Online fuzzy temporal operators for complex system monitoring

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Abstract

Online fuzzy expert systems can be used to process data and event streams, providing a powerful way to handle their uncertainty and their inaccuracy. Moreover, human experts can decide how to process the streams with rules close to natural language. However, to extract high level information from these streams, they need at least to describe the temporal relations between the data or the events.

In this paper, we propose temporal operators which relies on the mathematical definition of some base operators in order to characterize trends and drifts in complex systems. Formalizing temporal relations allows experts to simply describe the behaviors of a system which lead to a break down or an ineffective exploitation. We finally show an experiment of those operators on wind turbines monitoring.

1 Introduction

Complex systems are now equipped with hundreds of sensors which deliver continuous signals. Sensors provide either measurements at a dynamic or constant sampling rate (i.e. data streams, e.g. connected thermometers), either events whenever they are detected (i.e. event streams, e.g. presence detectors). Such streams are generally processed, filtered and combined to get higher level information. These operations can be applied to predictive maintenance of complex systems.

Predictive maintenance consists in monitoring an engineering system in order to detect changes in its exploitation and prevent damages. Having a continuous report of in-service systems allows an optimal use of it, the avoidance of important damages and early-stage failure detection. Moreover, it changes the organization of maintenance services by replacing scheduled and periodic maintenance and by minimizing the involvement of operators.

Artificial intelligence plays an important role in predictive maintenance [4] and provides system-specific solutions : signal processing and statistical learning techniques have been successfully applied to obtain a type of damage or a type of risk. Predictive maintenance mainly relies on data from process sensors (temperature, pressure, etc.) and test sensors (vibration, acoustic, humidity, etc.) [3]. In order to better handle the sensors inaccuracy and the uncertainty in the assessment of the system's state, fuzzy logic has been applied to predictive maintenance [8, 12].

Our work consists in developing an online fuzzy expert system which can take data or event streams as input. The goal is to reinforce the expressivity of such systems to let experts author their own rules with complex fuzzy relations. Gathering the knowledge of different experts can be a suitable approach to predictive maintenance, avoiding some difficulties of the techniques described formerly:

- no past data are needed to build the models;
- the decision can be explained through the trace of activated rules.

In the case of predictive maintenance, the rules consist in detecting patterns in time-series which lead to a damage. Numerous authors [1, 2, 11] state temporal relations are a prerequisite to describe such patterns. One can distinguish different approaches. On the one hand, fuzzy temporal relations [2, 5, 10] can be used to describe the temporality of events but are not always relevant for online causal reasoning. On the other hand, some papers suggest to linguistically describe time-series [6, 7] using fuzzy natural logic, specifically on complete time-series, i.e. in an offline way.

In this article, we remind 3 base fuzzy temporal relations which are then combined into more complex relations. The compositional paradigm we use allows to create new intuitive relations because they combined simple operators. The new operators are the first of a series of temporal operators which can be used to describe time-series. In our work, we make the following assumptions:

- sensors give correct timestamps: there is no uncertainty in the acquisition timestamps, but we take into account the vagueness in the relations between the timestamps;
- sensors values are fuzzified to both manipulate linguistic terms and manage their inaccuracy.

The article is organized as follows: the next section presents the previous work and the notations. The new temporal operators are described in section 3. In section 4, we describe their use by an application to wind turbine predictive maintenance. Finally, section 5 draws the conclusions and perspectives of this work.

2 Previous work

In our previous work, we introduced a compositional paradigm which consists in deriving specialized operators from base operators in the temporal domain [9]. In this paper, we take advantage from these operators to build new temporal ones for online characterization of time-series.

The temporal operators use two concepts to deal with event streams [9]. On the one hand, expiration is the faculty for a temporal expression to yell that its value has expired and must be re-evaluated. On the other hand, they are applied on a scope. A scope is a fuzzy set defined on a temporal domain, anchored at the present moment, and whose membership function gives the importance of a moment in this temporal domain. For instance, figure 1(c) shows such a scope representing "the last 10 seconds". Both concepts ensure a satisfying computational cost and allow an online execution.

Let E be a fuzzy expression, $eval(E, t)$ be the value of E at time t. Let S be a fuzzy scope and μ_S its membership function. In the remainder of this paper, we will use the following temporal operators:

- The occurrence operator which indicates if an expression has a degree of fulfillment strictly greater than 0 throughout the scope :

$$Occ(E, S, t_{now}) = \bigvee_{t \in supp(S)} eval(E, t) \wedge \mu_S(t) \tag{1}$$

  When its value is strictly greater than 0, it means that at least at one moment of the scope, the operand expression has been observed. It is a disjunction over all the moments t_i in the scope of conjunctions of the operand value at time t_i and the value of the scope membership function for t_i.

