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INTELLIGENT CONTROL USING ONLINE STABILITY-BASED KNOWLEDGE REPRESENTATION

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Abstract. In this paper, a new concept for intelligent control of stability in technical systems is proposed based upon the Situation-Operator-Model-based cognitive architecture of autonomous system. The novelty of the proposed method is that the controller can accomplish the task of control without knowing the detailed structure of the system plant, nor its physical behavior, because all the information needed in the control are gained by studying the phase portrait during the interaction process between the system and the environment, with the help of the static knowledge about the stability and the goal of control. Furthermore, the performance of the control is improved according to the experiences of the controller which are gained by the cognitive functions and stored in the learned knowledge base. These two features are realized within the framework built up by Situation-Operator-Model approach to represent the reality. An example of stabilizing a pendulum with unknown impulse disturbances is utilized to illustrate the approach.

1 Introduction and motivation

In control science one of the main research goals has been always the enhancement of the controller's ability to adapt variable situations either in the plant or in the environment, which is strongly connected to the goal of improving controller's ability dealing with imperfect models, model uncertainties, external disturbances etc.. Great progresses have been made by the classical control approaches such as robust control, adaptive control during the process conquering this aim. But these methods have their own limitations and fail when dealing with new and typically unknown situations beyond their programmed behaviors.

Therefore, instead of directly implementing or engineering system's behavior by fixed rules, it is very much desired that the controller can behave 'intelligently' to handle the various conditions. The term 'intelligent' implies the controller can perceive its environment and take rational actions to achieve the goal of control by acquisition, organization, and use of knowledge during the process of interaction with the environment, which in combination with the ability to represent these inside the considered unit is known as cognition [1, 2]. In other words, adding cognitive capabilities to technical systems will be very useful for the technical systems to gain high autonomy.

Cognitive technical systems are capable of perceiving the environment as well as aggregating knowledge and structuring this knowledge autonomously. According to the definition in [3], cognitive systems are characterized by their learning capabilities, representation of the relevant aspects of the environment, and their ability to realize situated behavior. The intelligence emerges from the ability to learn by gaining and structuring knowledge to construct a mental model and to use this knowledge in next interactions. From this point of view, the cognition process includes the following two aspects:

- representation inside the system allowing the mapping from the outside world to the internal mental model and
- the realization of cognitive functions and procedures (i.e., preception, interpretation, planning, execution, learning, etc.).

The classical description of systems like state space representation are insufficient and have difficulties in describing the cognitive behavior. As a result, a number of other methods have been developed to model cognition on a range of tasks, for example, ACT-R [4, 5], Soar [6, 7], and EPIC [8], to name the most well known symbolic architectures. These cognitive architectures are applied in the robotic researches. In recent years, a system-theoretical modeling approach has been proposed in [9], where a detailed situation-operator modeling (SOM) kernel is presented. SOM, developed to model the Human-Machine-Interaction, is understood as a structuring approach modeling the interaction of intelligent systems in general. Furthermore, based on this understanding, an architecture of a cognitive autonomous system is proposed [10] and experimentally evaluated in the application to a mobile robot building and updating the mental model during the interaction with the environments [3].

This contribution details for the given mechanical example the structure of knowledge base in the SOM-based cognitive architecture proposed in [10], and applies the modified architecture to realize the concept of cognitive stability control in a classical control system. The proposed approach requires no further information than the states of the system plant. All the information needed by the controller are gained by studying the phase portrait during the interaction between the system and its external environment.

The controller uses a static knowledge base to learn the system's features and help the cognition functions to generate control. The static knowledge base contains the understanding of stability expressed in phase portraits, how to estimate the disturbance from phase portraits, and the goal of control. Besides, the controller has a second knowledge base where learned (or interactive) knowledge is stored, which is necessary for the cognition functions to improve the performance of control. The knowledge in the learned knowledge base is changed within the process of the interaction between system and environment. These two features enlarge the range of the usage of this proposed method.

The concept is illustrated with an example of stabilizing a simple pendulum with unknown disturbances. The paper is organized in the following way: firstly, in Section 2 the architecture of SOM-based cognitive system will be briefly introduced. In Section 3 the task of cognitively stabilizing the pendulum with unknown disturbances is described. Thirdly, Section 4 introduces how to detect the boundary of the stable region using only phase portraits, which is an important part of the static knowledge base. Then in Section 5 the formulation of the proposed controller under the modified SOM-architecture is explained in detail. The next Section is about the realization of the proposed approach, with the simulation results included. Conclusions are made in the final Section of this paper.

