FUZZY TEMPORAL RULE-BASED SYSTEMS: NEW CHALLENGES

Senén Barro **Alberto J. Bugarín** **Purificación Cariñena** **Félix Díaz-Hermida** **Manuel Mucientes**

Departamento de Electrónica y Computación. Universidad de Santiago de Compostela
{senen, alberto, puri}@dec.usc.es, felixdh@usc.es, manuel@dec.usc.es

Abstract

Applications in control and/or monitoring usually demand an explicit representation and management of time. Fuzzy Temporal Rules (FTRs) introduce an explicit fuzzy representation of time, allowing relative occurrences of events, quantification, and other types of operators. In this model fuzziness can appear not only in the temporal references, but also in the sets of values and operators involved. This paper presents the most relevant features and applications of knowledge representation and reasoning within the FTRs framework. New challenges, both regarding automated learning of knowledge bases involving these rules and potential new fields of application in a number of areas, are also described.

Keywords: Fuzzy Temporal Rules, Fuzzy Temporal Reasoning, Evolutionary Fuzzy Systems

1 INTRODUCTION

Modelling of applications in control and/or monitoring by means of fuzzy rule-based systems usually demand an explicit representation and management of time. In propositions such as "*The temperature has been very low for a few seconds*", "*Vomiting started more than 15 minutes after the beginning of the radiation exposure*" or "*The distance to the wall has kept low in part of the last measurements*" time appears as a temporal reference for a number of events ("for a few seconds", "in the last measurements") or as a relationship between the occurrence of different events ("15 minutes after"). This explicit representation of time in propositions and the subsequent models for performing reasoning using these pieces of knowledge cannot be directly accomplished within the non-temporal propositions scheme "*X is A*" usual in fuzzy rule-based systems (or at least not in a direct and intuitive way).

Other expressions involving different types of operators, either describing relationships between the variables ("*the temperature in most of the tanks is high*", "*the minimum of the high pressure values*", "*the mean of the velocities in the vicinity of an obstacle*"), or stating the occurrence of events in a fuzzy temporal window ("*the mean of high temperatures in the last ten minutes*", "*the minimum of the recent values of high pressure*"), or even combinations of both ("*for a minute the mean value of the temperature in heater 1 was bigger than the mean value of the temperature in heater 2*") are examples of knowledge representation needs when modelling complex dynamic systems. Furthermore, in other fields like flexible querying or data mining it may become necessary to evaluate the fulfilment of complex relationships such as "*most of the people who entered the ER recently are young*", "*the maximum salary between middle-aged employees with low income*". To sum up, modelling such expressions demands an adequate semantic model that take into account an explicit fuzzy representation of time and consider that fuzziness can appear not only in the temporal references, but also in the sets of values and operators involved.

With the purpose of increasing the flexibility of the usual model for fuzzy propositions, some models that include time more or less explicitly as another decision variable have been proposed [15, 18, 9, 6, 8]. In [3] a model of fuzzy temporal rules (FTRs) that extended these proposals aiming to allow the fuzzy representation and reasoning on temporal and non-temporal references was described. A language was introduced which allows experts to describe their knowledge (including the temporal component) in a legible and flexible way, allowing relative occurrences of events, quantification and other types of operators.

Since this FTRs model is oriented to real-time applications, the signal values are assumed to be obtained with a given periodicity, or at least will be associated with successive time points. In a dynamic system the variables are obtained from measurements of external signals, whose values are changing in time, or can be inferred at particular time points. This makes it necessary to consider not only the current values of the signals, but also those previously observed, which allows to reason about the history of signal values.

The general expression of a FTR in this model is:

IF P_1 and P_2 and ... and P_M THEN C_1 and C_2 and ... and C_N

where P_m, $m = 1,...,M$ and C_n, $n = 1,...,N$ are Fuzzy Temporal Propositions (FTPs). For the sake of clarity, we will describe in what follows some of the most relevant features of the FTPs.

Propositions in the antecedent part of the rule represent facts where both temporal and non-temporal information can be fuzzy and can be given in an absolute manner, or relative to the occurrence of other facts. As an example, we present in Table 1 some of the rewriting rules of the grammar to construct these FTPs (the reader is referred to [3, 4] for a more complete description of the rules).