- The ratio operator which aggregates the different degrees of fulfillment of the operand expression E throughout a scope S:

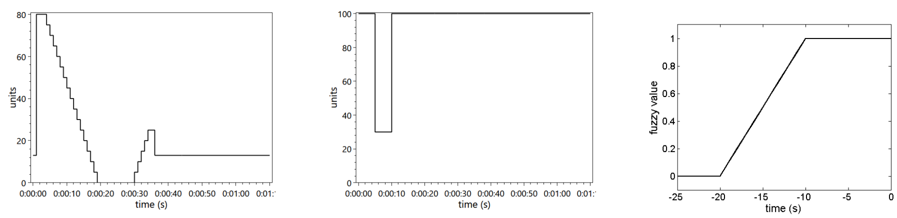
$$Ratio(E, S, t_{now}) = \frac{\int_{t \in supp(S)} eval(E, t) \wedge \mu_S(t)}{\int_{t \in supp(S)} \mu_S(t)} \tag{2}$$

  It aggregates the different values of the operand E on the scope S, divided by the area under the scope membership function. It is related to Zadeh's relative count applied on a fuzzy scope.

- The persistence operator which indicates if at each moment of S, the degree of fulfillment of E is strictly greater than 0:

$$StrictPers(E, S, t_{now}) = \neg Occ(\neg E, S, t_{now}). \tag{3}$$

  It equals 0 if there exists a moment t_i in the scope S such as $eval(E, t_i) = 0$. This is why we called it "strict". To moderate its definition, we can either replace the Occ operator by the $Ratio$ inside its definition, or simply use $Ratio$ instead of $StrictPers$.



(a) Signal of Input1 (b) Signal of Input2 (c) Fuzzy scope for the last 10 seconds

Figure 1: Examples of two signals and a fuzzy scope

In the next section, we use these operators to define new temporal operators to both characterize trends of time-series and to compare two of them. Adopting an iterative approach, we first define the following operators and we will add new ones when are not sufficient anymore.

3 Signal characterization operators

To illustrate the behavior of the operators, we introduce some examples of input signals and parameters we will use throughout this section.

For the sake of comprehension, figures 1(a) and 1(b) show two simple simulated signals. We will use these signals to illustrate the behavior of the operators and in the section 4, we will use more realistic signals.

In the remainder of this section, without loss of generality, the operators are defined upon the *Ratio* operator. As a consequence of the use of the *Ratio* operator, those operators are considered tolerant. Thus, if at some moment the input signal is changing for a short while, the direct effect of its change is smoothed. If a more strict behavior is needed, it is possible to replace the *Ratio* by the $StrictPers$ operator.

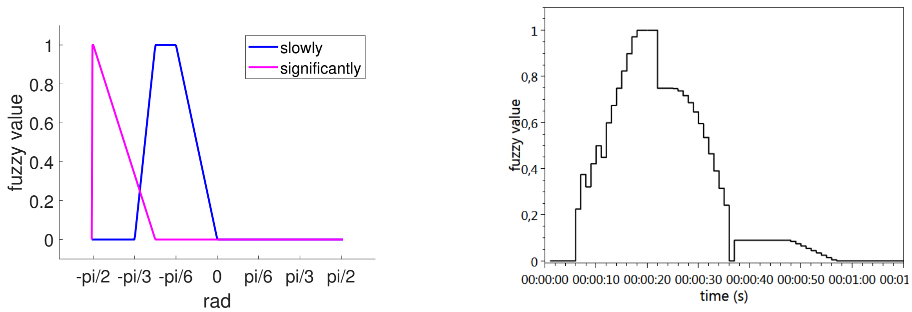
3.1 Growth, decline and variation

In predictive maintenance, it is important to be able to characterize drifts of some sensors, because it can lead to the detection of a damage. The goal here is to monitor the growth or the decline of an input value with operators such as:

$$\textit{input}\ \langle \textit{adverb} \rangle \text{ decreases/increases throughout } S.$$

where adverb is a fuzzy set which represents, for example, “slowly” or “significantly” and S is a fuzzy scope.

