A Pattern Recognition Approach to Intelligent Behaviour: Switching the Strategies

Laurențiu Frangu, Emil Ceangă, Sergiu Caraman, Yiannis Boutalis

***Abstract*—The paper deals with the intelligent pattern recognition control systems. The concept of strategic situation is introduced, in the context of hierarchical structured control systems. It allows the investigation of the properties of the pattern recognition based control systems. The interaction between the system that recognizes strategies and the environment is described, along with the examples of control systems that allow such an approach. A case study, carried out on a simple process, is presented, to illustrate the method in a plausible context.**

***Index Terms*—classifier, intelligent control, strategic situation recognition, strategy switching**

I. Introduction

The idea of switching the strategies of the control systems comes from the research groups dealing with intelligent control. It is supposed that the controlled system has to reach a global goal, which is influenced by the internal state and by the environment (including the human, as possible higher organized system). Because of the changes in the environment or in the internal state, the temporary objectives may also change, according to the juncture. According to the work of Saridis, in [1]-[3], the intelligent control system is structured such as distinct parts take decisions with distinct level of importance. The low-level decisions concern the local loops and the adaptation, while the higher level decisions have to choose the more appropriate strategy to follow, in the given conditions, in order to satisfy the global goal.

Examples of systems that need to choose the strategy can be found in the domain of the autonomous mobile robots. The "co-evolving predator and prey" problem involves the selection of the strategy for each of the actors. One solution is indicated in [4], based on genetic algorithms. It allows the evolution of both actors, even if the number of available strategies is limited (i.e. the strategies themselves do not evolve). Other examples of systems that change the strategy may be the control systems that choose the controller from a limited set of predefined ones, according to the temporary performance criteria. If the change in controller is determined by the change in the model of the controlled process, then the system is adaptive. On the contrary, if the change in controller is determined by the change of the temporary objective, then the new controller reflects a new strategy. One approach to the controller switching, regardless of the cause of switching, is the heterogenous control law, studied in [5]. The stability of the systems that switch the controllers is studied in [6], [7].

In this paper a complementary approach is proposed to the problem of switching among strategies. The strategy is chosen according to the temporary objective, by pattern recognition methods. The input signals for the recognition automaton are the internal state and the changes in the environment, including the behaviour of the controlled process, of the partners and competitors and of the higher organized system, which decides the global goal. This approach satisfies two out of four attributes of the intelligent systems, according to Albus [8]. On one hand, the system builds the *world model*, by learning from experimental data. In the learning stage, the system uses the data structure analysis algorithms, in order to decide the significance of each information that contributes to the recognition of the new temporary objective. On the other hand, the system has the ability of *behaviour generation*, because it follows a strategy of interacting with the environment, each time the pattern recognition automaton assigns an observed vector to the respective strategy. A class of vectors describes the situations when the particular corresponding strategy is appropriate. About the implementation, both classical and neural algorithms may be involved in the recognition of the strategies. This method continues the spirit of the papers dealing with learning control systems, which started with the works of Widrow ([9], [10]), S.K.Fu ([11]) and continued with the papers introducing systematically the notions of control situations ([12], [13], [14]).

The rest of the paper is organized as it follows: chapter 2 contains the basic concepts of this approach, concerning the structure of the intelligent system and the notion of strategic situation, while chapter 3 presents a very simple case study that allows the illustration of the method in a plausible context. Finally, the conclusions referring to this method are presented in chapter 4.

II. Concepts of Intelligent Control Systems, by Recognizing Strategy Situations

Saridis proposed in [1] a "Principle of Increasing Precision with Decreasing Intelligence for Intelligent Machines". According to his work, the hierarchical structure of what we call today intelligent systems is organized on three levels, as in Fig. 1.

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While the inferior levels have to cope with the local control loops and coordination, the superior level concerns the interaction with the higher organized environment, the global goal and the formulation of the (temporary) objectives that have to be fulfilled by the inferior levels. The communication with other actors (in the sense of negotiating the complementary tasks) and the scheduling of the tasks is also the job of the higher level. The strategy is the set of rules that manage the temporary objectives and the inferior level tasks, in order to satisfy the global goal. In the above mentioned structure, it appears as natural to assign the switching among strategies to the superior level. Finally, one can notice that the strategies do not form a continuous space, but a discrete set. While the results of control, prediction or adaptation differ by the continuous values of the external variables or of the parameters, the strategies can always be counted. More, one can suppose that their number is finite, so the organization level has to select the appropriate strategy, from a finite set, according to the changes in the environment. The discrete nature of this selection is in concordance with the abilities of the pattern recognition methods; this is why the presented approach becomes a natural solution for the strategy switching.