A **value constraint** is a non-temporal fuzzy value, defined on the universe of discourse of a given variable. Three types of value constraints can be applied to a signal: absolute ("Pressure is *high*"), relative to another reference signal through a point to point *value relationship*, as in "Pressure in heater 1 is *much greater than pressure in heater 2*", and quantified value constraints ("Pressure is *high in most of the heaters*").

A *filtered signal* represents a signal defined in the $[0, 1]$ interval, obtained after applying a value constraint to a variable, by means of a **linguistic filtering** process [14]: evaluation of the possibility distribution defining the constraint on each one of the signal values.

Sometimes it is necessary to establish **temporal constraints** on the set of time points where a signal is being evaluated. For example, it may be required that the value constraint is applied not over all the history of signal values, but only for a subset of time points. This subset will be defined by a temporal constraint, which can be an instant or an interval, fuzzy or not. Temporal constraints can also be absolute or relative, so they require the consideration of different relationships between temporal entities. We consider the following basic temporal entities: fuzzy temporal instant, fuzzy temporal duration, fuzzy temporal interval and fuzzy temporal relationships, assuming that all the basic temporal relationships (both qualitative and quantitative) between instants and/or intervals, and between temporal durations can be reduced to relationships between time points and durations. Some examples of this kind of relationships are [1]: *before, at the end of, when,...*.

A temporal constraint can also act as a *temporal context* [17] for signal evaluation, establishing a temporal window within which the degree of fulfilment of the proposition has to be obtained. Basically, a temporal reference can be described in an absolute manner ("*at 20:00*"), relative to the current time point ("*ten minutes ago*") or relative to the occurrence of an event ("*a little after an increase in pressure*", "*between 30 minutes and 2 hours after the beginning of the irradiation*" [8]).

Three types of operators are considered: quantifiers, specification operators and reduction operators. **Quantifiers** in the temporal part of FTPs allow to model expressions of the form $X\ is\ A\ in\ Q\ of\ T$ (for example, "*the temperature has been high in* most of the *previous half an hour*"), which introduce the central concept of *persistence* [2], related to the use of fuzzy temporal intervals as temporal references in the propositions: when a condition on a variable must be evaluated over a fuzzy temporal interval, it may be required that the value or condition is fulfilled, at least to some degree, for all the time points in the interval, or just for any of them. Between both extremes there is a continuous of situations ("*in most of the previous hour*") that have not yet been fully developed within the scope of temporal reasoning.

A signal **specification operator** selects a candidate among several, according to specific non-temporal or temporal, and maybe fuzzy, criteria. Examples of this type of operators are *first, last, maximum, minimum...* Thus, a proposition can refer to "*the maximum of pressure values in the last 30 minutes*", "*the last value of high temperatures*", "*the minimum of the velocity values in the proximity of an obstacle*"...

A **reduction operator** resumes a series of signal values in a single one, defined on the same universe of discourse. When describing dynamic systems we usually find expressions involving operators that act on the values observed or inferred for a variable on a temporal reference, in order to obtain a new value that does not necessarily have to match any of the original ones. Examples of these operators are: *mean value* or *accumulated value*.

Considering this type of FTP, expressions containing value relationships between variables can be described ("*Temperature in heater 1 is much greater than temperature in heater 2*"), with different degrees of structural complexity ("*Temperature in heater 1 in the previous seconds was much greater than temperature in heater 2 two hours ago*"). More generic structures can be described, where the temporal and value constraints in the proposition are rewritten in a more elaborate way: "*Pressure 1 was much higher than pressure 2, a little after temperature 1 was lower than temperature 2*", "*Temperature is low while pressure is high*". Related to the use of different operators, other expressions are: "*Most of the temperature values through the previous*

Table 1: FTP: General structure of a propositional clause.