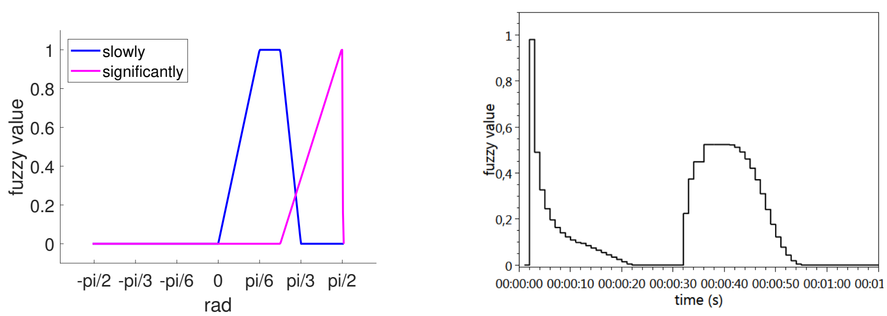
To compute a degree of fulfillment for such relations, saving all the values in the scope is not necessary. We chose instead to compute the gradient between the two last samples and then to characterize its direction with a fuzzy set corresponding to the adverb. The fuzzy set is thus defined on a quarter of



(a) Examples of "slowly" and "significantly" membership functions

(b) "Input1 significantly decreases throughout the last 10 seconds"

Figure 2: Examples of membership functions for the adverbs of the *Decreases* operator and result on Input 1



(a) Examples of "slowly" and "significantly" membership functions

(b) "Input1 significantly increases throughout the last 10 seconds"

Figure 3: Examples of membership functions for the adverbs of the *Increases* operator and result on Input 1

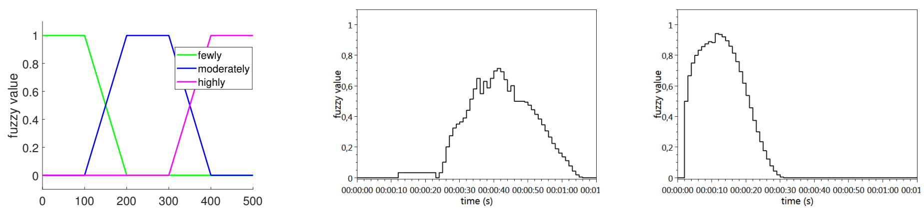
the trigonometric circle (top-right quadrant for the growth and bottom-right quadrant for the decline). Figures 2(a) and 3(a) show an example of membership functions for adverbs "slowly" and "significantly" applied respectively to the decline and the growth operator.

To aggregate the characterizations of the gradient over the scope, we can use the *Ratio*. Thus, the *Decreases* operator can be defined as:

$$Decreases(I, S, \mu_g, t_{now}) = Ratio(\mu_g(grad(I, t_{now})), S, t_{now}) \tag{4}$$

where I is the real input of the system whose values change, $grad$ is the direction of the gradient, and μ_g is the membership function of the adverb fuzzy set.

The *Increases* operator only differs from the *Decreases* operator because of the definition domain and the membership function of the adverb fuzzy set.



(a) Examples of "fewly", "moderately" and "highly" membership functions

(b) "Input1 varies fewly throughout the last 10 seconds"

(c) "Input1 varies highly throughout the last 10 seconds"

Figure 4: Examples of membership functions for the adverbs of the $Varies$ operator and results on Input 1

Figures 2(b) and 3(b) show respectively the result of operators *Decreases* and $Increases$ on the first input whose signal is shown in figure 1(a).

In a similar way, it is useful to be able to tell that the value of an input remains stable over time, with an operator like:

$$\text{input varies } \langle adverb \rangle \text{ throughout } S$$

where *adverb* is a fuzzy set which represents, for instance, "fewly" or "highly". The definition of the $Varies$ operator is based on the variance of its signal over S and on a fuzzy set which defines the *adverb* by characterizing the variance. The $Varies$ operator is defined by:

$$Varies(I, S, \mu_v, t_{now}) = Ratio(\mu_v(Var(I, supp(S))), S, t_{now}) \quad (5)$$

where I is an input of the system whose value changes, Var is the variance of the signal $I(t)$ over S and μ_v is the membership function of the *adverb* fuzzy set.

Figures 4(b) and 4(c) show the results of the $Varies$ operator on the first input (see figure 1(a)), using respectively the adverbs "fewly" and "highly" described in figure 4(a).