2 Brief introduction to SOM-approach

2.1 Situation-Operator-Model

Inspired by previous ideas of the situation calculus and of the event calculus, the Situation-Operator-Model is a uniform and homogenous modeling technique describing human learning, planning, and acting based on an underlying representation level [9]. Core of the SOM is to interpret facts and changes of the considered parts of the real world as a sequence of scenes which are changed by actions. Because of its generality in describing the real world, SOM can be used to not only realize technical supervisors to monitor the human-manchine interaction behavior but also, more importantly in this contribution, develop a cognition-oriented control to build autonomous systems.

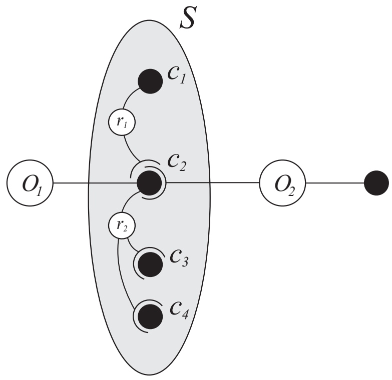

Figure 1: Graphical notation of SOM [9]

The key items in SOM-methods are: scene, action, situation, and operator [9]. The term 'scene' denotes a problem-fixed moment independent from time; 'operator' denotes effects and actions which change the scene; and the term 'situation' is used to describe the internal structure of a system and to model the scene. As shown in Fig.1, the situation S consists of characteristics c_i and a set of relations R denoting the inter-connection between characteristics. To describe the relations r_j, known problems-related modeling techniques, such as ODEs, DAEs, algorithms, or even graphical illustrations can be used [9].

The operator O, defined as functional term, models internal connections of situations as well as changes between situations. Therefore, the dynamical world results in a sequence of different situations connected by relevant operators respectively. By this way the structure and the dynamics of considered changeable reality is modeled within the framework of SOM [9].

2.2 Architecture of SOM-based cognitive system

The schematic representation of the SOM-based cognitive architecture is given in Fig.2. The signals from the sensors are pre-filtered firstly and compressed by extracting characteristics using the situation interpretation module. On the representational level, the SOM approach is used to structure the reality and to map this structure into the mental model of the system to enable planning and learning. The actual situation, the previously applied operators and the previous situations are stored. This mechanism can be understood as short-term memory. One or more goals are provided to the system and have to be translated into the SOM description. While the planning module requests information from the knowledge base, the learning module modifies and updates the knowledge base, which represents the learning capability of the autonomous system. Furthermore, the cognitive functions organize the situation interpretation, whose technical realization is novel.

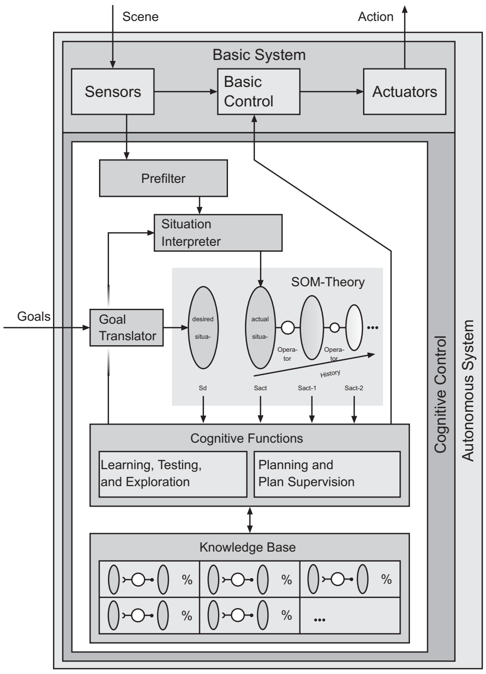

Figure 2: Architecture of SOM-based cognitive autonomous system [10]

The presented architecture builds the framework for autonomous and cognitive-based behaviors, where the mental model of the system is maintained and refined by cognitive functions (inner-processes), as illustrated in Fig.2. For the planning processes, the knowledge base (the implementation of the mental model) is searched for a sequence of operators to reach a given goal. The interaction with the environment yields facts about the outside world, and the ability to modify its knowledge base enables the robot to cope with changing goals and a dynamic environment.

