# A PATTERN RECOGNITION CONTROLLER APPLIED TO THE BIOPROCESS CONTROL

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Abstract: The paper deals with the pattern recognition control systems. The concept of command situation is introduced, in order to permit the analysis of the properties of control systems that determine the appropriate discrete command by classification. A case study, carried out on a biotechnological process, is presented, to show the performances of the pattern recognition controller, trained with data supplied by a MBPC procedure.

Keywords: Pattern recognition, classifier, biotechnology, Model Based Predictive Control

## 1. INTRODUCTION

There are many processes that justify using a discrete command. Among them one can notice:

- systems where the uncertainty (structural or determined by noise) is important. These systems may use a discrete actuator, cheaper than a continuous one (see the case of a biotechnological process);
- systems where the actuator must provide discrete commands, because of the nature of the process or for reliability reasons (hybrid systems, as the refrigeration plants);
- systems that require a complex control algorithm, time consuming, that cannot be computed within the sampling interval (e.g. the missile tracking the target).

All these cases are appropriate for using a discrete command. They need the building of an automaton that could compute this command, very closed to the optimal command and fast enough. The automaton learns how to act, making use of the recorded data, so it even can be used in a partially unknown environment. In the scientific literature, there are some papers, containing methods to determine discrete commands by learning processes. For example, (Grigore, *et al.,* 2000) applies a recognition control method to a tracking process, where the calculus has to be fast (the missile). The automaton is based on a neural network (Kohonen), that acts as an auto-associative memory. Even earlier (Nikolic, *et al.,* 1966), S.K. Fu and Nikolic have proposed a method to control a process by a dual procedure, where the current command is selected out of a limited number of commands, by a learning automaton. However, the mentioned papers did not develop a generalized theoretical frame for using a discrete command, that could permit the investigation of the essential properties of the pattern recognition based control systems.

This paper aims at systematically introducing the concepts implied by a pattern recognition controller and revealing the properties of the systems using such a controller. This approach is described in section 2. A case study, carried on by simulation, in the field of biotechnological processes, is presented in section 3. Finally, the conclusions referring to this method are drawn in section 4.

## 2. CONCEPTS OF AUTOMATIC CONTROL BY USING SITUATION RECOGNITION TECHNIQUES

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 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 command situations, used in a control algorithm. 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 $F$, which is to be extremized (figure1).

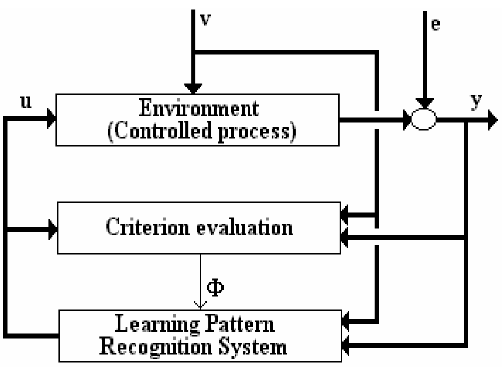


Fig. 1. The structure of the pattern recognition control system

Let $y$ be the output variable vector, $v$ - the measurable disturbing variable, $e$ - unmeasurable disturbance variable vector and $u$ - input vector. It is assumed that there exist $p$ input admissible values, $u_i$, $i=1,...,p$, forming the set $U_d$ of admissible discrete inputs. On basis of the output, input and measurable disturbing values

$$y(t), y(t-1),..., y(t-n_a) \qquad (1)$$

$$u(t-k-1), u(t-k-2),..., u(t-k-n_b) \qquad (2)$$

$$v(t-k), v(t-k-1),..., v(t-k-n_c) \qquad (3)$$

where $n_a$, $n_b$, $n_c$ are finite integers and $k$ is the dead time (in sampling period units), it can be defined the vector of observations:

$$z(t) = (y(t), y(t-1),..., y(t-n_a), v(t-k),...$$
$$..., v(t-n_b), u(t-k-1),..., u(t-k-n_c)) \qquad (4)$$

The learning system should make use of the experience accumulated up to that moment. So that, for any vector $z(t)$ of the environment observations, it determines the discrete input $u_i(t\text{-}k)$, $i=1,...,p$, to extremize the criterion $F$.

