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QUALITATIVE REPRESENTATION OF PROCESS TRENDS FOR SITUATION ASSESSMENT BASED ON CASES

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Abstract: Situation assessment in complex systems is often achieved by expert operators taking into account evolution of signals and comparing it with previous experiences. The criteria used by operators to compare actual situations with previous ones are not easily explainable and in fact they are part of the cognitive procedure. This paper proposes to use qualitative representations of signal trends as experienced cases. The work is centred in two main aspects. First, episodes based representation of signal trends proposed in the CHEM project is used as a description of cases. Then, a similarity criterion among signal representations is defined by a Dynamic Time Warping approach. The usefulness of the approach is shown in an illustrative example by representing and comparing signal dynamics with the goal of Situation Assessment. *Copyright © 2002 IFAC*

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1. INTRODUCTION

In the last decade Case Based Reasoning (CBR) has been tested as a successful methodology in many domains (diagnosis, design, help desk assistants, planning, finances or general decision-making applications, etc.). Although CBR has not been extended in industrial applications it has also been proposed for situation assessment in plant operation as it is described in (Brann et al., 1995) and for planning, diagnosis, troubleshooting, maintenance and quality management in the manufacture industry (Britanik and Marefat, 1995). The new challenge is to exploit CBR potentiality in order to perform on-line situation assessment based on an automatic evaluation of acquired data based on previous experiences. Interpretation of measured process signals and its association with operator experience is proposed to assist situation assessment based on the reuse of previous stored situation as cases. Since a great deal of the process data is available for the human operators and supervision engineers, abstraction procedures must be applied before reasoning. In this sense, qualitative representations are proposed to represent trends of signals (tendencies, oscillation degrees, alarms, degree of transient states...), one of these techniques is the representation of signals by means of episodes.

In the following section a brief introduction to CBR is given. Then, basic concepts related to episodes based representations are discussed and a representation based on the formalism proposed in the CHEM project is outlined. Next, in section 4, similarity methods are discussed with special emphasis on Dynamic Time Warping, which is proposed in section 5 to compare series of episodes. Finally, an illustrative example and some conclusions are explained in the last two sections.

2. CASE BASED REASONING FOR SITUATION ASSESSMENT

Case Based Reasoning (CBR) is a methodology proposed to problem solving by using previous experiences. Cases are registers containing a description of a problem and its solution. Thus, these cases can be reused for solving new problems. The reasoning procedure, in presence of a new problem, consists of retrieving registered cases according to similarity with respect to the enounced problem. Then, the retrieved solutions are adapted in order to propose an adequate solution to the actual problem. Finally, the obtained results are revised and the solved problem is retained as a new case (See Fig.1). These 4 operations (Retain, Retrieve, Reuse and Revise) are known as the CBR cycle. A more extended explanation of CBR methodology and foundations can be consulted in (Aamodt and Plaza, 1994; Lenz, et al. 1998).

This work is centred in two aspects of CBR methodology. First, to propose case definition suitable for situation assessment based on the association of acquired data and human expertise, under the constraint of dealing with dynamic data. Secondly, to define a similarity mechanism to perform the retrieval task dealing with a symbolic representation of signals trends.

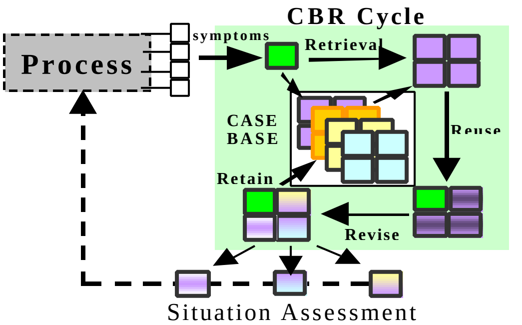

Fig. 1 CBR Cycle

2.1 Case definition

The conceptual definition of cases, considered in CBR, allows performing an association between two complementary views of process behaviour. 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 behaviour 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. According to this premise, cases are conceived as knowledge containers that perform the association between both: *C=[S(t),D]*. Where, *S(t)* represents *symptoms* that characterise the situations under study and *D* reflects the operator experience. *Symptoms* are representations of acquired signals obtained directly from data or after an abstraction procedure. The expert view is encapsulated in D: the evaluation (diagnosis) of the given situation, a set of actions to perform under determined situation or similar information needed to preserve process under normal operation conditions or for warning operator in posterior similar situations.