3 Cognitive stabilization of a pendulum

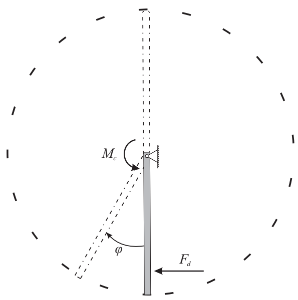

Figure 3: Pendulum example: Stabilizing the equilibrium in lower position

The stabilization of a pendulum is a classic control task because of its strong nonlinearities. As shown in Fig.3, the pendulum can freely rotate around its fixed end. In this paper, the equation of motion of the pendulum in state space is as follows

$$\begin{aligned} \dot{x}_1 &= x_2\,, \\ \dot{x}_2 &= -10\,sin(x_1) - x_2 + F_d\,, \end{aligned} \tag{1}$$

where x_1 and x_2 are the two states denoting the angular displacement φ and the angular velocity $\dot{\varphi}$ respectively. The system is perturbed by an impulse disturbance, denoting as F_d. From the previous knowledge it is known that the pendulum has two equilibrium points: the lowest position, and the inverted position. In this paper, it is assumed the stable working area of the pendulum is the neighborhood around its lower position. The control task is to suppress the disturbance caused by an unknown impulse force to prevent the pendulum passing its inverted position which will lead to instability.

The problem to be considered is a classical and old task in control, used here as an example for illustration. In this paper it is supposed that the pendulum's structural information, such as the weight, length and so on, is unknown.

The two actual states, the angular φ and the angular velocity $\dot{\varphi}$, are assumed measurable. This means the controller should learn the critical position of stability by itself and to react with the proper value of actuation to keep the pendulum in the stable working area when the system is perturbed by unknown disturbances. In Fig. 4 it is shown the phase portrait of this system under an unknown disturbance without control.

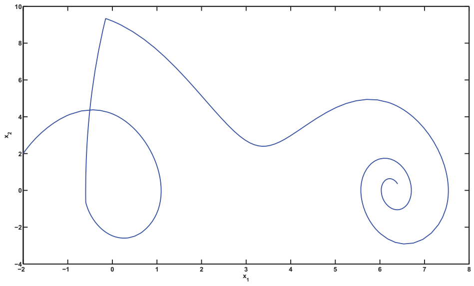

Figure 4: Phase portrait of pendulum under disturbances without control

4 Detect stability features during interaction

Because phase portraits require no more than the states of a motion but can provide very good qualitative information about stability, when only measurements of states are known (assuming full observability of the considered system), it is very suitable to adopt phase portraits as the 'raw' representation of the system dynamical behavior.

For a simple pendulum with damping, it is well known that its phase portrait is dominated by two kinds of nodes: stable focus and saddle points S_p, which are sequenced one after another, as shown in Fig.5.

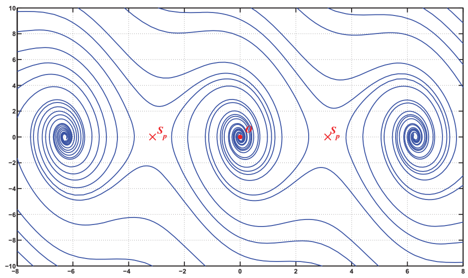

Figure 5: General illustration of a pendulum's phase portrait

From the energy point of view, systems will leave the original attractive region if the potential energy of the system is passing its local maximum. In the case of the pendulum, the local maximum of the potential energy corresponds to the saddle point. Thus, if it is detected that the trajectory is passing saddle points, it means that the system is leaving the attractive region of its former equilibrium point. So the two saddle points S_p next to the origin in the phase plane can be seen as the boundary of the local stability.

The problem now is how to find the two saddle points within the process of the interaction between the pendulum and its environment. By studying the phase portrait of the pendulum, it can be concluded that the phase trajectory will reach its local minimum when passing saddle points, if the state x_2 is greater than zero, and reach its local maximum if the state x_2 is smaller than zero. This feature can be used as criterion of instability to detect the boundary of the stable region.

It is assumed that in the beginning the pendulum is running freely near the origin without any input, so the pendulum will reach the saddle points only when it gains enough energy from the disturbances. Without disturbances, there will be no hints to the controller to know about the position of saddle points. In other words, without studying the interaction between the disturbances and the pendulum, the detection of the positions of saddle points can not be realized. From this point of view, in this problem the system stability features can only be learned from the interaction.