<table>
<tr><td>(R1) <Propositional clause>::= (<Proposition> | <Proposition><Value relationship><Proposition>)[<Temporal interval>]</td></tr>
<tr><td>(R2) <Proposition>::= (<Filtered signal> | <Signal>) <Temporal instant> |
| (<Operator> | <Quantifier>) (<Filtered signal> | <Signal>) [<Value constraint>] <Temporal interval></td></tr>
<tr><td>(R3) <Filtered signal>::= <Signal> <Value constraint></td></tr>
<tr><td>(R4) <Signal>::= TEMPERATURE | PRESSURE | ...</td></tr>
<tr><td>(R5) <Value constraint>::= (<Relative value constraint> | <Absolute value constraint>) [<Quantified value constraint>]</td></tr>
<tr><td>(R6) <Relative value constraint>::= <Value relationship> <Signal></td></tr>
<tr><td>(R7) <Absolute value constraint>::= HIGH | LOW | MORE THAN 30 | ...</td></tr>
<tr><td>(R8) <Quantified value constraint>::= <Quantifier> [<Signal>] (<Absolute value constraint> | <Relative value constraint>)</td></tr>
<tr><td>(R9) <Value relationship>::= GREATER THAN | LESSER THAN | SIMILAR TO |...</td></tr>
<tr><td>(R10) <Temporal instant> [...]</td></tr>
<tr><td>(R11) <Temporal interval> [...]</td></tr>
<tr><td>(R24) <Operator>::= <Reduction operator> | <Specification operator></td></tr>
<tr><td>(R27) <Quantifier>::= <Absolute quantifier> | <Relative quantifier></td></tr>
<tr><td>(R28) <Absolute quantifier>::= [APPROXIMATELY] (MORE_THAN_2 | LESS_THAN_7 | BETWEEN_3_AND_5 | ...)</td></tr>
<tr><td>(R29) <Relative quantifier>::= [APPROXIMATELY] (ALL | MOST_OF | HALF | PART OF | ...)</td></tr>
</table>

minutes have been high" (quantification), "*The maximum of temperature values between 6 and 8:30 was very low*" (specification) or "*The mean value of temperature in the last 48 hours was moderate*" (reduction).

1.1 APPLICATIONS OF FUZZY TEMPORAL RULES

The first real application of the FTR model was in the field of mobile robotics, namely in the implementation of two behaviours on a Nomad 200 robot: moving objects avoidance and wall-following [13, 12]. When the robot has to avoid a collision with a moving object, it is specially worthy to estimate the trend of the object. In that way, instead of taking a control action based on the current values of some variables, a more appropriate behavior can be obtained through the analysis of the movement of the object in the recent past (last few seconds). FTRs play a central role in this analysis, as they can cope with noisy measurements coming from the robot sensors and, at the same time, evaluate the trend of each variable. The control system was implemented with 114 rules divided in three modules: object course evaluation, behaviour selection, and behaviour implementation. A typical FTP for this behaviour is: "*the speed of the object is not increasing in part of the last seconds*".

The wall-following behaviour was implemented by several authors using fuzzy controllers. However, on the real robot this behaviour is quite sensible to spurious sensor measurements, which is reflected in oscillations of the robot along the path. That situation can be mostly solved taking control actions based on several consecutive measurements, discarding those that are noisy. A 321 FTRs system was impemented to that purpose. The system has been divided in three rule bases: straight wall, convex and concave corner. FTPs are like: "*right-hand distance diminishes a little approximately in the last measurements*". With this model, the persistence in the occurrence of certain events in time, and also temporal and value relationships between signals can be taken into account.

Another practical application of the FTR model was in the field of landmark detection for mobile robots in indoor environments (door-detection in a corridor [5]). This task constitutes a vital part within a complex navigation system in closed environments, since it provides information for robot localization in the environment, fundamental for planning trajectories and movements. It was developed again using real data from the ultrasound sensors of the robot, and good results have been obtained given the requirements of the system.

Door detection requires the consideration of two aspects: temporal relationship between consecutive detections in some sensors, and value relationships between the signals. Translating the knowledge associated to door detection into our FTRs model, two rules are obtained for the detection of doors on the robot's left and right side, respectively. To describe these rules, the temporal relationship "a few instants before" between the events "sharp rise" and "sharp fall" of the ultrasound signals was considered since the temporal distance between the current distance value provided by one of the sensors, and previous values provided by the other is the key for the detection of a door.

This temporal distance between the events marking the beginning and end of each door depends on the velocity of the robot. This velocity is not constant, but changes according to the environment (it decreases when the robot turns, or when an irregularity in the wall is detected, and it is bigger in straight wall situations [12]), so we take as a reference the velocity when the robot is getting close to a door. Since the velocity presents important oscillations, it is more adequate to consider the mean velocity in the neighbourhood of the door we try to detect. Thus, a FTP describing this situation, for doors on the left side, is: "*The mean value of the velocity in the previous instants to a sharp fall in* $UltrasoundSensor6$". The particular semantic expressions used in this application of FTRs to door detection are detailed in [5].

