The Fourteenth International Symposium on Artificial Life and Robotics 2009 (AROB 14th '09),
B-Con Plaza, Beppu, Oita, Japan, February 5 - 7, 2009

Making Decision in Two-Stage Identification System with Knowledge Updating

J. Swiatek, K. Brzostowski
Wroclaw University of Technology
Institute of Informatics
Wyb. Wyspianskiego 27, 50-370 Wroclaw, Poland

Abstract

In the paper an algorithm for knowledge updating in adaptive system to select scenario has been proposed. Taking into account specific character of the process, two-stage identification approach is used. The first stage is built for diagnostic purpose i.e. estimated parameters of the first-stage's relationship is utilised to make a decision at the second stage. Proposed algorithms to select scenario, at the second stage, rests on extracted knowledge from human expert and effects of diagnosis.

1 Introduction

Most of real control plants are strongly non-linear and uncertain due to measurement disturbances. Hence, it is difficult or sometimes even impossible to work out an exact mathematical model of the plant. Nowadays many approaches to control or support making decision do not require direct description of the process in order to work properly. We pay attention to those which are based on expert's knowledge.

Another way to cope with non-linearity and uncertainty is application of adaptive techniques in designing systems. In spite of the fact that it has been proposed three decades ago, it is still widely used.

1.1 Support making decision system

In the article the problem of building rehabilitation plan for patients is considered. The tasks can be decomposed into few stages which are shown in Fig. 1 and described in details in next paragraphs.

The first stage (*O1*) is used to asses the current state of the object and referring to biomedical problem of the paper and can be connected with making diagnosis.
Object at this stage is described by the vector of parameters $\mathbf{a_1}(k_1)$ and model $\Phi_1(y(k_1 - 1), \pi_1(k_1); \mathbf{a_1}(k_1))$. Measured signals $\pi_1(k_1)$ and $y(k_1)$

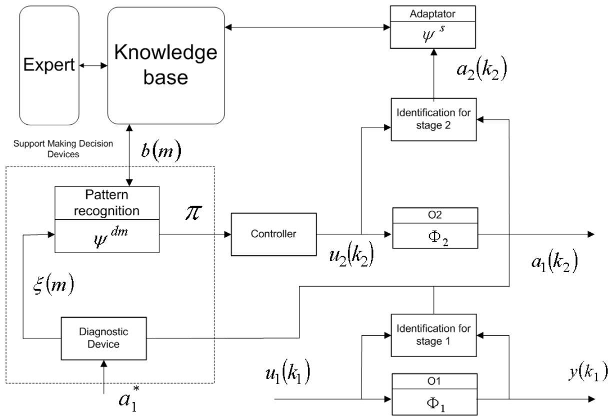

Figure 1: Support making decision system with knowledge updating and two-stage identification approach

are used only to determine values of model's parameters $\mathbf{a_1}(k_1)$ (identification at the first stage).

The second one (denoted as *O2*) plays the role in establishing the relationship between stimulation (exercises) and internal muscle's parameters $\mathbf{a_1}(k_1)$ which are calculated at the first stage. As it was mentioned proposed algorithms to select scenario based on *pattern recognition* approach and to make a proper decision the learning sequence is needed.

The main goal is to bring values of these parameters to desired $\mathbf{a_1^*}$. In order to do this, process at the second stage is employed. Its control action is denoted by $\pi_2(k_2)$ and model $\Phi_2(\mathbf{a_1}(k_1-1), \pi_2(k_2); \mathbf{a_2}(k_2))$ describes its influence on values of parameters $\mathbf{a_1}(k_1)$ of the model $\Phi_1(\cdot, \cdot; \cdot)$. We assume that model $\Phi_2(\cdot, \cdot; \cdot)$ (dependent on parameters $\mathbf{a_1}(k_2)$) approximates real relation between $\pi_2(k_2)$ and $\mathbf{a_1}(k_2)$. Controller performs sequence of actions $\pi_2(k_2)$ (scenario) chosen by the decision making device. Decision about scenario to be used is made on the basis of difference $\xi(k_2)$ between current values of parameters $\mathbf{a_1}(k_1)$ and desired ones $\mathbf{a_1^*}$. Scenario is selected from the knowledge base containing set of prespecified scenarios together with rules describing suggestions of their usage. For different current values of $\mathbf{a_1}(k_1)$ and desired $\mathbf{a_1^*}$, different control scenarios are proposed by well-known *kNN* rule.