*Definition*: It is called the **command situation** the set $S_i$ of vectors $z$ for which the discrete input $u_i$ is optimum in terms of objective fulfillment:

$$S_i = \left\{ z : \max_i \Phi(u,z) = \Phi(u_i, z), u \in U_d \right\} \qquad (5)$$

To establish the control algorithm means, in this case, to deduce by learning, the discriminating functions of the command situations. According to the nature of the environment and the way in which learning is performed, the automatic control systems using recognition of the command situations may use image information, transducer data and previously deduced partial models. Depending on the form of the criterion $F$, different control structures may result, some of them being very known control structures. For example, if the criterion is the distance $|w(t+1)-y(t+1)|$ ($w$ is the setpoint), which has to be minimized, then an "inverse model control" structure is obtained, aiming to a dead-beat controller. If the criterion is that imposed by a Model Based Predictive Control (MBPC) procedure, then the corresponding control structure is obtained, and so on. As an example of using the command situations in a control structure, we can consider the model of a first order process, having no dead-time. The model may contain a nonlinear part, without hysteresis, preceding the linear one. Then, the vector of observations is bidimensional, as in equation (6):

$$z(t) = (w(t+1), y(t)) \qquad (6)$$

Depending of the form of the nonlinear part, the command situations in the bidimensional space of observations have the shape presented in figure 2.

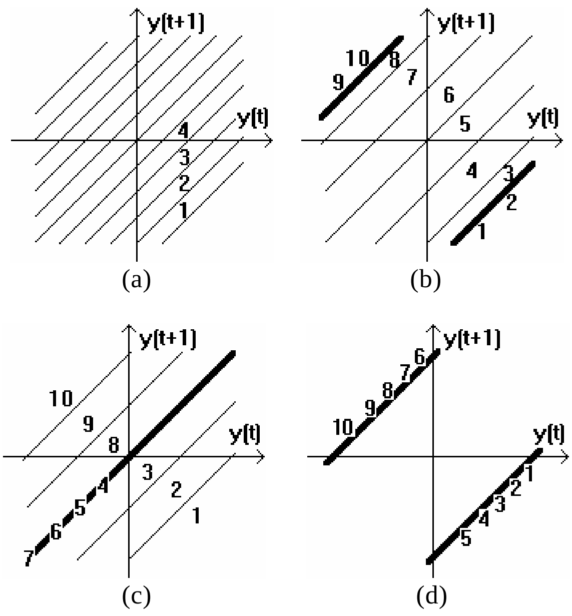


Fig. 2. The clusters aspect for some non-linearities

Frequently, these shapes are simple enough (as seen in figure 2), to permit linear discriminating functions. The parameters of the functions may be deduced by learning, using the recorded input and output data. This gives to the pattern recognition controller the learning attribute. Different techniques may be used to build the controller, such as: classical pattern recognition techniques (parametric or not), feed-forward neural networks or recursive networks. The technique involved does not affect the learning attribute. The learning of the parameters has similar properties of the noise rejection, as the classical identification methods.

Concerning the dynamical properties of the controller, they depend on the structure determined by the criterion $F$. Generally, the recognition of the command situation works in a feedback scheme, but not necessarily the dassical one, that uses the error. The recognition of the command does not provide the attribute of zero error in steady state. To introduce the integration effect, an external integrator is necessary and the increment of the command has to be recognized (similar to the *PI*-like fuzzy controllers).

Other concepts of automatic control by using situation recognition are:

- output situations (used for prediction);
- adapting situations (for adaptive control, similar to gain-scheduling);
- strategic situations (to switch the control strategy, when the objective changes);
- diagnose situations (used for diagnostic).

## 3. CONTROL OF A BIOTECHNOLOGICAL PROCESS, USING THE RECOGNITION OF DISCRETE COMMANDS. A CASE STUDY

The process involved takes place in a continuous stirred bioreactor and it is described by the equations (7) - (10), drawn from (Aoyama, 1995):

$$\dot{X} = (m - D) \cdot X \qquad (7)$$

$$\dot{S} = D \cdot (S_f - S) - \frac{1}{Y_{X/S}} \cdot m \cdot X \qquad (8)$$

$$\dot{P} = -D \cdot P + (a \cdot m + b) \cdot X \qquad (9)$$

with

$$m = \frac{m_{\max} \cdot (1 - P/P_m) \cdot S}{K_m + S + S^2/K_i} \qquad (10)$$

where

$X$ = cell mass concentration (6 g/l at the steady-state);
$P$ = product concentration (19 g/l at the steady-state);
$S$ = substrate concentration in the culture (5 g/l at the steady-state);
$S_f$ = feed substrate concentration in the culture (20.0 g/l at the steady-state);
$D$ = dilution rate (0.202 l/h at the steady-state);
$m$ = specific growth rate [l/h] given by (18), which includes the inhibition due to the substrate and the reaction product;
$Y_{X/S}$ = cell mass yield (0.4 g/g);
$a$ = kinetic parameter (2.2 g/g);
$b$ = kinetic parameter (0.2 l/h);
$m_{max}$ = maximum specific growth rate (0.48 l/h);
$P_m$ = product saturation constant (50 g/l);
$K_m$ = substrate saturation constant (1.2 g/l);
$K_i$ = substrate inhibition constant (22 g/l).