According to situation assessment goals main difficulties corresponds to represent *S(t)* in a suitable structure in order to guarantee CBR cycle. This is a common problem using CBR with dynamic systems early pointed by Ram and Santamaria (1997). This is also wider discussed in (Meléndez, et al. 2001a, b). The structure proposed in (Meléndez, et al., 2001b) takes into account a temporal interval characterised by initial ($X_0(t_0)$) and final states ($X_f(t_f)$) defined by significant *events*. Signals behaviour between both events are represented by the vector X(t):

$$S(t)=\langle (X_o,t_o),X(t),(X_f,t_f)\rangle \qquad t_o<t<t_f \quad (1)$$

In this work, an episode-based representation is proposed to describe X(t) between both events in a compact way as a succession of qualitative symbols.

2.2 Retrieval by similarity

The most common way of retrieving cases is to use a distance criterion, involving both numerical and qualitative attributes when necessary. Usually they are weighted functions. Other strategies are based on induction algorithms that perform search in a structured case base. The complexity of considering temporal series in the case definitions (symptoms) is considered in this work and after a review of different similarity functions dynamic time warping (DTW) algorithm has been adapted to perform this task.

3. EPISODES BASED REPRESENTATIONS

The general concept of **episode** was introduced in the field of qualitative reasoning by Williams (1986), who defined an episode as a set of two elements: a time interval, named **temporal extent** and a **qualitative context**, providing the temporal extension with significance. This definition allows defining an episode as explicitly as the qualitative context.

A general formalism for the representations of signals by means of episodes, the *Qualitative Representation of Process Trends*, can be found in (Cheung and Stephanopoulos 1990). This formal approach introduces the concept of **trend** as a sequence of episodes characterised by the signs of the first and the second derivative. It has a practical extension in the triangular and trapezoidal representations. Stephanopoulos et al. (1997) have applied the above representation to the analysis of industrial fermentation data. The methodology consists of three components developed by Bakshi and Stephanopoulos (1994a,b). First, a wavelet signal decomposition that acts as a noise removing filter; second, the triangular representation of smoothened process signals, and finally a search algorithm that makes use of decision trees and Shannon’s entropy comparisons for the identification of certain classes of process outcomes. The methodology has been implemented as a part of a broader system referred to as *dbminer©* aimed at fermentation database mining, diagnosis and control.

Janusz and Venkatasubramanian (1991) proposed a qualitative description of signals consisting of *primitives, episodes, trends and profiles*. Primitives are based on the sign of first and second derivatives (positive, zero or negative). Thus, nine basic types compose the set of primitives. The *trend* of a signal consists of a series of *episodes*, and a *profile* is obtained by adding quantitative information. Drawbacks due to noise and discontinuities are rectified by an error correcting code (ECC) acting as a postprocessor (Rengaswamy 1995). Later, Rengaswamy and Venkatasubramanian (1995) refined the language using a syntactic pattern recognition approach where a fixed-size neural network was used to identify the primitives. Vedam and Venkatasubramanian (1997) proposed an adaptive trend identification algorithm based on wavelet theory. Then, the identified primitives are used as input to a knowledge base to perform fault diagnosis. This system, called W-ASTRA, is demonstrated on a fluidised catalytic cracking unit. An improvement is developed by Rengaswamy et al. (2001) and utilised in (Dash et al, 2001), where a new procedure that identifies piecewise unimodals represented as quadratic segments is used to identify qualitative shapes of trends.

The formalism described in (Meléndez and Colomer, 2001) extend previous formalisms to both qualitative and numerical context in order to be more general. It means that allows building episodes according to any feature extracted from variables. According to this formalism, a new representation allows to describe signal trends depending on the second derivative, that can be computed by means of a band-limited FIR differentiator (Colomer and Meléndez, 2001) in order to avoid noise amplification. The qualified first derivative at the beginning and end of each episode is used in order to obtain a more significant representation. Then, a set of 13 types of episodes is obtained (Fig. 2).