Presented scheme has straightforward interpretation as a rehabilitation process. Model on the first stage represents a patient [2], model on the second stage describes influence of rehabilitation exercises on the state of the patient, decision maker together with knowledge base represents a physician and controller is a therapist. Adaptation and knowledge updating means that physician learns by experience.

2 Problem formulation

Let us consider that a set of accessible control actions (which are called *scenarios*) is denoted as Π and has a following form:

$$\Pi = \{\pi_1, \pi_2, \ldots, \pi_H\}, \tag{1}$$

where H is the number of all scenarios.

Each scenario is composed by make the most of instructions stored in finite set: $U_2 = \{u_{21}, u_{22}, \ldots, u_{2L}\}$. Where L is the number of all available instructions.

Taking into account it is possible to show the structure of single scenario: $\pi = \left(u_{2l_1}, u_{2l_2}, \ldots, u_{2l_M}\right)$. Where M is the instructions' number used to combine scenario.

Now, let us define function $d^{dm}(\cdot, \cdot)$ to measure distance between current value $\mathbf{a_1}(k_1)$ and desired $\mathbf{a_1^*}$:

$$\xi(k_2) = d^{dm}\big(\mathbf{a_1^*}, \mathbf{a_1}(k_1)\big). \tag{2}$$

It was supposed that the value of the parameter $\mathbf{a_1}(k_1)$ is known and was determined as a result of resolving identification task at the first stage [2].

Process of planning rehabilitation for spastic people can be formulated as the making decision problem. As a result of solving the multi-stage decision process it is gained following sequence:

$$\big(\pi(1), \ldots, \pi(K_2-1); \xi(1), \ldots, \xi(K_2)\big). \tag{3}$$

It is clear that the number of all admissible sequences may be large. The problem is to rate them and choose optimal by using performance index. Let us define following performance index Q^{dm} written below:

$$Q^{dm}\Big(\pi(1), \pi(2), \ldots, \pi(K_2-1); \xi(1), \xi(2), \ldots \\ \ldots, \xi(K_2)\Big) = \sum_{k_2=1}^{K_2} q^{dm}\Big(\pi(k_2), \xi(k_2)\Big), \tag{4}$$

where $q^{dm}\Big(\pi(k_2); \xi(k_2)\Big)$ is local assessment of decision in $k_2 - th$ stage for $\xi(k_2)$.

Applied defined criterion function (4) for sequence (3) leading to optimisation task:

$$Q^{pd}\Big(\pi^*(1), \pi^*(2), \ldots \\ \ldots, \pi^*(K_2-1); \xi(1), \xi(2), \ldots, \xi(K_2)\Big) = \\ = \min_{\pi^*(1), \pi^*(2), \ldots, \pi^*(K_2-1) \in \Pi} Q^{pd}\big(\pi(k_2), \xi(k_2)\big), \tag{5}$$

and for stochastic plant:

$$\mathbb{E}\Big[Q^{pd}\Big(\pi^*(1), \pi^*(2), \ldots \\ \ldots, \pi^*(K_2-1); \tilde{\xi}(1), \tilde{\xi}(2), \ldots, \tilde{\xi}(K_2)\Big)\Big] = \\ = \min_{\pi^*(1), \pi^*(2), \ldots, \pi^*(K_2-1) \in \Pi} \mathbb{E}\Big[Q^{pd}\big(\pi(k_2), \tilde{\xi}(k_2)\big)\Big], \tag{6}$$

where $\tilde{\xi}(k_2) = g_w\Big(\xi(k_2), w(k_2)\Big)$. Function $g_w\Big(\cdot, \cdot\Big)$ describes influence of the disturbance $w(k_2)$ on $\xi(k_2)$. In consequence, as a solution of formulated above optimisation task (5 and 6) it is given decision making algorithm written below:

$$\pi^*(k_2) = \psi^{dm}\Big(\xi(k_2); \mathbf{b}\Big), \tag{7}$$

where $\xi(k_2) \in D^*_{\xi(k_2)}$:

$$D^*_{\xi(k_2)} = \Big\{\xi(k_2) : Q^{dm}\Big(\pi^*(k_2); \xi(k_2)\Big) < \\ < Q^{dm}\Big(\pi(k_2); \xi(k_2)\Big) \qquad \forall_{\pi \in \Pi}\Big\}. \tag{8}$$

For stochastic plant algorithm to select scenario has form similar to (7) i.e.:

$$\pi^*(k_2) = \psi^{dm}\Big(\tilde{\xi}(k_2); \mathbf{b}\Big), \tag{9}$$

In this paper classical formulation of the decision process has been shown, where the horizon K_2 is finite.