3.2 Comparison

The last family of operators in this article concerns comparison between two input values throughout a scope; one of them can be a fixed value, for instance a threshold. For instance, an expert may want to express that the signal of an input is extremely less than another value:

$$\text{input1 is } \langle adverb \rangle \text{ less/greater/close than/to input2 throughout } S.$$

The idea behind these operators is to compare at each time the two values and to characterize the difference between them with a fuzzy set (the adverb).

Then, we aggregate the point-to-point comparisons with the *Ratio* operator. Thus, we can define $LessThan$, $GreaterThan$, $CloseTo$ as:

$$LessThan(I_1, I_2, S, \mu_{lt}, t_{now}) = Ratio(\mu_{lt}(I_1(t_{now}) - I_2(t_{now})), S, t_{now}) \quad (6)$$
$$GreaterThan(I_1, I_2, S, \mu_{gt}, t_{now}) = Ratio(\mu_{gt}(I_1(t_{now}) - I_2(t_{now})), S, t_{now}) \quad (7)$$
$$ClosteTo(I_1, I_2, S, \mu_{ct}, t_{now}) = Ratio(\mu_{ct}(I_1(t_{now}) - I_2(t_{now})), S, t_{now}) \quad (8)$$

where μ_{lt}, μ_{gt} and μ_{ct} are the membership functions of the adverb fuzzy set which characterizes the difference between the two signals $I_1(t)$ et $I_2(t)$. The operators differ by the definition of the adverb fuzzy set.

Figure 5(b) shows the application of the $GreaterThan$ operator on the input signals shown in figures 1(a) and 1(b) with the adverb "much"(figure 5(a)).

(a) Example of "much" membership function for a comparison with $GreaterThan$

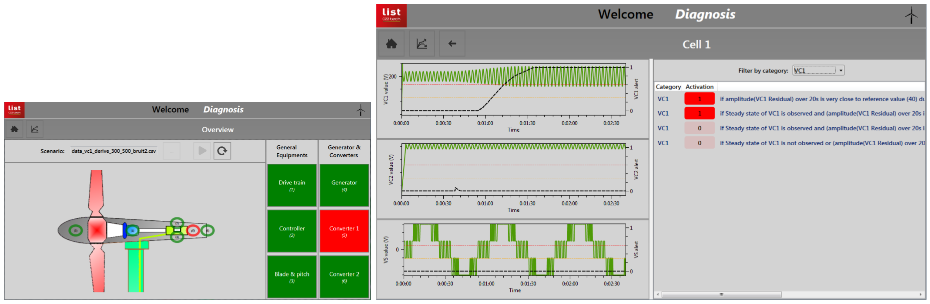
(b) "Input1 is much greater than input2 throughout the last 10 seconds"

Figure 5: Example of membership function for the adverb of the $GreaterThan$ operator and result on Input 1 and Input 2

4 Application to a drift detection

The goal of the presented work is to apply fuzzy expert systems to predictive maintenance of complex systems. As illustration, we developed a specific software for wind turbines. Figures 6 show some screenshots of our tool. It provides an overview of the system (figure 6(a)) and can locate with a circle the suspected default. The tiles on the left indicate the state of each sub-system of the wind turbine : a green tile indicates it is fully functional while a red tile indicates a critical state. By clicking on a tile, it is possible to access a more detailed view (figure 6(b)) with the signals, the output of the fuzzy expert system, and the rules with their activation which give an explanation of the decision contrarily to other approaches.

In this paper, we focus on the characterization of one of the sub-systems: the rotor-side multicellular converter. It occasionally suffers from drifts which are clues that the energy production is not optimal. It consists of serial cells, each one containing two switches with complementary values. The combination of the values of all the switches in the converter defines a "mode". Among the



(a) Screenshot of the system overview

(b) Screenshot of the detailed view

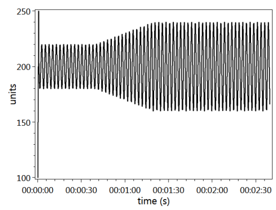
Figure 6: Screenshots of the application for windturbines

other variables, the dynamics of the converter is also described by VC_i which is the floating voltage of the capacitors C_i of each cell. An instance of a controlled drift of VC_i is shown in figure 7(a). According to the mode, the drift can be detected or not. It results in the computation of the new signal VC_i residuals by subtracting the mean reference value to VC_i according to the mode as defined in [13] (figure 7(b)). Then, we defined a rule base for detecting such a drift composed of:

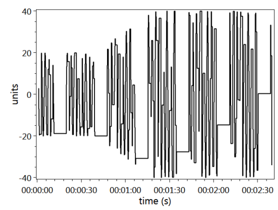
- First, rules for defining the nominal values of the system. To compute that, we wait for a steady state during at least 20 seconds and we compare the actual values of the amplitude of VC_i residuals to the values provided by the constructor.
- Then, rules for monitoring a drift and, according to its importance and its duration, to yield a suitable level of alarm.

