the cognitive perceptor *tames* the disturbance by *attenuating* its power from one cycle to the next for the entire duration of the disturbance.
ii) Under the influence of the executive attention built into the pre-adaptation mechanism, *ideally* there would be two phenomena:
   - With the sudden jump in the entropic state due to the disturbance, the set of potential actions selected from the action library are deliberately *ignored* by the *probabilistic decision-making mechanism* in Fig. 1.
   - In place of the potential actions so ignored, the decision-maker looks to the past experiences stored in the executive memory as candidates for cognitive actions.

[2]In cognitive neuroscience, the internally composite cycle is referred to as the shunt [5].

Referring to Fig. 1, the probabilistic decision-maker computes the *combined distribution* pertaining to the two distributions, one on the left of the decision-maker and the other on its right. Furthermore, this combined distribution could be weighted in favour of the distribution on the left or that on the right. Finally, a *maximum-a-posteriori* (MAP) function is applied to the resulting combined distribution to pick the "best cognitive action" on the environment, by means of which the next global cycle resumes.

B. First Experimental Results on Risk Control

The experiment described herein is intended to demonstrate how indeed cognitive dynamic systems could satisfactorily control directed information flow in the presence of a severe disturbance. The experiment is concerned with the tracking of a falling object in a nonstationary environmental space, where the falling object experiences the disturbance described as follows. The disturbance is introduced by strengthening power of the system noise in the state-space model and then reducing it again down to its initial setting, all of which is done in a prescribed time duration in the manner illustrated in Fig. 3. Throughout the experiment, the falling object is tracked by a radar, under four entirely different structures:

i) The radar tracker uses a cubature Kalman filter (CKF).
ii) The cognitive controller employs the CKF in its perceptor but with no attention.
iii) The cognitive controller is as described in ii), but this time it operates under the influence of perceptual attention
iv) Finally, the cognitive controller is fully equipped by operating under the combined influence of the perceptual as well as executive attention.

The influence of attention added to the perceptor operates in a manner similar to the way in which it was described in Section II, wherein the attention builds on a local perception-action cycle.

However, to simply matters for this first experience on risk control we follow a procedure built on multilayer perceptrons rooted in neural computation. To elaborate, probability distribution of the system noise is adapted on a cycle-to-cycle basis by observing a window of past residual errors available from the CKF. Under this scenario, a popular approach to estimate the parameters of a state-space model is the expectation-maximization (EM) algorithm, described in [16].

In this paper, however, we opt to use an approach based on neural computation. According to [17], residual errors[3] of a Kalman filter form a white sequence when the filter is set up with correct model parameters. With this point in mind, we simplify matters by assuming that the amplitude spectrum of the residual errors due to the CKF is expected to be "flat for a long sequence of errors." On the other hand, if the filter is set up with imprecise model parameters, whiteness of residual errors does not hold. Thus, in our experiment, we attempt to adapt the distribution of system noise by analyzing amplitude spectra of successive residual errors. For this purpose, we use a multilayer perceptron that takes the amplitude spectrum of a window of successive residual errors as its input; then, it identifies the extent to which the current value of system noise variance should be increased or decreased at each iteration[4].

To add the influence of executive attention on the controller part of the cognitive dynamic system, we use an approach that is similar to the one used for perceptual attention, namely, through the use of a *long-term memory* within a local feedback loop. This long-term executive memory is adapted in a cyclic manner: With every new action that is performed on the environment, the executive memory is updated capturing knowledge about the working environment, with which the cognitive controller is interacting. The executive memory provides knowledge about the action space in a probabilistic manner, describing how likely each one of those actions were to be selected in the course of all interactions that the controller had with the environment, overall independent experiments in the past, representing long-term past experiences.

As depicted in the left-hand side of Fig. 1, output of the executive memory is then combined with the policy that is generated by the cognitive controller at each cycle, hence forming a new probabilistic description for possible actions. The end result will be a new policy that considers both the long-term experience captured in the executive memory and the short-term experience that is achieved during the current experiment that is being attended. Finally, at each iteration, the feedback loops (both global and local) are closed by selecting the most likely action from the policy and feeding that cognitive action to the environment and executive-memory.