The process is appropriate to present the behaviour of a control system, based on command situation recognition. It has a low order model, but nonlinear, because the parameters are variable. The static characteristic of the process is presented in figure 3, showing the nonlinear behaviour. The objective of the control is to maintain the functioning around the point ($X$=6,1 g/l; $D$=0.2 l/h), which is optimal with respect to the product extraction (biomass or enzymes). The nonlinear behaviour justifies the use of a Model Based Predictive Control procedure, as presented in (Camacho, *et al*., 1999; Frangu, *et al.*, 2001). The chosen structure in the paper mentioned above is presented in figure 4.

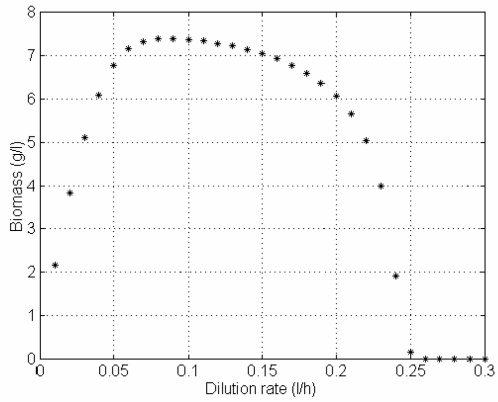


Fig. 3. The static characteristic of the process

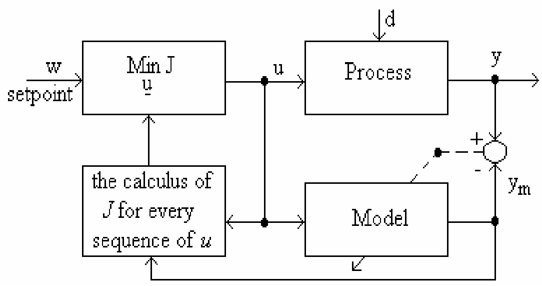


Fig. 4. MBPC structure

The criterion to be minimized is:

$$J = \sum_{k=N_1}^{N_2} d^2(k) \cdot [w(t+k) - y(t+k/t)]^2 + \\ + \sum_{k=0}^{N_u - 1} l^2(k) \cdot [u(t+k/t)]^2 \qquad (11)$$

where $y(t+k/t)$ is $k$-step ahead prediction of the system output on data up to time $t$; $N_1$ and $N_2$ - the minimum and maximum prediction horizons; $N_u$ - the control horizon; $w(t+k)$ - the future setpoint; $d(k)$ and $l(k)$ - the weighting coefficients of the errors and of the commands, respectively. It has to be mentioned that, according to the nature of the command of the bioreactor, the criterion $J$ uses the cost of $u(t)$, not the cost of $\Delta u(t)$, as usually indicated for MBPC. The solution is found by exhaustive searching. The MBPC procedure provides good results, in terms of tracking error and transient response. However, even if it uses small size parameters (the command horizon is $N_u$=2, the output horizon is $N_2$=8), the computation time is large, no matter if the command is continuous or discrete. This is the reason why the control needs a procedure that should keep the good performances of MBPC, but less time consuming.

The solution proposed in this paper is to use an automaton to recognize the command situations. They are defined as in equation (5), where the discrete values of the command ($D$) are: {0; 0.05; 0.1; 0.15; 0.2}. Initially, the vector of observations contains the values $X(t)$, $S(t)$ and $w(t+1)$, knowing that the order of the process is 1. Here, the setpoint is the value of $X$ to be obtained at the next step. To every vector of observations is associated the index of the command situation, i.e. the discrete value of $D(t)$. To record the learning set, a test signal, containing equally low and high frequencies, was applied as setpoint to the MBPC procedure. The values of the setpoint are around the optimal value of 6 g/l.

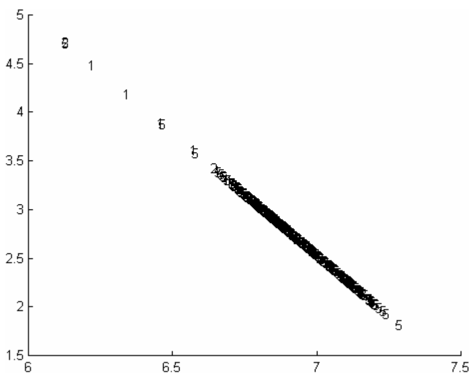

Fig. 5. The projection on the plane $X(t)$, $S(t)$

To choose a classifier, the projections of the learning set on the planes determined by the coordinates were studied. It results that one of the values $X(t)$ and $S(t)$ is unnecessary, because they are linear dependent, as presented in figure 5. (In fig. 5 and 6, the numbers represent the index of the command situations.) Consequently, the vector of observations contains only the values $w(t+1)$, $X(t)$, as in equation (12). The new vectors form the clusters presented in figure 6. Their position is represented simplified in figure 7.