Although the structure of the propositions involved in these three tasks was quite simple (this meaning they did not made use of all the expressiveness of the FTRs model) the quality of the results obtained made us feel optimistic about the applicability of the model. Nevertheless further work should be done in order to successfully extend the application of the FTRs model to different real complex applications. Given the huge number of rules that have to be defined for complex behaviours such as the ones previously mentioned, a natural continuity of the work done was to introduce some automatic learning mechanism for the generation of the FTRs, at least for a part of the model (if not for the complete set of rules in the grammar). In this way, the process of construction of the fuzzy temporal knowledge base (FTKB) would be automatic, saving development time and allowing the model to be applied in many different fields, by users not specially skilled in the underlaying formalism. The next section presents the application of an evolutionary algorithm to learn a FTKB for the classification of moving objects in mobile robotics.

2 AUTOMATED EXTRACTION OF FTRS FROM DATA USING EVOLUTIONARY COMPUTATION

Learning of a FTKBs in the field of mobile robotics for the detection of people and other moving objects was described in [11]. A correct classification of these objects is fundamental for the development of a number of tasks for human-robot interaction. This is a usual scenario in real environments, where people walk together, and carry objects (like suitcases, trolleys, etc.). In these situations, the density of moving objects is high, and there are occlusions between moving objects, so the detection and tracking difficulties are higher [10] than for individual objects. Detection of people moving in groups is therefore a truly complex pattern classification task that demands evaluating spatial-temporal information rather than classifying a pattern as a moving object by solely using the current values of some variables. In this realm, quantifying the fulfillment of a linguistic label by a set of data (spatial pattern), and analyzing the persistence of this fulfillment in a temporal reference (temporal pattern) is accomplished by means of FTRs made up of FTPs involving both spatial and temporal quantification. In this section we describe a pattern classifier system for the detection of moving objects using laser range finders data that has been learned through an evolutionary algorithm [11]. The laser sensors emit several beams, each one in a given direction. When a beam hits an obstacle, it is reflected and registered by the scanner's receiver. The time between the transmission and the reception of the pulse is known as the time of flight. With this information, the distance measured in the direction of each beam can be calculated. The existence of moving objects in the surrounding of the robot can be determined by two basic features:

1. A moving object appears in the distance histograms of the lasers as a local minimum.
2. As other static objects (like the legs of a table, a wastepaper basket, etc.) can share this characteristic, the object that has generated the local minimum must also be new at that position. This condition is verified using an occupancy grid map, and calculating the probability $P_{new}^{i,j}$ that the detected object is new in that cell.

The rules for the detection of moving objects must take into account information about the size of the local minimum (the gap between the object that produces the local minimum and the obstacles behind), the number of beams of the local minimum, and the probability of a new object in each of the cells of the local minimum. This last characteristic distinguishes between static and moving objects. The analysis of $P_{new}^{i,j}$ can also generate false positives. These errors can be reduced if, instead of taking into account $P_{new}^{i,j}$, the system analyzes this probability in different time instants. Moreover, some cells of the local minimum can have a high probability of containing a new object, but others not. The system should also quantify how many cells must have a P_{new} above a threshold.

A FTP that is able to perform the spatial filtering of successive values of $P_{new}^{i,j}$ is the following:

P_{new} *is high in most of the cells in part of the last instants* (1)

This type of FTP (*X is A* <*in* Q_s *of*> S_s <*in* Q_t *of*> S_t), where X ($P_{new}^{i,j}$) is a linguistic variable, A ($high$) represents a linguistic value of X, Q_s ("*most of*") and Q_t ("*part of*") are fuzzy quantifiers, S_s is the (fuzzy) set of reference ("*cells*"), and S_t (" *the last instants*") is a temporal reference, can be formally described in the framework of the FTR model.

The syntactic tree representing FTP in (1) according to the grammar proposed in [3] is shown in Figure 1. In this proposition quantifiers are applied both to the non-temporal part of the proposition (*in most of the cells*) and to the temporal part (*in part of the last instants*).

