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CASE BASED APPROACH FOR SUPERVISION. APPLICATION TO PID CONTROLLERS

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Abstract: Case Based Reasoning (CBR) is proposed as a methodology for the diagnosis and fine tuning of PID controllers. CBR methodology is used to retrieve knowledge acquired in previous situations of process operation. Then, this knowledge is represented as associations between symptoms and diagnostics. These associations are conceived as cases. Symptoms are obtained directly from acquired signals in significant situations and diagnostics represents the evaluation of the process response according to such situations. In the example presented cases are proposed to adjust controller parameters in order to accomplish the required performance specifications. *Copyright © 2002 IFAC*

Keywords: PID Controllers, Reasoning, System Diagnosis, Dynamic Systems, Process Control.

1. INTRODUCTION

Since the former works related to supervision of controllers based on knowledge (Åström et al., 1986), many techniques have been proposed with this goal. Among all of them, expert systems (Lee T.H. et al., 1993), fuzzy techniques (Passino and Yurkovich, 1998; Årzén 1995) and neural networks have been extensively used. The common goal to take advantage of knowledge to detect misbehaviors, to diagnose and, finally, to retune the controller (Åström K.J. et al., 1993; Bobál 1995). The approach proposed in this paper is based on the application of Case Based Reasoning (CBR) methodology and its application to supervise PID controllers.

The results obtained in applying CBR in different domains (finances, medical diagnostic, repair manuals, help desk assistant, etc.) as a problem solver- methodology have meaning to think that similar results can be obtained dealing with dynamical process. Main drawbacks are due to the temporal dependence of acquired data in front of static registers commonly used in CBR.

There exist some contributions involving dynamic systems reasoning in specific domains as in robotic planning (Ram and Santamaria 1997), weather forecasting (Hansen B.K. 2000) or batch processes control (Meléndez J. et al., 2000). Although CBR is an application dependent technology, these applications have in common the use of acquired data from sensors to characterize the system behavior.

This paper provides a brief introduction to the CBR methodology, stepping inside on how it can be applied to PID controller supervision. In a more detailed description, a possible case structure is proposed, since this is a fundamental aspect to succeed in applying CBR. The use of these cases or experiences is described in following sections according to CBR cycle. Finally, an application example, where PID controller is used to regulate a laboratory plant is described.

2. CASED BASED REASONING CYCLE AND SUPERVISION

Case Based Reasoning is a methodology that gets profit of previously registered experiences (*cases*) structured and organized in a *case base* in order to solve new problems. Cases are conceived as associations between problems and solutions. Reasoning is performed by applying a four task method (4R-cycle): **R**etrieve, **R**euse, **R**evise and **R**etain (Fig.1).

Retrieve implies to found previous solved problems analogue to the actual one. It is usually implemented using either similarity criteria or inductive methods.

Then, retrieved cases (one or more) could be ***Reused*** in order to propose a solution to the new problem. The simplest reusing method is to copy a retrieved solution while other methods imply the definition of adaptation mechanisms. Thus, the outcome is a proposed solution that must be ***Revised*** before being applied definitively. The cycle is completed by ***Retaining*** this new experience (problem + solution) in case of being interesting enough.

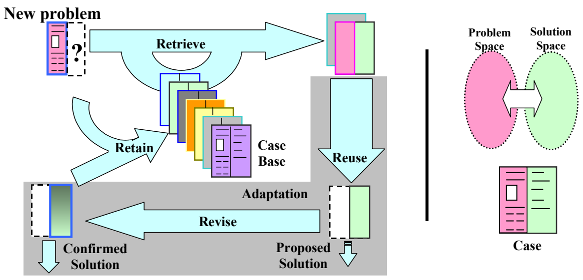

Fig. 1. The CBR cycle.

The evolution of the cycle through time increases the accumulated experience of the systems. According to the desired granularity in the case base (it depends on the problem and solution space) some mechanisms must be introduced in order to maintain representativity of stored cases.

