REVIEW OF SCIENTIFIC INSTRUMENTS **81**, 10E126 (2010)

Event recognition using signal spectrograms in long pulse experiments[a]

J. González,[1,b)] M. Ruiz,[1] J. Vega,[2] E. Barrera,[1] G. Arcas,[1] and J. M. López[1]
[1]*Grupo I2A2, Universidad Politécnica de Madrid, Ctra Valencia Km. 7, Madrid 28031, Spain*
[2]*Asociación EURATOM/CIEMAT para Fusión, Avda Complutense 22, Madrid 28040, Spain*

(Presented 19 May 2010; received 13 May 2010; accepted 27 August 2010; published online 26 October 2010)

As discharge duration increases, real-time complex analysis of the signal becomes more important. In this context, data acquisition and processing systems must provide models for designing experiments which use event oriented plasma control. One example of advanced data analysis is signal classification. The off-line statistical analysis of a large number of discharges provides information to develop algorithms for the determination of the plasma parameters from measurements of magnetohydrodinamic waves, for example, to detect density fluctuations induced by the Alfvén cascades using morphological patterns. The need to apply different algorithms to the signals and to address different processing algorithms using the previous results necessitates the use of an event-based experiment. The Intelligent Test and Measurement System platform is an example of architecture designed to implement distributed data acquisition and real-time processing systems. The processing algorithm sequence is modeled using an event-based paradigm. The adaptive capacity of this model is based on the logic defined by the use of state machines in SCXML. The Intelligent Test and Measurement System platform mixes a local multiprocessing model with a distributed deployment of services based on Jini. © *2010 American Institute of Physics.* [doi:10.1063/1.3494273]

I. INTRODUCTION

The acquisition of signals during fusion experiments provides knowledge of the physical properties of plasma.[1] As the duration of discharge increases, the analysis of these signals in real-time and under more complex functional requirements becomes more relevant. The acquisition and processing systems applied in this context should provide simple models. In particular, they should allow for the design of experiments in which the sequence of signal processing steps will be determined by the evolution of the experiment.

The Intelligent Test and Measurement System (ITMS)[2,3] developed by *Universidad Politécnica de Madrid* and *Asociación EURATOM/CIEMAT para Fusión* is a real-time data acquisition and processing distributed system. In ITMS, the sequence of signal processing is determined based on prior events. The flexibility and adaptive capacity of this model lie in the fact that the underlying logic of the experiment is defined by state machines expressed in SCXML. The ITMS platform combines a local multiprocessing model with a distributed deployment based on the ability of each node to provide full functionality in the form of services based in Jini. This paper proposes the design of adaptive models for signal classification using morphological patterns in spectrograms. Both the ITMS platform and the signal classifiers that the scientific community has developed in recent years are used. This system can direct the flow of processing based on the spectrogram classification results. In short, this system defines an experiment in which the processing of data acquired can be governed by the evolution of the plasma state. The specific algorithm development could be responsible for the detection of magnetohydrodinamic instabilities, L-H/H-L transitions or disruptions, for example.

II. TOOLS FOR FUSION SIGNALS CLASSIFICATION

The signals, which are acquired during fusion diagnostics, reflect the physical properties of the plasma. The analysis of these signals allows for the study of the behavior of plasma during different discharges, for characterization of the physical phenomena observed, and for detection of any loss of confinement or disruption.[4] Disruption arises suddenly and inevitably and can jeopardize the integrity of the reactor.

In recent years, various methods have been designed to perform the extraction of relevant features in the acquired signals. Based on these classification systems, which enable the structured storage and retrieval of signals through database management systems using physical criteria in the query, parameter characterizations have been proposed, for example, morphological characteristics obtained through techniques of structural pattern recognition.[1] Various techniques of artificial intelligence, as well as other advanced treatments of signals, have been used to implement automatic classifiers. Some of these specialize in the prediction of the relevant disruptions. With the increase in the duration of discharge time, proposals able to work in real-time become more relevant. Various approaches are based on artificial neural networks,[5] support vector machines,[6] or fuzzy logic combined with regression trees.[7] These approaches not only highlight the importance of characterizing and classification of signals but also make it possible to detect events

[a]Contributed paper, published as part of the Proceedings of the 18th Topical Conference on High-Temperature Plasma Diagnostics, Wildwood, New Jersey, May, 2010.
[b]Author to whom correspondence should be addressed. Electronic mail: jgonzalez@i2a2.upm.es.

associated with the results of the classification in real-time. The detection of these events provides an opportunity to propose experiments in which control logic is directed by the evolution of the experiment. The result is a reactive system that can adapt to the context.