5 Formulation of the controller based on SOM architecture

5.1 Structure of the SOM cognitive-based controller

Specified into the particular problem in this paper, the architecture developed in [10] is modified slightly in order to be used in this example, as shown in Fig.6.

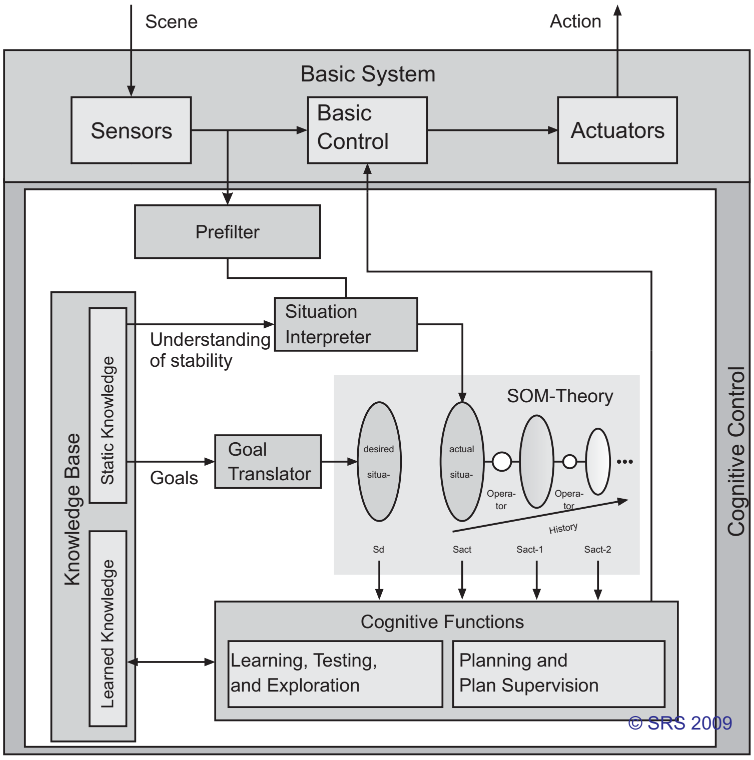

Figure 6: Modified SOM-based structure of the cognitive controller

The difference comes from the structure and the utility of the knowledge base. Here the knowledge base consists of two parts: the static knowledge base and the learned-knowledge base. The static knowledge base contains knowledge that will not change when the system is running, such as the understanding of stability in phase portraits, goal of the control. The learned-knowledge base contains nothing in the beginning, but will gain the knowledge from the interaction, such as the boundary of the stable region and the experienced control, to help the cognitive functions to improve the controller's performance. The whole process is like this: the controller is taught some knowledge in advance, and then the controller uses what it has been taught to gain new knowledge, and in turn the new knowledge is utilized by the controller to better accomplish the task .

Firstly, the pre-filter takes the measurements of the states, compresses the signal information from phase portraits into the SOM form, and transfers the current situation to the situation interpreter. Given in advance the static knowledge base about how to understand stability, the situation interpreter can detect stability features of the system as a new characteristic in the situation, and give out a stability judgement. The cognition functions compare this judgement and the desired stable situation, and then generate a suitable feedback control to the basic system, by which the control loop is formulated.

In the last step of the loop, the generated solution with respect to certain disturbance is stored in the learned-knowledge base. It is not necessary for the cognition functions to find the perfect control at one time. But the cognition functions should give out a better solution for the same situation compared with the solution generated at former times. The improvement is made according to the former solutions stored in the learned-knowledge base. When a better solution is made, it is again stored in the learned-knowledge base and replaces the older ones which means that as long as there is possibility for the cognitive function to improve the control, the learned-knowledge base is always changing interactively.

5.2 Situation-Operator-Model of the pendulum example

The essential part of this architecture is the description of the interaction with the environment as situation-operator-model. To transfer this framework to the stability control of the pendulum, the characteristics of the pre-filtered situation have to be defined in advance and not changeable by the system. The scene has to be modeled as a situation according to the sensing capabilities of the system, and all possible actions which depend on the actuators of the system have to be modeled as operators.