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A **B C D E F G H I J K L M**

Fig. 2 Useful set of episodes

A major benefit of this set of episodes for assessment tasks is that discontinuities and stability periods (usual in abnormal and in normal situations respectively) are explicitly represented by means of 5 types of episodes (ù é—û ë). This representation has been adopted to represent symptoms in the case definition.

4. COMPARING TIME SERIES. DYNAMIC TIME WARPING

There are numerous studies that have been carried out to compare sequences of data in several applications. In this section, some models are observed with the aim of store cases according to symptom similarity.

Agrawal et al. (1995b) present a shape definition language (SDL) for retrieving objects contained in histories based on shapes. SDL allows converting original data in a qualitative description of their evolution and its comparison. Agrawal et al. (1995a) introduce a model of similarity based on the notion that two time sequences are said to be similar if they have enough non-overlapping time-ordered pairs of subsequences that are similar. Other indexing methods to locate subsequences within a collection of sequences are presented by Faloutsos et al (1994) or Chan and Fu (1999), witch uses a Haar wavelet transformation for the time series indexing problem.

A new representation, adopted by Keogh and Pazzani (1998), consists of piecewise linear segments to represent shape and a weight vector that contains the relative importance of each individual linear segment, allowing a user to define a variety of similarity measures.

Another useful measure of strings similarity is the length of a longest common subsequence, based on the edit distance required in passing from one string to another one. Paterson and Dancík, (1994) carry out a revision of some of the existent solutions.

A methodology for pattern recognition based on episodes is described in (Bakshi and Stephanopoulos 1994b). Each pattern is represented by a string of primitives identified by means of a pattern grammar. The string that captures all the features necessary for classification is determined by matching the distinct syntactic descriptions, which represent similar events in these trends. Pattern matching facilitates extraction of qualitative and quantitative features used for solving the classification problem resolved by means of the technique of induction by decision trees.

Most of algorithms that operate with time series of data use euclidean distance or some variation. However, these distances are very sensitive to small distortions in the time axis. A method that tries to solve this inconvenience is Dynamic Time Warping (DTW), that uses dynamic programming (Silverman, 1990) to align time series with a given template so that total distance measure in minimised. DTW has been widely used in word recognition to compensate the temporal distortions related to different speeds of speech. Next, a brief notion of DTW is described.

Given two time series X and Y, of length *m* and *n* respectively

$$X=x_1,x_2,...,x_i,...,x_m \qquad Y=y_1,y_2,...,y_j,...,y_n \qquad (2)$$

DTW will find a sequence W of k points on a m-by-n matrix where every element (i,j) contains the distance $d(x_i,y_j)$ between x_i and y_j. The path W is a contiguous set of matrix elements that minimise the distance between the two sequences.

$$W=w_1,w_2,...,w_k \quad \max(m,n)\leq k \leq m+n \qquad (3)$$

$$w_k=[i_k,j_k] \qquad (4)$$

where i_k and j_k denote the time index of trajectories X and Y respectively. In order to find the best path W, some constraints on the matching process are considered, main ones are:

- Constraints at the endpoints of the path, $w_1=[1,1]$ and $w_k=[m,n]$
- Continuity constraints, matching paths cannot go backwards in time, this is achieved forcing i_{k+1} ³ i_k and j_{k+1} ³ j_k.

The path is extracted by evaluating the cumulative distance D(i,j) as the sum of the local distance $d(x_i,y_j)$ in the current cell and the minimum of the cumulative distances in the previous cells. This can be expressed as:

$$D(i,j)=d(x_i,y_j)+\min[D(i-1,j-1),D(i-1,j),D(i,j-1)] \quad (5)$$

Several modifications of this technique have been introduced in order to apply the method in several situations. In (Keogh and Pazzani 1999) a modification of DTW is introduced to operate on a higher level of data abstraction through a piecewise linear representation. (Keogh and Pazzani 2001) consider a higher level feature of shape considering the first derivative of the sequences. Caiani et al. (1998) adapt the DTW approach to the analysis of the left ventricular volume signal for an optimal temporal alignment between pairs of cardiac cycles. (Vullings et al. 1998) implement a piecewise linear approximation and segment the signal into separate heartbeats. DTW also is used in (Kassidas et al. 1998) to synchronise batch process trajectories in order to reconcile timing differences among them.