The design of this FTP involves the definition and tuning of ten parameters (linguistic labels and quantifiers) per rule for this application. Moreover, drastic changes in the characteristics of the environment or the moving objects could affect the accuracy of the pattern classifier system, making useless the tunned parameters. Therefore, an evolutionary algorithm based on the cooperative-competitive approach

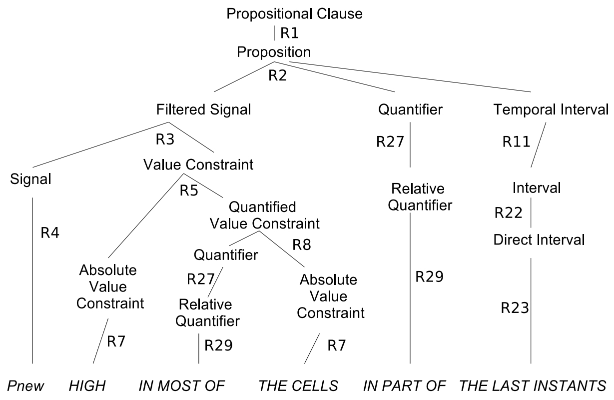

Figure 1: Syntactic decomposition of FTP: $P_{new}^{i,j}$ *is high in most of the cells in part of the last instants*.

has been used to learn a pattern classifier that was tested with data obtained with a *Pioneer II* robot equipped with two laser range scanners.

Experiments have been performed with a five-fold cross-validation. Results showing the average and standard deviation values of the five-fold cross-validation for the number of rules of the knowledge base, false positives (*fp*), false negatives (*fn*), and percentage of examples correctly classified (% correct) over the training and test examples sets are shown in Table 2. The percentage of examples correctly classified over the test set is 96,10%, despite the number of moving objects, their high concentration in small areas of the hall, and the movement of the robot (see [11] for more details).

Table 2: Results of the five-fold cross-validation.

	Training ($\overline{x} \pm \sigma$)	Test ($\overline{x} \pm \sigma$)
#rules	25.60 ± 5.32	—
fp	11.40 ± 5.73	2.20 ± 2.95
fp	19.60 ± 7.57	7.40 ± 3.21
% correct	96.85 ± 0.61	96.10 ± 1.74

The fact that people move in groups increases the difficulties in the detection, as compared with a single person, because cells that were originally free are occupied in successive time instants by different moving objects (legs). Thus the values of $P_{new}^{i,j}$ are lower. During the experiment up to ten people moved around the robot, which means 20 moving objects at the same time. Such a high number of moving objects concentrated in a few and small areas of the environment generates partial (and total) occlusions of the objects, modifying the values of the gaps and the number of beams of the detected moving objects. Also, more than half of the time the robot was moving, making harder the discrimination of new objects as the scan matching errors increase.

3 OPEN ISSUES AND NEW CHALLENGES

Taking into account the FTR model features there are a number of open issues, both in the area of the most appropriate strategies and techniques for automatic discovery of rules and in the area of real applications of the model.

3.1 AUTOMATIC LEARNING OF FTRS

One of the challenges that must be tackled to extend the use of FTRs is the adaptation of the existing genetic fuzzy systems to the FTR paradigm. FTRs have a complex and variable structure. This structure can change not only at the rule level (as a conventional fuzzy rule), but also at the proposition level. Therefore, it is necessary to define a context-free grammar to generate only those structures that are valid. Genetic programming seems to be the most adequate frame to learn the rules, due to its ability to work with chromosomes with very different shapes. Moreover, the size of the search space is much larger than that of a conventional knowledge base, due to the complex syntax of the rules, the dependence on the temporal reference framework, the existence of reduction, specification and quantification operators, temporal membership functions, etc. In this context parallel and/or distributed approaches for the execution of the algorithm should be taken in consideration as options.

Another challenge is the construction of the training dataset. Generally, examples only provide information of the spatial part of the propositions, i.e., they do not contain temporal information. Thus, the temporal part of the proposition has to be learned from scratch, trying to improve the performance of the corresponding rule or knowledge base. Usually, the initial population is composed of conventional fuzzy rules that evolve into FTRs, because the consideration of the temporal part of the proposition contributes to an increase in the performance. Of course, the inclusion of temporal information in the initial population could accelerate the convergence of the learning algorithm, and improve the results. However, how this temporal information could be included remains an open issue.

3.2 NEW FIELDS OF APPLICATION OF FTRS

FTRs have been successfully applied in the field of mobile robotics, but there are many other fields which could benefit from the extended capabilities of this model as opposed to traditional non-temporal rules.

3.2.1 Medicine

In the process of diagnosing a disease a lot of information is obtained from the patient, producing a variety of data stored in different places: administrative data, physiological signals (ECG,...), results from clinical tests (blood analysis,...), etc. Specially in the case of data from laboratory tests, diagnosis or therapeutical procedures, most of the data are temporal. In some cases, it is relevant to know the relative occurrence of an event with regard to other events; in other cases, what is interesting is the duration of an event. Temporal patterns can be used to distinguish between different pathologies, or to support the choice of a given therapy.