3 Pattern recognition in decision support process

Practically, determining solution for task (5) or (6) may be expensive and time consuming. To resolve described problem, the pattern recognition algorithm with knowledge updating was proposed. To design the proper decision making procedure in this case it is required to fix the learning sequence which is denoted by $X^{K_{dm}}$ and has following form:

$$X^{K_{dm}} = \left\{ \left(\xi^{(1)}, (\pi^*)^{(1)}\right), \left(\xi^{(2)}, (\pi^*)^{(2)}\right), \ldots \ldots, \left(\xi^{K_{dm}}, (\pi^*)^{K_{dm}}\right) \right\}. \quad (10)$$

General form of knowledge-based algorithm is shown below:

$$\left(\tilde{\pi}^*(1), \tilde{\pi}^*(2), \ldots, \tilde{\pi}^*(K_2 - 1)\right) = = \psi^{pd}_{PR}\left(\xi(k_2), X^{K_{dm}}; \mathbf{b}\right), \quad (11)$$

where (10) is updated in each *m-th* step of process i.e.: $X^{K_{dm}}(m) = X^{K_{dm}}(m-1)$.

4 Algorithm for knowledge updating

There are many different approaches in adaptive control or support decision systems to apply learning process. One of them is *adaptation through identification* where parameters of the algorithm $\psi^{dm}\left(\xi(k_2); \mathbf{b}\right)$ or $\psi^{dm}\left(\tilde{\xi}(k_2); \mathbf{b}\right)$ are updating step-by-step as a result of identification of the object's model.

In the expert systems another methodology can be applied. It is connected with concept of storing information in the system. Instead of changing algorithm's parameters it is possible to update and validate knowledge which is embedded in the knowledge base.

In the considered problem knowledge which is collected in *knowledge base* is used to support decision process and it is possible to update it if necessary. In real tasks frequently is needed to update expert's knowledge because it has been obsoleted or was not correctly prepare before had been applied to the system.

Discussed system uses knowledge base (10) which can be updated or validated at each m-th step of the adaptation process: $X^{K_{dm}}(m) = X^{K_{dm}}(m-1)$.

In the paper two different algorithms have been proposed. First approach is characterised, by using *performance index* (4) one new item to add to learning sequence is selected. Below the algorithm of updating knowledge is listed:

Algorithm 1:
(1) Put control sequence $\{\pi(k_2)\}_{k_2^M=1}^{K_2^M}$ and measure output $\{a_1(k_2)\}_{k_2^M=1}^{K_2^M}$ and $\{\xi(k_2)\}_{k_2^M=1}^{K_2^M}$ for object at the second stage. K_2^M is the length of the measured sequence;
(2) For each error $\xi(k_2^M)$ where $k_2^M = 1, 2, \ldots, K_2^M$, calculate value of the *performance index* (4) in k_2-th step;
(3) Select error value $\xi(k_2^M)$ for which control action has been done and value of *performance index* is the smallest;
(4) Add new item $\left(\xi^{K_{dm}+1}, (\pi^*)^{K_{dm}+1}\right)$ to learning sequence $X^{K_{dm}}$.

The second version of the updating method is as follows: at the first step new element is selected (by using *performance index* (4)) and - in the second step - the worst from knowledge based is chosen as well. Then, new item in the learning sequence is not added but replace the worst one. Algorithm for the second version is as follows:

Algorithm 2:
(1) to (4) the same as for **Algorithm 1**;
(5) Replace it by new one (from step 3).

5 Simulation studies

In order to test proposed algorithms to select scenario with knowledge updating modification simulation environment has been built. There is a straight relation to biomedical application. In [4] a model of fatigue in human skeletal muscles has been proposed. The mathematical relationship allow us to model activation of muscle by physical exercises and produced force. Having set of different scenarios (exercises routes) it is possible to select them in the right order during training cycle to reach the aim of control. This aim can be defined as a desired value of force which is produced by athletes during exercises.

In Fig. 2 effect of support of making decision has been shown for which value of the performance index $Q^{dm} = 0.0086$. In figures 3 and 4 the same process has been conducted but for algorithm with knowledge updating. Value of $Q^{dm} = 0.0081$ for the second approach and for first $Q^{dm} = 0.0075$.