5. DTW APPLIED TO EPISODES BASED REPRESENTATIONS

As it have been commented previously, DTW is a technique that allows to obtain a more robust measure of similarity between two sequences with different longitudes that they are not exactly aligned in the time axis. As disadvantages, it is an algorithm computationally expensive and it could fail in the alignment by trying to solve the variability in the Y-axis by warping the X-axis. In this section, a modification of the DTW algorithm that allows to solve these inconveniences is introduced.

Table 1 Local distance between episodes.

	┐	┌	╭	∩	╮	\	_	/	╰	∪	╯	┘	└
┐	0	.72	.85	.7	.62	.67	.75	.9	.8	.87	.95	1	.67
┌	.72	0	.7	.62	.77	.82	.75	.75	.87	.95	.87	.67	1
╭	.85	.7	0	.52	.8	.85	.6	.27	.9	.82	.65	.8	.87
∩	.7	.62	.52	0	.45	.6	.6	.6	.82	.9	.82	.87	.95
╮	.62	.77	.8	.45	0	.27	.6	.85	.65	.82	.9	.95	.87
\	.67	.82	.85	.6	.27	0	.55	.8	.27	.6	.85	.9	.75
_	.75	.75	.6	.6	.6	.55	0	.55	.6	.6	.6	.75	.75
/	.9	.75	.27	.6	.85	.8	.55	0	.85	.6	.27	.67	.82
╰	.8	.87	.9	.82	.65	.27	.6	.85	0	.4	.8	.85	.7
∪	.87	.95	.82	.9	.82	.6	.6	.6	.4	0	.45	.7	.62
╯	.95	.87	.65	.82	.9	.85	.6	.27	.8	.45	0	.57	.77
┘	1	.67	.8	.87	.95	.9	.75	.67	.85	.7	.57	0	.72
└	.67	1	.87	.95	.87	.75	.75	.82	.7	.62	.77	.72	0

The representation of a sequence as episodes reduces the calculation time by decreasing the amount of manipulated data. Likewise, the qualitative character that defines an episode avoids the problem of the variability in the Y-axis. Therefore, this algorithm allows aligning episodes to obtain a global distance. The problem is to define a local distance between episodes. In this sense, a chart of distances between the 13 types of episodes, based on the qualitative state and auxiliary characteristic that define each type, must be defined (Table 1). However, these local distances could be subject to the criterion of the user, giving more importance to some types. This is the case shown in Table 2, where the criterion has been to distinguish three groups, with higher distances between types of different groups.

Table 2 Local distance between episodes.

	┐	┌	╭	∩	╮	\	_	/	╰	∪	╯	┘	└
┐	0	1	1	.75	.25	.5	1	1	.75	1	1	1	1
┌	1	0	.25	.75	1	1	1	.5	1	1	.75	1	1
╭	1	.25	0	.5	1	1	.75	.25	1	1	.5	.75	1
∩	.75	.75	.5	0	.5	.75	.5	.75	1	1	1	1	1
╮	.25	1	1	.5	0	.25	.75	1	.5	1	1	1	.75
\	.5	1	1	.75	.25	0	.5	1	.25	.75	1	1	.5
_	1	1	.75	.5	.75	.5	0	.5	.75	.5	.75	1	1
/	1	.5	.25	.75	1	1	.5	0	1	.75	.25	.5	1
╰	.75	1	1	1	.5	.25	.75	1	0	.5	1	1	.25
∪	1	1	1	1	1	.75	.5	.75	.5	0	.5	.75	.75
╯	1	.75	.5	1	1	1	.75	.25	1	.5	0	.25	1
┘	1	1	.75	1	1	1	1	.5	1	.75	.25	0	1
└	1	1	1	1	.75	.5	1	1	.25	.75	1	1	0

6. ILLUSTRATIVE EXAMPLE

As example, the results of the comparison of signals using several techniques are presented. Four signals (Fig. 3) with the same duration in time, but with different temporary misalignments and variability in the Y-axis are considered. The goal is to obtain a measure of similarity.