According to supervisory goals, cases are conceived as registers containing associations among symptoms (abstracted from acquired signals), faults, diagnostics and actions, acquired in specific situations (Melendez et al, 2001b). Thus, identification of analogue symptoms is the criteria for retrieving the associated diagnostics and actions, constrained to the control specifications, in order to overcome the supervision problem. Moreover, according to case structure, CBR cycle can be applied to retrieve partial information. It means that the same case base could be used in fault detection or as a consulting assistant to obtain information about possible symptoms related to a specific fault.

3. PID SUPERVISION

The PID controller is a paradigm of control widely studied, not being the scope of this article to enter again on how the different parameters of a PID controller affects the output of the process. See for instance (Aström K. J. and Hägglund T. , 1995). The goal is to supervise the PID behavior by using information obtained from the process to evaluate the performance of the regulator in order to perform a fine tune of its parameters on line.

The proposed approach is different to the common one of tuning controllers off line after performing some experiments and evaluating the obtained response of them in order to adjust definitively the parameters. The proposal is closer to parameters adaptation without using any model of the process.

From the output signal of the process it is possible to obtain different indices that describe the behavior to be diagnosed in order to tune of the associated controller: the initial value in a set point change, the desired set-point, the maximum overshoot, the ratio of change and the steady state error could be the most representative ones.

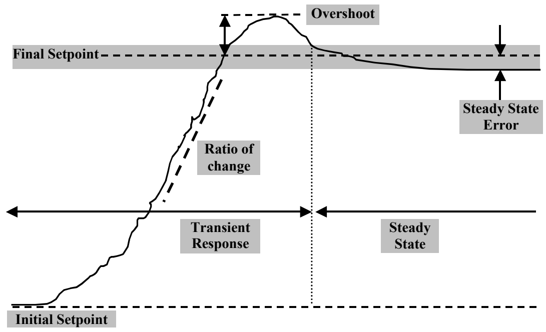

Fig. 2. Response of a process and some representative indices.

Most of these indices have a direct relationship with the parameters of the PID controllers: Kp, Ti and Td. For instance: A big overshoot can have a direct relationship with Kp and Td parameters. The goal is to associate these parameters in the response with PID ones for significant situations. The supervision of the PID controller will use this parameter-response association in conjunction with an evaluation of the control quality. For this proposal the classical criteria related to the error can be applied: IE, IAE, ISE, ITSE, ISTE as described on (Escobet and Puig 1995).

So, the on line evaluation of the response can be used to fire retrieval of cases for an on line adjustment of the parameters. In similar way a significant change in the set point or a variation in the working point for nonlinear systems can also fire the retrieval.

4. DEFINITION OF A CASE STRUCTURE FOR PID SUPERVISION

When dealing with dynamic systems, CBR difficulties start in the definition of cases. Process dynamics depends on the interaction of its components, materials, and energy consumption. Therefore, reasoning about process dynamics implies to store historical evolution of variables in cases in a suitable form. The register of previous situations has to contain history of such situations represented by variables. This leads to the continuous problem of CBR pointed, and still open, by Ram and Santamaria (Ram and Santamaria 1997) related to case representation: "How should 'continuous cases' be represented?, When do cases start and end (in the temporal sense)?, When are two experiences different enough to warrant consideration as independent cases? What is the scope of a single case?".

The conceptual definition of cases, considered in CBR, allows performing an association between two complementary views of process behavior. The first of them is provided by acquisition systems as flows of data that are systematically collected and stored. The other view is the human perception of process behavior enhanced by the expertise and experience. They are two different views of the same reality (Langseth, et al. 1999), the process, which must be combined in order to improve the global knowledge of process needed in assessment tasks.

Referring to the PID controllers, several signals are involved: setpoint, process output, control signal and error. In order to evaluate the system response, it is not necessary to register the whole sampled signal but only some significant indices as is depicted in Fig. 2. Thus, the structure of a case (C) is proposed to be (Fig.3):

C= [Specifications, Response indices, PID parameters, Evaluation].

In a fine tuning application *Response indices* are though to be used for retrieval constrained to the *Specifications*. While the *PID parameters* are the solution to be adapted taking into account the *Evaluation* of the retrieved cases.