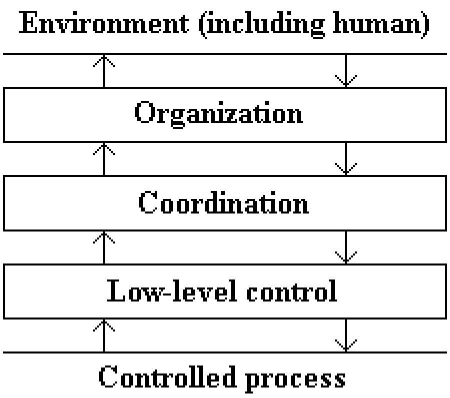

Fig. 1: The structure of an intelligent control system

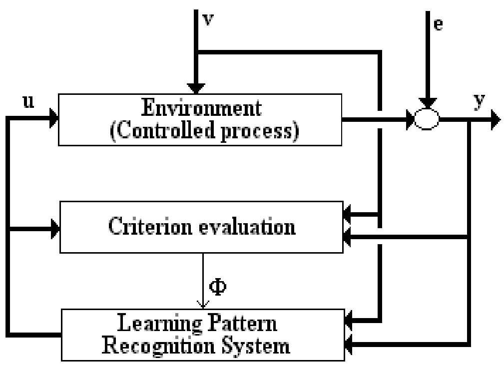

Fig. 2: The structure of the pattern recognition control system

Essentially, any recognition operation implies the adoption of a decision with respect to the set of attributes observed, which form a pattern vector belonging to a certain class out of a finite set of classes. In the automatic control field, such classes are generally called "control situations". Stating the concrete objectives of the decision as regards the classification of the pattern vector, as well as the entire set of attributes making up the pattern vector, determine some distinct meanings of the control situations. Generally, prediction, control, adaptation, diagnose, etc., may be subjects of a control situation approach. In the sequel, the purpose is to define the strategic situations, used in the context of intelligent control systems.

The recognition learning system is considered to work in an unknown or partially known environment, having to carry out a certain objective. The measure of carrying out said objective is estimated by criterion Φ, which is to be extremized (Fig. 2).

Let y be the output variable vector, v - the measurable disturbing variable, e - unmeasurable disturbance variable vector and u - input vector. They form the vector of observations, as in (1):

$$z(t) = (y(t), y(t-1),..., y(t-n_a), v(t-k),... \\ ..., v(t-n_b), u(t-k-1),..., u(t-k-n_c)) \qquad (1)$$

This vector is appropriate for the low-level actions of control, prediction and adaptation, no matter what kind of algorithm is used for these tasks. We can assume that supplementary information is added to this vector, for using it at the organization level. Such information may be the diagnose about the internal defects of the controlled system, the changes in the state of the competitors or partners and the changes in the objectives transmitted by the higher organized systems. Let us consider that the controlled system can implement r different strategies, according to the characteristics of the environment. Changing the strategy means to change the law that determines the command, as in (2):

$$u^i(t) = T_i(z(t)), \quad i = 1,..r\ , \qquad (2)$$

where the function $T(.)$ defines the strategy labeled i, corresponding to the temporary objective i (for example to maximize the criterion J_i) and $z(t)$ is the observation vector.

Definition: It is called a **strategic situation** the set of vectors $z(t)$ that correspond to the better strategy, out of the r possible, with respect to the global goal of the system, estimated by the criterion Φ. The strategic situation labeled i is described by (3):

$$S_i = \{z(t) / \max_k \Phi[T_k(z(t))] = \Phi[T_i(z(t))]\} \qquad (3)$$

The purpose of the approach based on recognition is to use the previous experience of the system to recognize those of its states or of the environment, that require a particular objective, corresponding to a particular strategy.

Some examples of such cases are described in the sequel. A control system may switch between a surviving strategy and a competing one, according to its ability to cope with the external conditions. In this case, the vector of observations has to contain some synthetic information about the interaction with the environment. Another case is formed by the control of biotechnological processes, where the variability of the food requires the system to switch between the strategies appropriate to the respective food. Usually there is no indicator of the quality of the food, so the available information for recognizing the strategic situation is the record of the measured variables only. In this case, the vector of observations has to be extended with synthetic parameters, extracted from wide horizon records.