In the pendulum example, the scene is the measurements of actual states from sensors. The pre-filter compresses the phase trajectory in the form of situation model as pre-filtered situations; and then the pre-filtered situation is further detailed by the situation interpretation module where the parameters for new characteristics are generated by applying a set of relations.

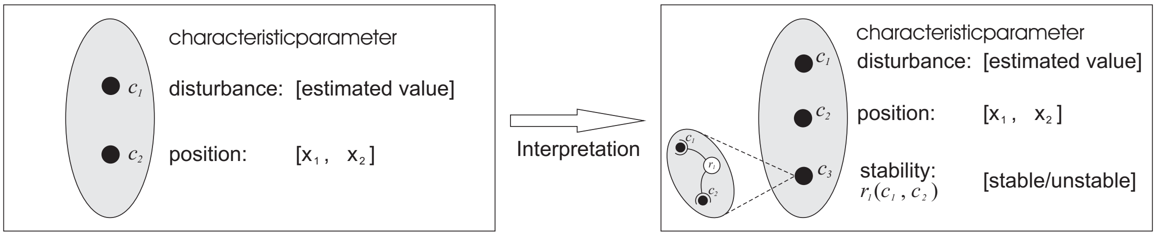

Figure 7: From pre-filtered situation to interpreted situation

As shown in Fig.7, the predefined situation contains two characteristics: estimation of disturbance c_1 and the current position c_2 in the phase plane. By applying the knowledge detecting stability features, new characteristic c_3 about information of stability will be generated in the interpreted situation. The detected stability feature and the causal relation r_1 will be stored in the knowledge base.

The basic function of the actuator in this example is to implement an impulse torque to bring the pendulum back. Therefore, the operator in the SOM of the pendulum has a very simple structure: depending on the characteristics (c_1, c_2, c_3) of current situation, the magnitude and the direction of the control, as the elements of operator O_T, are obtained from the communication with cognitive functions, and will change the characteristic 'position' in the following situation, as shown in Fig.8.

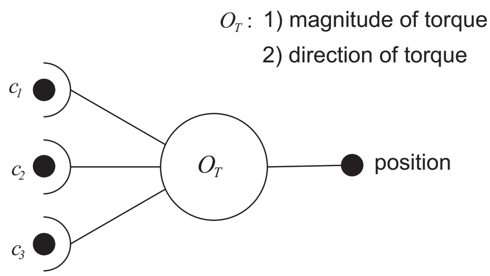

Figure 8: Mental operator of the pendulum

6 Realization of control

As mentioned in Section 5.2, the operator has two characteristics: the magnitude and direction of the control force. As for the direction, it can immediately be determined when the boundary of the stable region is determined because it should always point to the direction inwards to the region. The magnitude is determined by a searching technique with communication to the learned knowledge base.

As x_2 is the angular speed, ${x_2}^2$ can be used as an estimation of kinetic energy at a time instant and should have relation

$$E_k = p\,{x_2}^2\,, \tag{2}$$

with the true kinetic energy E_k, where p is a positive unknown parameter. Because the disturbance is an impulse and lasts for only a very short time, according to the law of kinetic energy, it is reasonable to use $\hat{F}_d$,

$$\hat{F}_d = \frac{\Delta {x_2}^2}{\Delta x_1}\Big|_{\Delta t = t_s - t_b}, \tag{3}$$

as the estimation of the disturbance, where Δ denotes the difference calculation, t_b and t_s are the starting and ending time of disturbance respectively. The absolute value of $\hat{F}_d$ is used as the initial value of the magnitude used in the seeking process for the final proper magnitude of the control.

A complete control process is shown in Fig.9. The system is disturbed at time $t = 2s$ and the impulse disturbance is estimated when it is over. The controller detects the phase trajectory is passing a saddle point when $t = 3.2s$, and implement the first control with the initial magnitude same as the estimation of disturbance, denote as $\hat{F}_{d_1}$. Clearly the magnitude is too great for a suitable control, for it makes the phase trajectory go to another saddle point, shown in the case when $t = 4.5s$. At the time when the situation interpreter detects the second saddle point,