III. EVENT-BASED SYSTEMS: ITMS

ITMS[2,3] is a platform designed to deploy scalable data acquisition and processing systems based on events, using PXI and CompactPCI hardware. ITMS is formed by a set of nodes each of which has the capacity of local parallel processing in real-time with the possibility of hot swap for processing algorithms. Each node represents one or more services available through the mechanisms of publication–subscription. Thus, ITMS is a service-oriented architecture of adaptive and intelligent data acquisition and processing systems.[3] Each ITMS node may be governed by a state machine whose behavior is defined by a statechart expressed in State Chart XML (SCXML), a general-purpose event-based state machine language with which it is very easy to define the behavior of a system under a reactive paradigm. Currently, there are two available implementations of a SCXML engine: APACHE COMMONS JAVA, which is not in real-time, and a specific development in LABVIEW RT. Finally, a network of ITMS nodes provide global distributed processing capabilities that could be synchronized via IEEE1588 event synchronization using *ad hoc* hardware.[8] ITMS provides the ability to easily implement remote participation applications.

IV. EVENT EXTRACTION FROM SPECTROGRAMS

The spectrogram of the signal encodes the information on the time-frequency domain. This information has been used to classify acquired signals. Detering *et al.*[9] proposed a practical structured analysis of multichannel time series measurements from experiments on magnetic confinement fusion. The proposal included a procedure for extraction of significant features in the time-frequency domain using artificial vision techniques for segmentation of the spectrogram. As the duration of the discharge increases, performing this classification in real-time and accomplishing different tasks depending on the results begin to be interesting. As noted in Sec. II, there are also many implementations of classifiers whose efficiency has been tested. It is interesting to reuse these systems and to develop experiments that identify plasma behaviors through the analysis of the spectrogram of the signals. To show a simple example of the strategy to follow, we analyze a simple signal that includes a chirping mode and we develop a simple algorithm to extract of image processing meaningful forms of the spectrogram. In practical experiments, this signal represents the source of data that identifies the physical behavior of the plasma that we want detected.

The development of this kind of experiment in ITMS is simple. On the one hand, the processing power of an ITMS node allows for carrying out the algorithms for extracting significant features. On the other hand, the existence of an engine that governs the system facilitates the interconnection with external classification systems. This engine also allows the processing sequence to be event-driven and the processing algorithms to be changed in different experimental phases. Figure 1 shows the deployment of the system in an experiment to characterize signals with the parameters of HU. At the top are the signals acquired by the ITMS node. These signals are processed, and the results are a HU set of invariant moments. These HU moments are the features of the signal, and they are sent to classifier system. Then, the classifier system identifies the class of signal, and it communicates the result. Figure 1 shows also an outline of the state machine (dynamic behavior) and icons that represent the profiles and virtual instruments (VIs) (static knowledge). The bottom of Fig. 1 explores the interior of the ITMS node showing only the specific elements required for each experiment. Internally, and in parallel, the ITMS node executes the engine that governs the entire course of the experiment. This engine has been specifically developed in LABVIEW RT using the same methodology applied in the development of language processors (translators, compilers, and interpreters). Modeling an experiment in ITMS consists of defining the static knowledge (which input channels to acquire and which algorithms to use) and the dynamic behavior (which events have to be detected, what system transitions they produce, and which algorithms must be changed in response).[3] The static knowledge is formed by a set of profiles and a set of processing algorithms. Each profile is a file XML that links channels with processing algorithms. The processing algorithms are developed with LABVIEW VI. These VIs can include algorithms implemented in more generic languages such as C/C++ or in more specific languages such as MATLAB. The first advantage of this approach is that each virtual instrument is designed exclusively for a specific goal. The VI is therefore independent of other tasks, thus facilitating reusability and maintenance.

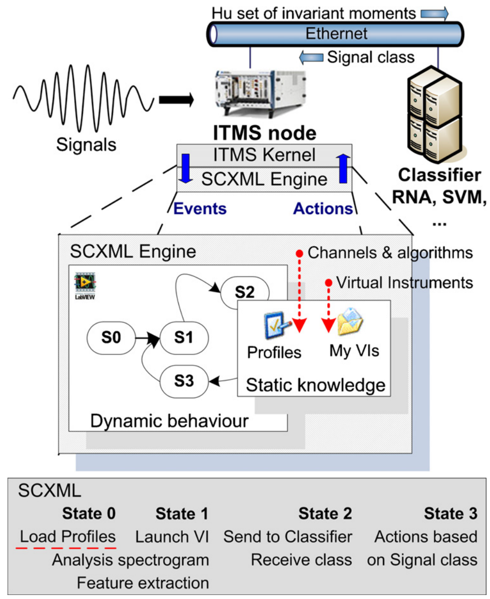

FIG. 1. (Color online) Upper area: The signal is processed by the ITMS node to extract the features (Hu moments). They are sent through the network to the classification system that identifies the class. Middle area: Software layer detail of ITMS. Lower area: Description of each state.