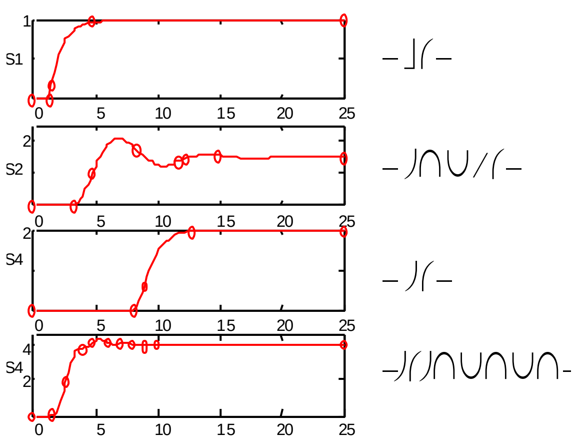

Fig. 3 Signals to be compared and its representation

First, the Euclidean distance is used. Results , shown in Table 3, don't allow a correct comparison (0 value represent a complete equality). Due to the variability in the Y and X-axis the results are clearly faulty. Better results are obtained with an amplitude scaling and synchronising the responses, although they continue being incorrect due to the misalignment in the X-axis (Table 4).

Table 3 Similarity using euclidean distance

	S1	S2	S3	S4
S1	0	0.16	0.396	3.959
S2	0.16	0	0.34	2.94
S3	0.396	0.34	0	3.32
S4	3.959	2.94	3.32	0

Table 4 Similarity using euclidean distance

	S1	S2	S3	S4
S1	0	4.78	0.72	1.99
S2	4.78	0	5.21	5.17
S3	0.72	5.21	0	0.42
S4	1.99	5.17	0.42	0

The results presented in Table 5 are obtained by using a classical DTW algorithm. The result is not the desired again. However, since the algorithm is only sensitive to the variability in the Y-axis, a better results are obtained after an amplitude scaling (Table 6). Now, certain similarity between S4 and S1, S3 can be observed. This fact occurs because the amplitude scaling generate similar values and the misalignment in the Y-axis is solved by the DTW algorithm.

Table 5 Similarity using classical DTW

	S1	S2	S3	S4
S1	0	0.135	0.283	4.01
S2	0.135	0	0.083	2.82
S3	0.283	0.083	0	1.775
S4	4.01	2.82	1.775	0

Table 6 Similarity using classical DTW

	S1	S2	S3	S4
S1	0	3.427	0.008	0.036
S2	3.427	0	3.424	2.576
S3	0.008	3.424	0	0.0318
S4	0.036	2.576	0.0318	0

Finally, the tests carried out with the proposed approach of DTW by considering the qualitative representation are shown in Table 7 and Table 8. As it could be expected, the algorithm distinguishes in better way similar patterns because not numeric values but the behavior is considered.

The difference of local distances between types of episodes defined in Table 1 and Table 2 doesn't affect too much the global measure of similarity, although it allows to obtain a finer measure. The difference resides in defining a major or minor distance between those episodes with a different behavior. The obtained values are a normalised distance, so 0 represent a complete equality.

Table 7 Similarity using proposed DTW and Table 1

	S1	S2	S3	S4
S1	0	0.31	0.144	0.415
S2	0.31	0	0.221	0.237
S3	0.144	0.221	0	0.357
S4	0.415	0.237	0.357	0

Table 8 Similarity using proposed DTW and Table 2

	S1	S2	S3	S4
S1	0	0.285	0.0625	0.325
S2	0.285	0	0.214	0.25
S3	0.0625	0.214	0	0.3
S4	0.325	0.25	0.3	0

7. CONCLUSIONS AND FUTURE WORK

This work is focused on two main aspects of CBR (case definition and case retrieval) for situation assessment. The paper shows the use of episodes representations of signal proposed in the CHEM project as experienced cases. Then, a similarity criterion among signal representations is defined by a Dynamic Time Warping approach for case retrieval. Main problems appear due to the complexity in the comparison of sequences. If quantitative characteristics are not decisive in order to distinguish two classes, the solution rests in making an alignment and a comparison on the temporal axis. But matching the episodes being based in a temporal alignment of data could not align those episodes with identical qualitative characteristics. A same class could correspond to slower or faster process dynamics. Future work must consider the time as another factor to keep in mind in the measure of similarity, considering the comparison of sequences of episodes with different longitude of time, with different number of episodes, and different longitude of each.

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