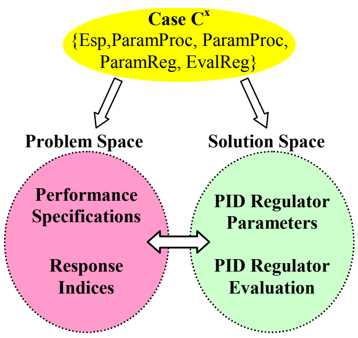

Fig. 3. Structure of a case. Each case is composed by a Problem Space and a Solution Space. Problem Space defines the expected performance. Solution Space describes how that performance was achieved.

The expertise is encapsulated in the association of this information related to the evaluation (diagnosis) of the controller. As said before this evaluation can be obtained through quantitative calculated criteria (See previous section) or by qualitative information provided by the plant engineer. The quality of the evaluation process is of vital importance when choosing a new controller or diagnosing the existing one in the cases retrieval process.

5. RETRIEVE AND REUSE

Retrieval is usually performed by applying distance criteria or using inductive mechanisms. In this work a combination of both is proposed as it is explained in the example.

The core of the CBR system is the case retrieval mechanism. Most of the used criteria for case retrieval are based on the concept of distance. They are used to obtain the k-nearest neighbors of a case, C^A, from a case base containing *cases*, designed by C^B. The following is a general expression used for distance calculation between *cases*. They are supposed to be composed by a set of N attributes x_i which similarity is measured by a function, *SIM()*:

$$SIM\,(C^A, C^B) = \left[\sum_{1}^{N} f(w_i) \cdot sim(x_i^A, x_i^B) \right]^{\frac{1}{r}} \quad (1)$$

Attributes are expected to be both symbolic and numerical, then a suitable expression for similarity calculation between attributes (*sim()*) must be defined. It is common to calculate distance between symbolic attributes according to an overlap distance, as it is expressed below. Although other criteria could be used (tables, fuzzy, etc.)

$$sim(x_i^A, x_i^B) = \begin{cases} 0 & x_i^A = x_i^B \\ 1 & x_i^A \neq x_i^B \end{cases} \quad (2)$$

On the other hand, numerical attributes are compared according to some classical distances:

$$sim(x_i^A, x_i^B) = \left| x_i^A - x_i^B \right|^r \quad \begin{cases} r = 1 \rightarrow Manhat\tan \\ r = 2 \rightarrow Euclidean \\ r = 3 \rightarrow Cubic \end{cases} \quad (3)$$

Moreover, the importance of each attribute is weighted, w_i, in order to obtain the global distance. The election of these weights is performed according to the importance of each attribute with respect to the others in the *case*. Its influence in the distance criteria can be applied directly with a multiplier effect or using a normalized function of them $f(w_i)$. For instance, an exponential function could be used to emphasize differences among them as is suggested in (Sanchez, et al. 1998). This normalized and exponential weight-sensitive distance function based on Manhattan distance is used in (Sanchez, et al.1996) in diagnostic application with this goal.

Weights are manually adjusted depending on the results obtained during the retrieval. No methodology has been yet defined to choose the value of the weights and 'try and error' is still the best policy to apply.

The use of distance-functions allows obtaining an ordered list of retrieved *cases* from the case base according to a similarity criterion. Thus, the most, in fact the K most, similar *cases* (K-Nearest Neighbor), can be used to adapt the new solution according to a transformational relation.

The number of attributes in a case is supposed to be the same as the number of attributes in the problem situation, with the only difference that not all the attributes in the problem situation have been specified. As we can see on Fig.4, $p_0 \ldots p_m$ are the known attributes in the problem situation, in fact is the specification of the desired response of the process. While $p_{m+1} \ldots p_n$ represent the non-specified attributes or what it will be the same, the expected solution obtained from the case retrieval. Comparing each case on the case base with the problem situation and applying their correspondent weights $w_0 \ldots w_n$, generates the similarity indexes $sim(p,c^1) \ldots sim(p,c^n)$ which are really a distance between the situation problem and the stored cases. Cases will be retrieved according to this similarity index. This similarity index reflects how similar the actual situation is to a past experience.