When the amount of temporal data stored in a database relative to a particular patient is too large to be globally examined by a human expert, it would be useful to have an automatic tool that can extract relevant information from these data, which can assist the expert in diagnosing a given disease or the degree of severity of an illness.

Development of an automatic tool for standard polysomnographic analysis is currently undergoing, aiming to provide the physician with new information from the intelligent processing of the set of polysomnography signals. The use of techniques for temporal abstraction of the information from two perspectives (solutions based on domain knowledge, and solutions based on supervised learning) needs to be complemented with the design, development and implementation of new computational tools for information fusion and analysis of association relationships in the information obtained from patients follow-up.

In particular, it could be of interest to extract fuzzy temporal association rules from a database of temporal events, which have been obtained from a preprocessing of the polysomnographic data. In this sense, existing algorithms for association rules extraction must be adapted, since none of the proposals in the literature deals with actual fuzzy temporal information, but only time stamps associated to the data. Furthermore, it would be interesting to include the concept of more complex relationships/operators such as quantification in the associations extracted from the rules, in order to evaluate for instance the severity of an illness.

3.2.2 Trends analysis in economy temporal series

In fields like economy, the problem of qualitatively describing information provided by indicators (e.g. the trend of a temporal series: increasing, decreasing or approximately constant) is far more complex than in more analytical-friendly fields. Although statistical techniques can be used to analyse temporal series, we want to stress that a linguistic qualitative description of these signals (as usual for example in finances reports or economic argumentation) is very useful to provide accurate and brief information that compiles all the numeric data. As an example, an "approximate trend" of a signal S could be defined involving temporal information and quantifiers as:

- *S is approximately increasing/decreasing around t*: when the percentage variation is *significantly superior/inferior* to 0 in *most of the* points close to t.

- *S is approximately constant around t*: when the percentage variation is *significantly close* to 0 in *most of the* points close to t.

Here, *significantly superior/inferior* to 0 is a fuzzy number, and *most of the* a fuzzy quantifier.

There are plenty of common-use examples in these areas that need to be modelled using similar fuzzy semantic approaches, such as: "*the oil production is becoming stagnant in the last years*" (reinterpreted as "*in at least about the 80% of the approximate period of the last 5 years, the increasing in oil production was negative or only slightly superior to 0*"); "*the variation of the yearly variations of home prices has been close to 0 in the last months*"; "*the correlation between the significant falls in the yearly variation of the number of initiated homes, and the significant increases in the unemployment rate in the real state sector six months later, has been very high in the last year*" (in this case using correlation quantifiers such as those described in [7]).

Several promising application fields of this kind of expressions can be identified:

- **Fuzzy filtering.** Applying quantifiers to percentage variations extends the possibilities of fuzzy filtering. For example, in Figure 2 (top) the yearly percentage variation of the number of initiated homes is shown for the period Jan. 1992-Oct. 2007. Figure 2 (bottom) shows the result of evaluating the quantified expression "*In most of the last six months the yearly variation in the number of initiated houses has significantly fallen*". Periods of negative trends are easily detected by means of a fuzzy quantified expression.

- **Argument assessment.** Reasoning in economy is plenty of examples of expressions that can be modelled and evaluated by means of a combination of percentage series and fuzzy quantifiers. For example, the degree of fulfillment of expression "*the oil production is becoming stagnant in the last years*" could be evaluated in order to check the validity of the argument.

- **Linguistic summaries of series.** This would allow automatic detection of positive, negative and stagnant trends in a temporal series. For example, the proposition "*the unemployment trend is increasing in the last year*" (reinterpreted as "in most of the last twelve months, the yearly unemployment variation was increasing") could be an automatically generated summary as a result of a fuzzy temporal rule-based analysis of the unemployment rate.

- **Temporal causal analysis.** Let us consider the expression "*the correlation between the significant falls of the yearly percentage variation of initiated homes, and the significant increases of the yearly percentage variation in the unemployment rate in the real state sector six months after that, has been very high in the last year*". Evaluating the expression on experimental data, if for some range of the temporal difference (six months in the example) the fulfillment of the expression is very high a possible causal relation could be detected.