The same biotechnological process has to be driven, in the launching stage, according to the evolution phase of the population of microorganisms. There are at least three evolution phases and their corresponding control strategies:

- the lag (or initial) phase, when the food has to be low;
- the exponential growth phase, when the food has to be provided according to the growth of population;
- the steady phase, having a different control law, because the control system alternates the feeding and starvation cycles, in order to obtain the maximum production.

The selection of the appropriate controller is made on the basis of strategic situations recognition. The vector of observations consists of: pH, O_2, CO_2 and the biomass concentration. The recognition solution is also preferred because of the complicated mathematical models, affected by large uncertainties.

Finally, in the case of motion planning for autonomous vehicles, the density of the obstacles may determine the switching between a long way strategy and a strategy of "minimum way to exit the crowded area". The vector of observations has no more the meaning of input and output vector, merely it is an array of the constitutive elements of the environment, detected by the sonar, video sensor or other transducers.

III. A Case Study: The Strategies of the Backer Truck

The statement of the problem used as case study is simple: a truck has to dock oriented the back side to the target. The docking target is a narrow opening in a wall, as presented in Fig. 3 (together with an unsuccessful docking). The truck may use more controllers but, because of the back-side restriction, the last one will always be a dedicated controller for backer docking. It is obvious that the initial position is determinant for the success of the backer docking and that there are initial positions that do not allow the immediately use of this controller. Consequently, it will be necessary to add at least one controller, for the task of moving off the truck from the target. The objective of the last used controller is the correct docking, while the objective of the first used is to find a good intermediate position, that becomes initial position for the other. Switching between them is a strategy problem, because of the different objectives of the two controllers.

In this case study the recognition of the strategic situations is used for switching the controllers. Mainly, the recognition automaton has to detect if the initial position allows the use of the final controller, or an intermediate movement is necessary. The position is described by three variables: the coordinates of the back side of the truck (*x* and *y*) and the orientation angle of the truck, with respect to the wall (θ). The first two are not dimensional, because of scaling to the truck length, while the angle is expressed in radians. To justify the necessity of the angle, Fig. 4 presents two docking attempts, having as initial positions the same *x* and *y*, but different orientation angles.

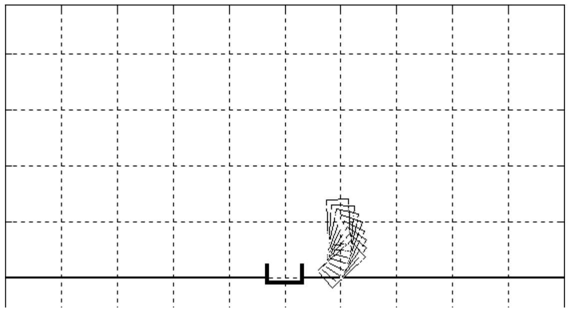

Fig. 3: The docking space, the target and an example of unsuccessful docking

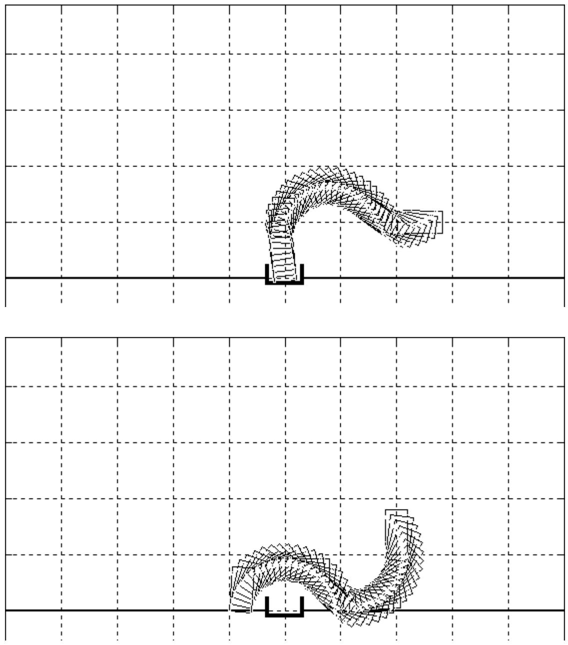

Fig. 4: Docking from initial positions that differ by orientation only, (2, 1, 0) and (2, 1, π/2)