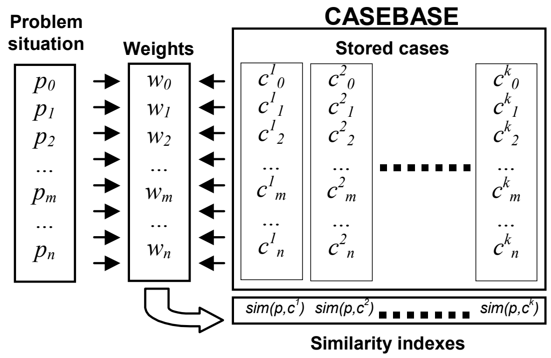

Fig. 4. Matching between the problem situation and the cases of the case base. $p_0 \ldots p_n$ represents all the attributes in a problem situation. $p_0 \ldots p_m$ are the specified attributes while $p_{m+1} \ldots p_n$ are the non-specified attributes. $c^1 \ldots c^k$ are all the stored cases in the database. $w_0 \ldots w_n$ are the weights applied to calculate de similarity indexes $sim(p,c^1) \ldots sim(p,c^n)$.

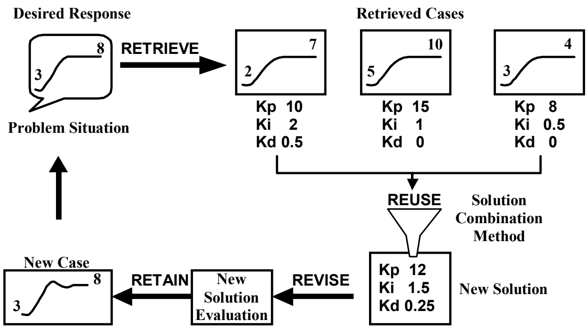

Fig. 5. Global Representation of the CBR cycle applied to the control/supervision of a PID controller application.

On a later step, in the reuse process, the retrieved cases could be used to build a solution to the actual situation. The solution can be composed by just using a retrieved case *as is*, providing the parameter used in that past situation or by building a solution using a combination method of the parameters of the retrieved cases.

6. REVISE AND RETAIN

Provided the new possible solution, the CBR cycle will be soon closed. Just a few steps remain. The solution must be tested in the revision process. This implies a validation of the provided solution calculating the quality of control criteria. Depending on the values obtained, is decision of the expert (or other decision mechanisms) to store all the information generated during all the cycle as a new case, increasing the knowledge in the case base. This information contains the problem specifications, the provided solution and its evaluation, which can be later used on future queries.

7. AN ILLUSTRATIVE EXAMPLE

The application exposed is a PI level regulator in a water tank system. A pump fills a tank from another one that is placed in a lower level. Water returns then to the lower tank by the effect of gravity. The goal is to achieve a certain level in the higher tank by regulating the water pump through a PI controller. PI controller will be used instead of a complete PI controller.

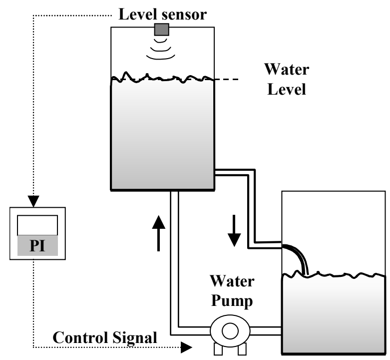

Fig. 6. Level Regulation Process. PI regulator controls water level of the higher tank.

This is a time varying non-linear system. Its dynamics depends on the working point and the total amount of water. A good regulation of the process is achieved by tuning the parameters of the controller according to the working point. The CBR methodology applied to the regulator allows retrieving the successful parameters for a certain change of set points. This way, the PID controller is constantly adapted to the process dynamics, and improves the general behavior of the process.

First of all there is the necessity to obtain a first case base to start with. A sample initial case base (see Table 1) could contain different kinds of information: Case identifiers, data about the experiment, results about the experiment, evaluation of the response through the error (IE, IAE,ISE), the parameters used (Kp, Ti, Td) and high level information obtained from the expert. All this information will later be used to retrieve the most similar cases to a problem situation. Performance specifications required for the controllers are a maximum settling time Ts=1 min, a margin band δ=±0,5cm, and a maximum P.O. (Percent Overshoot).These specifications are omitted in the case structure because they are common to all controllers.