Figures 8 show the membership functions used to compare the amplitude of VC_1 residuals (figure 7(c)) to its reference value and different expressions computed to detect the drift. Once the steady state has been observed, the expression verifying that the amplitude of VC_i residuals is very close to the reference value (figure 8(b)) is associated with a null alert (figure 9(a)), and the one verifying that it is much higher than the reference value (figure 8(c)) is associated with a high alert. The defuzzified value of the alert is shown by a black curve in figure 9(b). The drift is applied between 40 and 80 seconds. It begins to be detected after only 15 seconds which is the delay necessary to compute the *Ratio* operator on the chosen temporal scope. Then, the alert value gradually rises until it reaches its maximum value 40 seconds afterward.

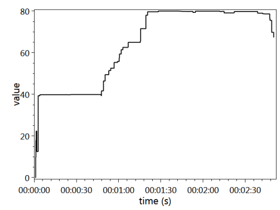
Monitoring a system with fuzzy temporal rules enables both to estimate a continuous value of the output (an alert here) and to know which rules are activated and led to the results. All the membership functions used as well as temporal scopes have to be chosen according to the application in order to characterize a normal or abnormal behavior of each sub-system. They can be learned when sufficient data of sub-systems are available.



(a) VC_1 values

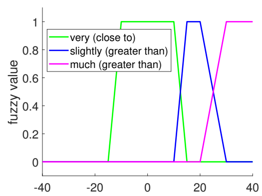


(b) VC_1 residuals

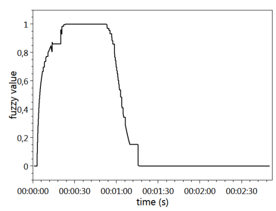


(c) Amplitude of VC_1 residuals over 20 seconds

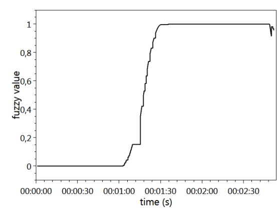
Figure 7: Input example for floating voltage of capacitor C_1



(a) Membership functions for comparing amplitudes of VC_1 residuals to the reference value

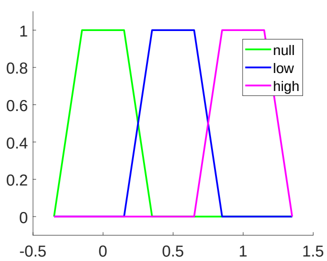


(b) "Amplitude of VC_1 residuals is very close to reference value during the last 20 seconds"

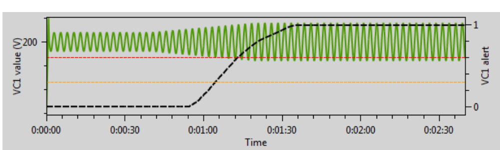


(c) "Amplitude of VC_1 residuals is much greater than the reference value during the last 20 seconds"

Figure 8: Examples of membership functions for comparing the amplitude of VC_1 residuals to the reference value and results of comparison operators



(a) Membership functions for output "alert"



(b) VC_1 signal (left-hand axis) and defuzzified value of a drift alert between 0 and 1 (right-hand axis) superimposed

Figure 9: Example of membership functions for alerting a drift detection and application of detection rules on VC_1 signal

5 Conclusion

In this article, we use a compositional paradigm to build new temporal operators to characterize the kinetics of input values. From simple and intuitive operators like the ratio and the persistence, the temporal aspect is easily handled. These operators can take into account both the temporal uncertainty and the vagueness of the relation between the values.

With such operators, online fuzzy expert systems can play an important role in predictive maintenance or health monitoring. Experts can describe their knowledge about the systems and describe the clues which lead to damage detection from sensors signals. The decision making process can then be justified to the user by tracing activated rules. Moreover, such expert systems are independent of the system on which they are applied, contrary to statistical models which are system-dependent.

The perspectives of our work is to formalize more operators which are suitable for predictive maintenance, like online operators to characterize the seasonality or the periodicity of time-series.

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