Consequently, the vector of observations contains three components, as in (4):

$$z = [x, y, \theta]^T \tag{4}$$

Only the present values are necessary (no past values). The vectors belong to one out of two classes, representing the strategic situations: "the initial position allows the success, by using a single back movement (a single controller necessary)" and "the initial position does not allow the use of a single controller (supplementary movements necessary)". In order to learn the partition of the space of observations in the two domains, corresponding to the classes, a number of 407 experiments were carried out by simulation, using the conditions and the fuzzy controller presented in the toolbox of Matlab 5.2.1. The initial position was randomly generated. The recorded variables in the training set were the components of the initial position $z(t)$ and the success (or unsuccess) of the attempt (the index of the class). The mean failure rate was about 35%. To illustrate the aspect of the experimental data, Fig. 5 contains the projection of the training set on the plane of the variables *x* and *y* (index "1" means success).

Obviously, the classes are not separable in this reduced order space, even if positions close to the target seem to offer less success of the docking. Additionally, the border between the classes has not a simple form. Accordingly, the chosen classifier is a non-parametric one, based on the method of the potential functions.

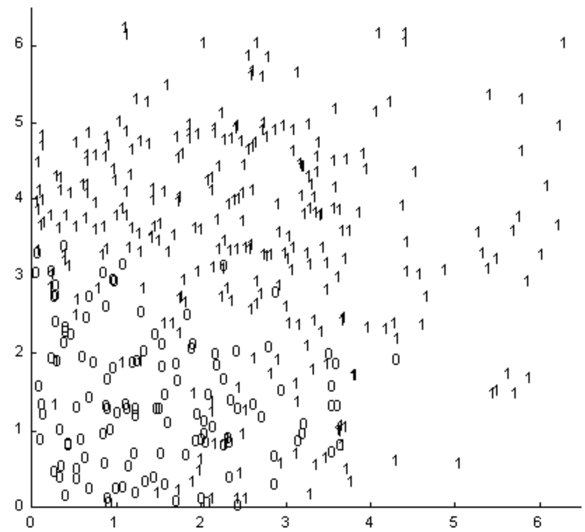

Fig. 5: The two-dimensional projection of the training set

There are two functions, one for each class, defined as in (5):

$$f_i(z) = \sum_{k=1}^{n_i} \exp\left(-\frac{\|z - z_{ik}\|^2}{h^2} \right), \qquad (5)$$

where i is the class index, z is the vector to be classified, z_{ik} is one of the n_i vectors in the training set, belonging to the class i, the norm may be any one and h is a scaling parameter. The pattern to be classified, z, is assigned to the class presenting the maximum value of the potential function (the class represents the strategy to choose). The influence of the parameter h is important as it concerns the variance of the border. In this experiment it was chosen at the value 0.8.

To examine the classifier, a set of 92 new docking experiments were carried out, in the same conditions (the test set). The decision of the recognition automaton, working on the coordinates of the initial position, was interpreted as the necessity to switch or not to switch to a supplementary controller, before the final docking task. The following events were considered decision errors:

- the automaton decided that a single step docking will be successful, but the docking starting from that specific initial position failed;
- the automaton decided that a supplementary movement, controlled by another controller, is necessary, but the single step docking was successful.

The error rate was less than 7%, i.e. a considerable improvement of the docking ability. This means that the recognition of the strategic situations is useful in the context of the experiments that present different temporary objectives, associated to different controllers. The job of the recognition system is to discriminate what objective is the most important in each moment, in order to satisfy the global goal.

IV. CONCLUSIONS

The previous simple examples show how switching the strategy, according to the temporary objective, can contribute to better reaching the global goal of the control system. This approach is suitable when the following conditions are met: there is no mathematical model for the evaluation of the efficiency of the possible strategies, but there is lot of past experience about the interaction between the system and the environment. In such conditions, the human approach is imitated, i.e. the present optimal decision is taken on the basis of similar past events. The key feature of this approach is the learning capability of the pattern recognition automata, which exploits the past experience for building a behavioural model of the world.

The following conclusions can be drawn:

1. the introduced concept of strategic situation is useful at the superior level of the hierarchical organized system;
2. some examples of systems who can use this approach were presented;
3. the possibility of using this method to switch among controllers is proved by an experiment (carried out by simulation). However, the same method may be used in a more general context, when different strategies involve not only different controllers, but different temporary objectives and interaction modes;
4. further work has to be done, in order to examine the properties of the system, other examples of systems that switch among strategies and a comparison with the other methods of strategy switching.

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