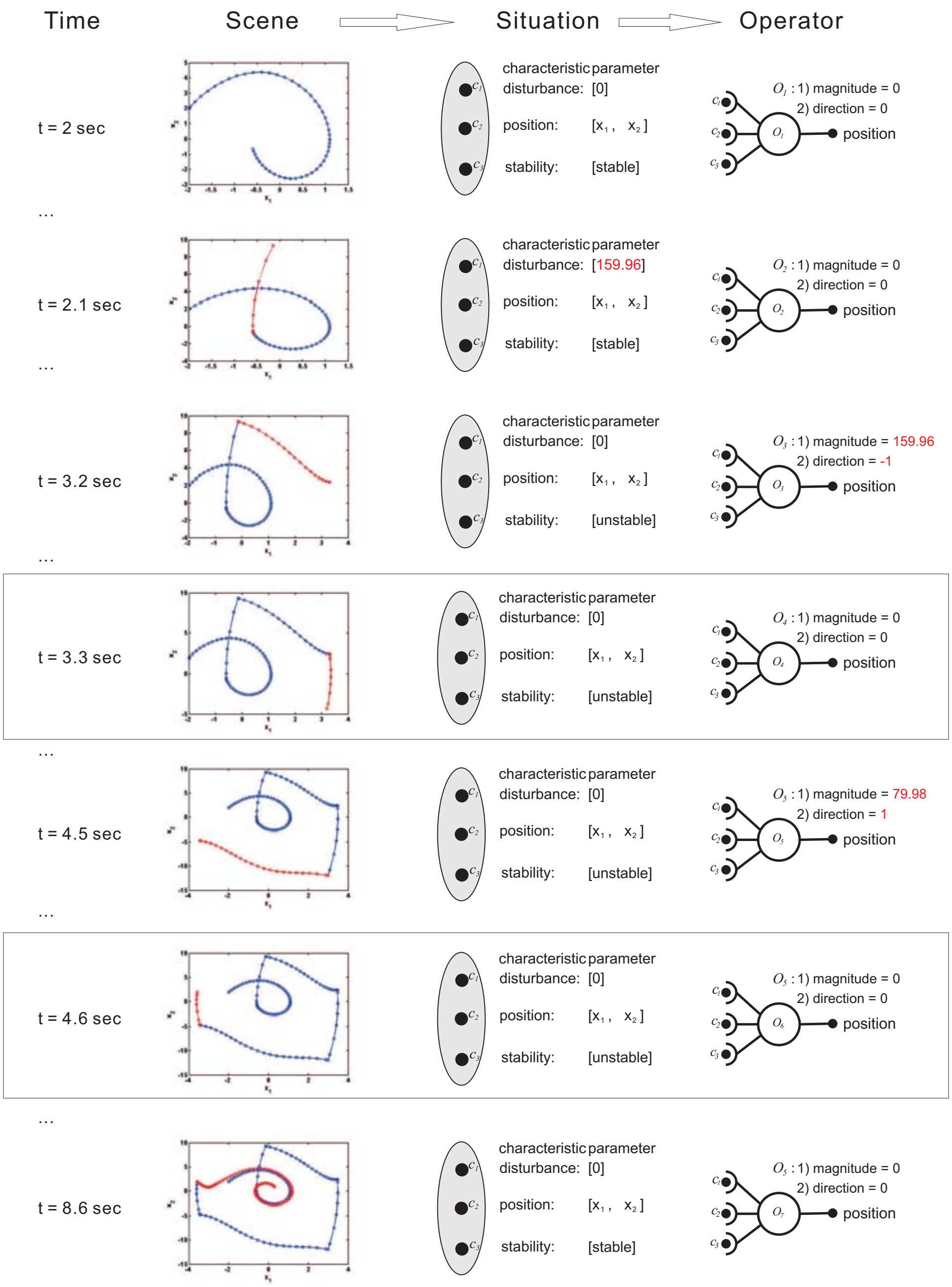

Figure 9: An example of a successful control sequence

a second control with the magnitude half of the estimation of disturbance, $\hat{F}_{d_2}$, is implemented, which brings the system back to the stable region.

The control in Fig.9 is successful but not perfect. Because it needs two times to bring the pendulum back to the stable region. To improve the control next time, the whole process of this control is stored in the learned knowledge base. Next time when the same disturbance occurs, the cognitive function will look up the knowledge base, but utilize $\frac{1}{2}(\hat{F}_{d_1}+\hat{F}_{d_2})$ as the initial magnitude. The newly generated control needs only one time to bring the pendulum back, which means the control is improved. The improved case is shown in Fig.10.