$$z(t) = (w(t+1), X(t)) \qquad (12)$$

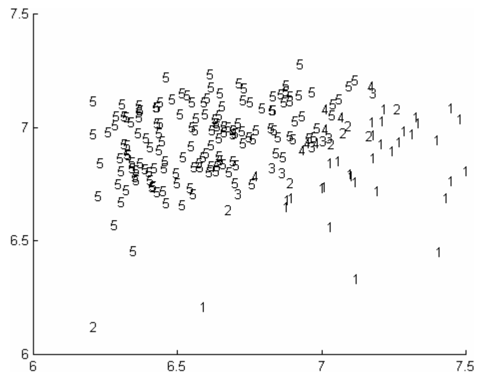

Fig. 6. The clusters in the plane $w(t+1)$, $X(t)$

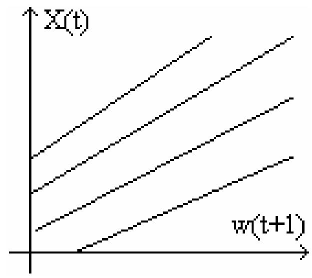


Fig. 7. Simplified separation of the clusters

It is obvious that the classes may be separated by linear discriminants, even if the noise and the effect of the product $P$ determined a small superposition of their clusters. The discriminant functions were chosen the straight lines separating optimal the clusters. The analytic form of the functions is:

$$X(t) = m \cdot w(t+1) + n \qquad (13)$$

Their parameters were obtained by a regression procedure and are listed in table 1.

Table 1

| | Separated clusters | | | |
|---|---|---|---|---|
| | 1-2 | 2-3 | 3-4 | 4-5 |
| Parameters | | | | |
| $m$ | 0.97 | 0.98 | 0.99 | 1.0 |
| $n$ | -0.52 | -0.37 | -0.22 | -0.07 |

It is to mention that the classifier is linear, but the process involved is nonlinear, the straight lines having different slopes. The test of the pattern recognition controller is presented in figure 8, where the command is provided by the command situation recognition automaton. Two elements are relevant:

1. the discrete command produced a chattering effect, but this does not disturb the process. The error is small enough, so the result is near optimal;
2. the error is identical to the case when the on-line MBPC procedure was applied. This proves that the recognition of the command situation provides the same performance, in a less time consuming algorithm.

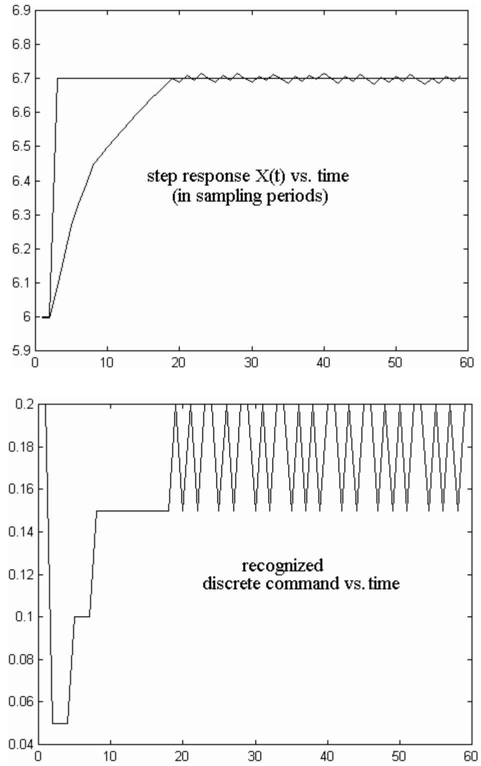


Fig. 8. The step response and the command

## 4. CONCLUSIONS

The following conclusion can be drawn:

1. it was introduced a concept that unifies the previous attempts to use discrete commands;
2. some control structures using this concept have been presented;
3. the possibility of using this method is proved by an experiment (carried out by simulation). The properties of the control structure, as seen in fig. 7, are those of MBPC, except the computing time, that is very short.
4. The case study shows that, on a large area around the desired steady state of the bioreactor, a near-optimal discrete command can be deduced easily and fast. The influence of *S* and *P* is insignificant;
5. Future development of the subject must evaluate: the influence of the disturbances, the dynamic properties of the process and the possibility of using the recognition of command situation to hybrid systems.

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