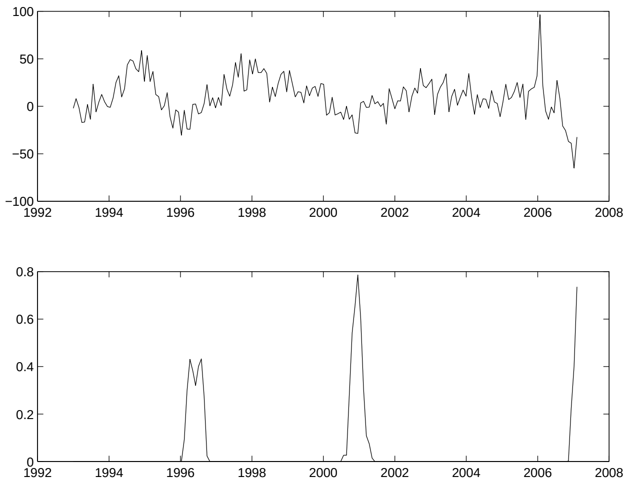

Figure 2: Fuzzy percentage quantified filtering of the number of initiated houses.

The most interesting features of this approach are:

- The approximation is linguistic, fuzzy and easily interpretable.
- Quantifiers, temporal granularity, and linguistic variables are all fuzzy thus being able to cope with uncertainty.
- Fuzzy quantifiers let us avoid outliers (usually due to noise); in this way, the result does not depend on a particular increase in a decreasing series.
- Working with percentage variations allows us to operate with independence of the base signal. As absolute values of series are not involved, certain signal independence is achieved.
- And perhaps the most remarkable, *common sense* expressions (e.g., economic arguments) can be evaluated.

3.2.3 Business intelligence

Organizations and companies have carried out in the recent years a huge effort to improve their productivity by means of automating their business processes. Such automation was achieved through defining workflows that describe the coordination of the execution of the activities that have to be performed in order to achieve the goals stated in the business process [16].

Execution of workflows is typically performed in the company information system, where all the data that are generated during the execution are stored. Examples of such data are: who was the person/process that performed a given activity, when it occurred, which was the information used,... Starting from such data a process mining stage can be done, aiming [16] (i) to reconstruct or discover processes for an automatic definition of the workflow associated to the activities performed by the members of the organization during the execution of a business process, (ii) to evolve processes, aiming to monitor the workflow execution in order to detect exceptions or execution conditions of activities that may produce changes in the initial workflow.

The techniques proposed for process mining are typically based on the identification of causal temporal relationships among the events recorded in the information system. Temporal rules in this context could allow to detect the execution order of the activities or to avoid repetition of activities or deadlocks. Within this context, frameworks for temporal representation and reasoning involving representation of changing relationships over time (instants, intervals, and topological relationships among them) are now starting to be used for development of semantic-based approaches to business intelligence applications.

3.2.4 Industrial and other applications

Monitoring, supervision, diagnosis and control of processes are areas where a number of elements coexist, making them a potential field of application for temporal information processing techniques. In complex environments such as chemical or environmental processes, power and water-treatment plants a huge number of signals have to be processed, temporal evolution of indicators is relevant, and also temporal relationships between events needs to be considered. Furthermore knowledge-based approaches in these fields are becoming a common-use tool for the design of advanced intelligent systems and researchers are paying increasing attention to them. Developing a support software suite for defining and executing Fuzzy Temporal Knowledge Bases (those involving FTRs), with facilities for rule editing, debugging, code generation, and automated learning of rules from data is a must for solving complex applications in industrial systems using FTRs.

4 REMARKS

Although Fuzzy Temporal Rules provide a general framework for the representation of knowledge and reasoning in complex systems, the applications developed to date (mostly in the field of intelligent control and classification in robotics) do not fully exploit all the syntactic and semantic richness of the model. The natural niche for application of FTRs is monitoring, control, diagnosis and other complex tasks in dynamic systems, and these fields demand that tools and methodologies are available for making easier the design and/or automatic learning of fuzzy temporal systems. This is in our opinion the main challenge to be faced in the near future for achieving a successful use of temporal reasoning based systems in these fields.

Acknowledgements

Authors wish to acknowledge Spanish Ministry for Education and Science and Xunta de Galicia for their financial support under grants TIN2005-08521-C02-01, TIN2006-15460-C04-02 and 07SIN005206PR.

References

[1] S. Barro, R. Marín, J. Mira and A. Patón. A model and a language for the fuzzy representation and handling of time. *Fuzzy Sets and Systems*, vol. 61, pp. 153–175, 1994.