In fact, the searching methods for the most suitable magnitude so that the actuator is driven for only one time has the similar mechanism with the Binary-search method which is used to solve equations numerically. The magnitude at the ith iteration, $\hat{F}_{d_i}$, can be expressed as

$$\hat{F}_{d_i} = \frac{1}{2}(\hat{F}_{d_{i-1}} + \hat{F}_{d_{i-2}}). \qquad (4)$$

After several iterations, the magnitude will converge to the region inside which the value is suitable to realize one-time control. This searching process is graphically illustrated in Fig.11.

It is possible to stabilize the pendulum before the magnitude suitable for one-time control is found, just as the

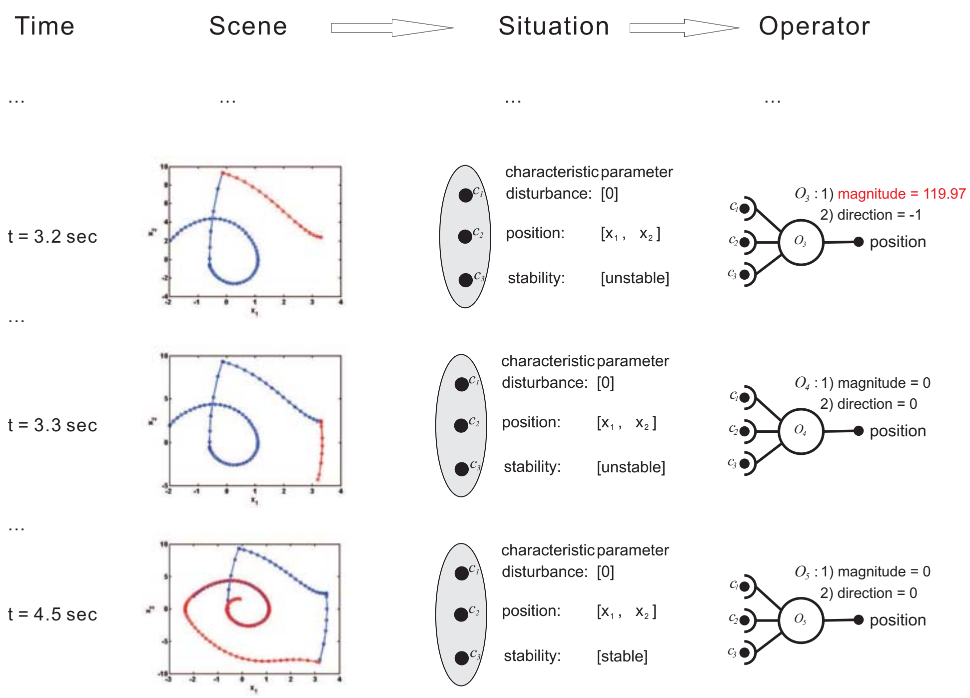

Figure 10: Improved control sequence

situation in Fig.9. But the interaction history of the former control will be stored as the gained knowledge in order to help the searching algorithm to find the suitable control magnitude with which only one time of actuation is needed to fulfil the control goal, by which the cognitive-based control of the pendulum is realized.

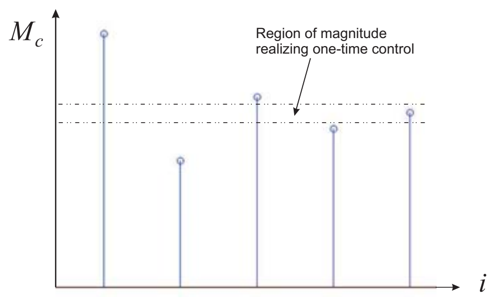

Figure 11: Illustration of searching for suitable control

7 Conclusion

This contribution has presented a concept of cognitive-based stability control using a specific architecture of SOM-based cognitive autonomous system, illustrated with an example of stabilizing a pendulum with unknown impulse disturbances. The proposed control has a knowledge base consisting of two parts: static knowledge base and learned (or interactive) knowledge base. The controller does not have to know the detailed structure of the system plant, nor its physical behavior, because all the information needed in the control are gained by studying the phase portrait during the interaction process between the system and the environment by utilizing the static knowledge about the stability and the goal of control. The learned knowledge base is utilized by the cognition functions to store the experiences of control which are used to improve the performance of the controller. The next step of this work is to apply the proposed approach to a more complex system.

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