Table 1 Initial case base

ID Case	initial	final	P.O.	Ts	Kp	Ti	Td
29	4	8	7%	0:00:20	22	10	0
30	8	12	2%	0:00:14	22	10	0
31	12	16	2%	0:00:14	22	10	0
32	16	12	6%	0:00:24	22	10	0
33	12	8	10%	0:00:17	22	10	0
34	8	4	16%	0:00:19	22	10	0
35	4	8	18%	0:00:37	12	6	0
36	8	12	9%	0:00:34	12	6	0
37	12	16	6%	0:00:33	12	6	0
38	16	12	15%	0:00:50	12	6	0
39	12	8	28%	0:01:04	12	6	0
40	8	4	35%	0:00:36	12	6	0
41	4	16	5%	0:00:53	12	6	0
42	16	4	39%	0:02:34	30	1	0

This initial case base has been constructed using 3 different controller configurations (Kp=22 Ti=10, Kp=12 Ti=6, Kp=30 Ti=1) according to specifications. To each configuration, except the last one, we have evaluated a sequence of changes in the set point (4-8-12-16-12-8-4). Once an initial case base has been constructed is it possible to start a retrieval of the most similar cases to a situation.

Our first experiment was based on querying about a possible change between 6 and 10; a situation not included in the case base, and tries to obtain a successful controller. A similarity criterion has been calculated applying a Manhattan distance giving a weight of 100 to the final set point, 50 to the initial set point and 50 to the overshoot and 0 to the rest of the weights in order to not give importance to the other parameters.

$$sim(C^A,C^B)=\left[\sum_{1}^{N} f(w_i)\cdot sim(x_i^A,x_i^B)\right] \qquad (4)$$

$$sim(C^A,C^B)=w_{ini}\left|ini^A-ini^B\right|^1+w_{final}\left|final^A-final^B\right|+w_{over}\left|over^A-over^B\right| \qquad (5)$$

$$sim(C^A,C^B)=50\left|ini^A-6\right|^1+100\left|final^A-10\right|+50\left|over^A-15\right| \qquad (6)$$

Following this similarity criteria and ordering the results obtained was a table as we can see on Table 2.

The query on the CBR engine can be refined through a decision tree built (see fig.7) using the performance specifications as restrictions, reducing the number of cases to retrieve and improving the quality of the retrieved result. The parameters of the retrieved cases could be combined to provide a valid controller to the process.

Table 2 Similarity results obtained from the example

ID	ini	final	P.O.	Kp	Td	Ti	sim
35	4	8	18%	12	6	0	427
36	8	12	9%	12	6	0	624
29	4	8	7%	22	10	0	690
38	16	12	15%	12	6	0	719
34	8	4	16%	22	10	0	725
33	12	8	10%	22	10	0	772
30	8	12	2%	22	10	0	965
32	16	12	6%	22	10	0	1153
39	12	8	28%	12	6	0	1165
41	4	16	5%	12	6	0	1192
37	12	16	6%	12	6	0	1366
31	12	16	2%	22	10	0	1559
40	8	4	35%	12	6	0	1678
42	16	4	39%	30	1	0	2324

CBR compared to other methodologies has the ability to be adaptable to environment changes. For instance, an expert system could not deal with environment changes such as water evaporation unless it was codified in its rules. CBR instead will offer a possible solution to alterations in behavior. Perhaps this solution would not be as good as expected at first glance, but the combination and revise mechanisms will refine the result until a proper solution is found.
CBR can be integrated in processes in progress, thus allowing on-line learning (training).Learning capacity, adaptation and on-line training characteristics of the CBR systems are quite interesting for its application to industrial processes where these issues are often required.

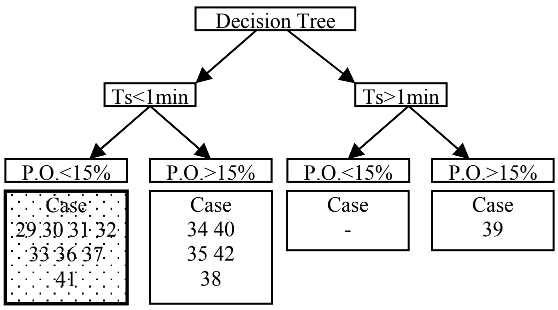

Fig. 7. A decision tree based on performance specifications.

8 .ACKNOWLEDGEMENTS

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