[2] P. Cariñena, A. Bugarín, and S. Barro. Un modelo para la cuantificación de la persistencia en proposiciones temporales borrosas. In *Actas del VIII Congreso Español sobre Tecnologías y Lógica Fuzzy (ESTYLF'98)*, 1998, pp. 109–116.

[3] P. Cariñena, A. Bugarín, M. Mucientes, F. Díaz-Hermida, and S. Barro. *Technologies for Constructing Intelligent Systems 2. Tools*, ser. Studies in Fuzziness and Soft Computing. Springer-Verlag, 2002, vol. 90, ch. Fuzzy Temporal Rules: A Rule-based Approach for Fuzzy Temporal Knowledge Representation and Reasoning, pp. 237–250.

[4] P. Cariñena. Un modelo de Reglas Temporales Borrosas para el razonamiento sobre sistemas dinámicos. Ph.D. Dissertation. University of Santiago de Compostela, 2003.

[5] P. Cariñena, C.V. Regueiro, A. Otero, A. Bugarín and S. Barro. Landmark detection in mobile robotics using fuzzy temporal rules. *IEEE Transactions on Fuzzy Systems*, vol. 12, no. 4, pp. 423–435, 2004.

[6] B. Carse, T. Fogarty and A. Munro. Artificial evolution of fuzzy rule bases which represent time: a temporal fuzzy classifier system. *International Journal of Intelligent Systems*, vol. 13, pp. 905–927, 1998.

[7] F. Díaz-Hermida, P. Cariñena, A. Bugarín. Efficient evaluation of similarity quantified expressions in the temporal domain. *Soft Methods for Integrated Uncertainty Modelling -SMPS2006*, pp. 191–198. ISBN: 3-540-34776-3.

[8] H. Kindler, D. Densow, and T. Fliedner. A pragmatic implementation of medical temporal reasoning for clinical medicine. *Computers in Biology and Medicine*, 28, pp. 105–120, 1998.

[9] H. Maeda, S. Asaoka and S. Murakami. Dynamical fuzzy reasoning and its application to system modeling. *Fuzzy Sets and Systems*, 80, pp. 101–109, 1996.

[10] M. Mucientes and W. Burgard. Multiple hypothesis tracking of clusters of people. In *Proc. IEEE/RSJ Int. Conf. Intelligent Robots and Systems (IROS)*, pp. 692–697, 2006.

[11] M. Mucientes and A. Bugarín. People Detection with Learned Quantified Fuzzy Temporal Rules. In *Proc. 16th IEEE Conference on Fuzzy Systems (FUZZ-IEEE'07)*, pp. 1149–1154, 2007.

[12] M. Mucientes, R. Iglesias, C.V. Regueiro, A. Bugarín, and S. Barro. A fuzzy temporal rule-based velocity controller for mobile robotics. *Fuzzy Sets and Systems*, 134, pp. 83–99, 2003.

[13] M. Mucientes, R. Iglesias, C.V. Regueiro, A. Bugarín, P. Cariñena, and S. Barro. Fuzzy temporal rules for mobile robot guidance in dynamic environments. *IEEE Transactions on Systems, Man and Cybernetics - Part C: Applications and Reviews*, 31(3), pp. 391–398, 2001.

[14] J. Presedo, J.A. Vila, S. Barro, F. Palacios, R. Ruiz, A. Taddei, and M. Emdim. Fuzzy Modelling of the expert's knowledge in ECG-based ischaemia detection. *Fuzzy Sets and Systems*, 77, pp. 63–75, 1996.

[15] D. Qian. Representation and use of imprecise temporal knowledge in dynamic systems. *Fuzzy Sets and Systems*, 50, pp. 59–77, 1992.

[16] W.M.P. van der Aaslt, B.F. van Dongen, J. Herbst, L. Maruster, G. Schimm and A.J.M. Weijters. Workflow mining: A survery of issues and approaches. *Data Knowledge Engineering*, 47(2), pp. 237–267, 2003.

[17] A. van der Maas, A. ter Hofstede and P. de Vries Robbé. Formal description of temporal knowledge in case reports. *Artificial Intelligence in Medicine*, 16(3), pp. 251–282, 1999.

[18] J. Virant and N. Zimic, Attention to time in fuzzy logic. *Fuzzy Sets and Systems*, 82, pp. 39–49, 1996.