6 Summary

In the paper adaptive system to select scenario has been considered. The main idea is connected with utilisation of pattern recognition approach and expert's knowledge. In general, for proposed algorithm only suboptimal solution can be found. To improve performance of the proposed system in process of selecting scenarios to plan rehabilitation for spastic people

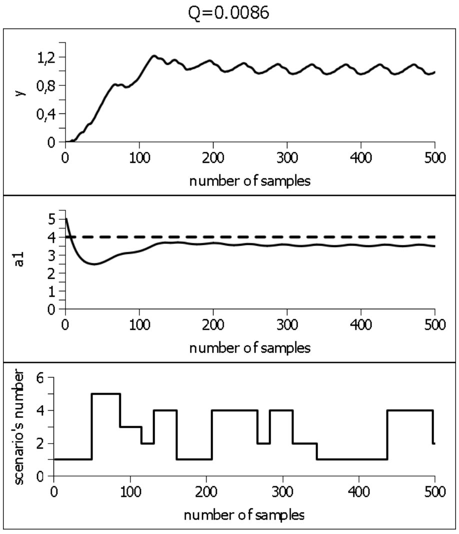

Figure 2: Effect of support decision making process for algorithm of scenario selecting based on *kNN* rule

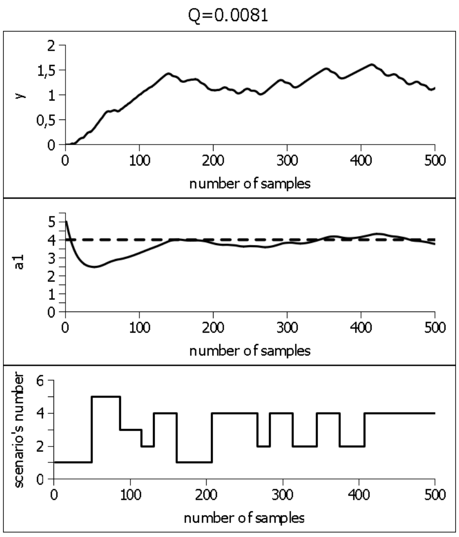

Figure 3: Effect of support decision making process for algorithm of scenario selecting based on *kNN* rule with make the most of knowledge updating rule in first version

adaptive techniques have been applied.

It worth stressing that the computational cost of application additional algorithms are not very high so the total efficiency is still low and lowest that for exact algorithms of the optimisation task (5) or (6) defined in section 2.

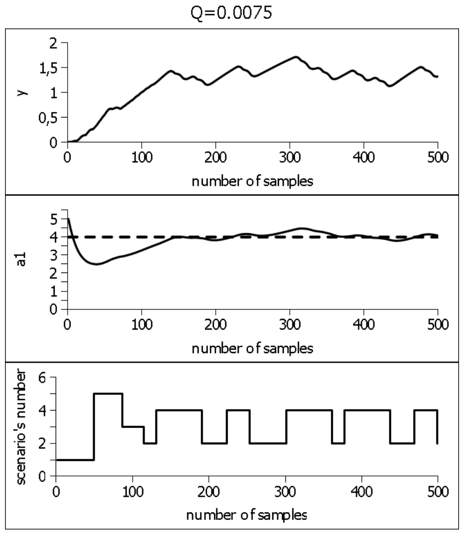

Figure 4: Effect of support decision making process for algorithm of scenario selecting based on *kNN* rule with make the most of knowledge updating rule in second version

References

[1] K. Brzostowski and J. Swiatek, "Selecting Scenario in Adaptive System with Neuro-fuzzy Decision Maker" *Proceedings of Nineteenth International Conference on Systems Engineering*, pp. 195 - 200, 2008.

[2] K. Brzostowski, "Some Problems of Neuromuscular System Identification Using Two-Stage Principle" *Proceedings of the 16th International Conference on Systems Science ICSS*, pp. 467 - 476, 2007.

[3] Z. Bubnicki, "Learning process in a class of knowledge-based systems" *Kybernets*, Vol. 29, pp. 1016 - 1028, 2000.

[4] L. Frey Law and R. Shields, "Mathematical models use varying parameter strategies to represent paralyzed muscle force properties: a sensitivity analysis" *Journal of Neuroengineering Rehabil*, 2005.

[5] J. Swiatek, *Two Stage Identification and its Technical and Biomedical Applications*, Scientific Papers of the Institute of Control and Systems Engineering of the Wroclaw Technical University, 1987. (in polish)