Continuing on with the experiment, it is important to note that a disturbance with a ratio of 30 dBs at its peak point is applied by increasing the magnitude of system noise measured with respect to the part attributed to stationary system noise; clearly, this is a very severe disturbance to deal with. With this disturbance in mind, the results of the experiment involving the different tracking structures are plotted in Fig.4. Careful examination of the results plotted herein are summarized as follows:

i) The CKF, working as the target tracker on its own, is a complete failure as soon as the disturbance starts to dominate the observables.
ii) The cognitive controller with no attention, tracks the target nicely. But, as soon as the disturbance occurs, the target trajectory moves upward until it reaches the tip of the disturbance; thereafter, it loses control and trails along in a manner somewhat similar to the CKF under the first scenario.
iii) Next, the cognitive controller with perceptual attention follows the trajectory of scenario ii), but this time the perceptual attention helps the controller to start recovering from the disturbance once its tip is effectively reached.
iv) Finally, the fully equipped cognitive controller performs the best among all the four trackers, due to the combined use of perceptual as well as executive attention, which should not be surprising.

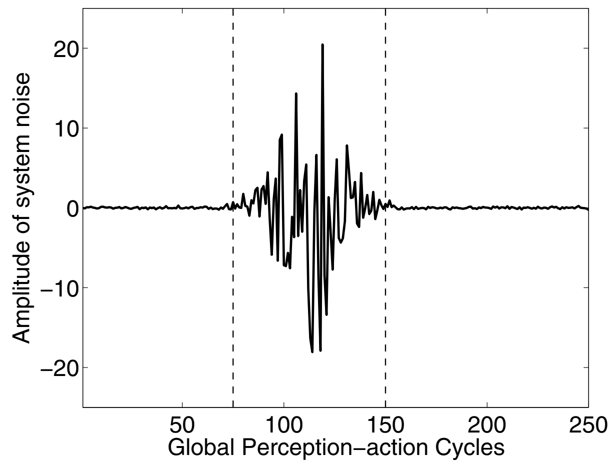

Fig. 3: The overall amplitude of system noise, including a sever disturbance for the entire duration from 75 to 150 cycles.

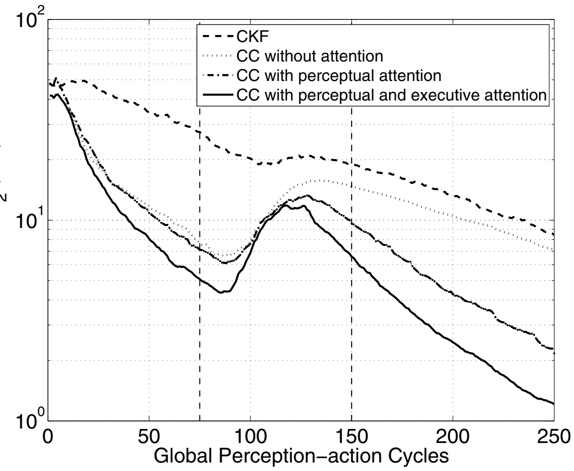

Fig. 4: Learning curves of the four different trackers; Monte Carlo simulations where used for generating each one of the learning curves.

As stated in the title of this section, the results presented herein on risk control due to the unexpected occurrence of a sever disturbance are brand new and therefore noteworthy. Being the first step toward solving the risk control problem, there is more to be done to improve the design of the system in its perceptual as well as executive parts, including the pre-

[3]By definition, residual error is the difference between an actual measurement and its previously predicted value.

[4]The window size is 20 samples and the multilayer perceptron has two hidden layers with 48 and 32 neurons, respectively.

adaptation mechanism. This will be done to achieve the ideal scenario described in part A of this section as closely as possible.

VI. Discussion

A. Summary of Cognitive Control in Cognitive Dynamic Systems

Recognizing that cognitive perception and entropic state play key roles of their own in the make-up of cognitive control, they are both included in this summary:

- Cognitive Perception:
  a) Source-separation for modelling the behaviour of observables, wherein the relevant information in the environmental observables is separated from the irrelevant information, which is achieved under the influence of perceptual attention.
  b) Bayesian estimation of the state of the environment, which is realized by operating on the model parameters computed under point (a).
- The two-state model:
  The model is made up of the *traditional state-space model* for target-state estimation, and the *new entropic state of the perceptor*. The entropic state is defined as a measure for lack of information in the state posterior, which is computed in the perceptor. Most importantly, the entropic state provides the feedback information from the perceptor to the controller.

B. Cognitive Control: A New Way of Thinking

The realm of control theory, as we know it today and for ever more, is about controlling the *state of the environment*, which naturally embodies estimation theory as an integrated part of the system. Broadly speaking, the literature of control includes adaptive control, stochastic control, fuzzy control, intelligent control, and others, each of which has established a legacy of its own in the literature.

On the other hand, cognitive control in cognitive dynamic systems is about *controlling the state of the perceptor*, which is defined as the entropic state. In a related manner in words: the function of cognitive control is to control the directed information flow in the system on a global cyclic basis. Cognitive control is therefore a new contribution to the literature. It is worth mentioning that in practice, both state control and cognitive control may exist side by side, specially so when we mimic the brain.

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