The VI developed to extract the features of the signal starts by making the spectrogram. We choose the short time Fourier transform (STFT) for spectral decomposition. The

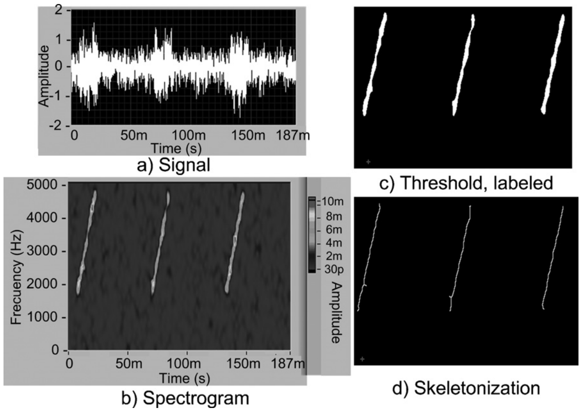

FIG. 2. Artificial vision phases: (a) acquired signal; (b) spectrogram; (c) the matrix pixels showing the detected shapes; (d) the matrix pixels showing the processed shapes.

settings for STFT are as follows: Hanning window type, 64 sample window length, 512 frequency bins, and 4 time steps. These parameters can be adjusted depending on the nature of the experiment. In this particular experiment, STFT was applied to a noisy chirp signal acquired with a 10 kHz sampling frequency (Fig. 2). Except for the frequency difference, such a signal is not inconsistent with Alfvenic cascades observed in JET (Ref. 10) or DIII-D. The next step is to convert the spectrogram into an image (matrix pixels). For this purpose, the techniques and tools provided with LABVIEW Vision Development Module can be used. The image processing begins with thresholding. This is done adaptively according to the image histogram. The result is a binary image to which processes of morphological change by closures and openings (sequential implementation of erosions and dilations) can be applied to smooth blobs (erase holes and smoothen edges) if applicable. Then, the blobs are discretized using a labeling algorithm (Fig. 2). Finally, we performed the skeletonization of the blobs, which results in several well-defined objects. Having identified the significant forms of the spectrogram, each HU moment was obtained. The moments are invariant to operations of rotation, translation, and scale, and they are the characteristics that describe the detected forms.

The dynamic behavior is formed by events that may occur, by the feasible states of the system, and by the transitions that link them. The dynamic behavior is represented by a state machine whose function is to govern the flow of the experiment. The time taken to process the SCXML of the experiment was 62 ms. In the first state, the profiles are loaded in the memory, and the state machine evolves to the next state. In the next state, the VI described above is launched. When the engine of the state machine receives an event (Fig. 1: Events) from the VI, it makes a change of status (if applicable). The function associated with the new state then carries out the processing of the extracted features (Fig. 1: Actions). For this, the engine can either replace the VI (hot swap operation) by another VI designed for this operation or it can use a classification tool referred to in Sec. II (Fig. 1). These classification tools only need to include a simple service layer capable of receiving and sending events to the engine. Specifically, it is sufficient that the classification tool has a TCP/IP port with a basic application layer protocol. With this strategy, any external application can be reused by simply establishing a channel to receive events as messages. The result of classification is referred back to the engine of the state machine which internally evolves through the transitions and states. The system adapts its behavior, if necessary, and it can modify the processing algorithm (hot swap). The state machine thus becomes the system logic controller.

V. DISCUSSION

The main idea is to provide simple and versatile tools that enable experiments with event oriented plasma control. The ITMS features allow the researcher to focus on the development of control-actuator algorithms that manipulate the plasma given the signal class. These algorithms are developed as functional units specific to each phase of the experiment. Thus, the sequencing logic is outside of the modules and these can be independent. The implementation of acquisition and processing test in the ITMS platform is organized around a state machine that describes the behavior of the system. This state machine is a logic controller because it allows separate control logic from the processing algorithms. This approach is similar to the inversion of control. The presence of the state machine makes the code more efficient, easier to debug, and helps organize the program flow. It also allows integrating other existing systems with minimal coupling. It allows systems, which are not designed to interoperate, to work together. The result is a reactive system designed under an event-driven paradigm. This paradigm is traditionally used and therefore is very natural in data acquisition and control systems. We intend to design an experiment using event oriented plasma control and implement the ITMS system on a real discharge.

ACKNOWLEDGMENTS

This work is funded by the Spanish Ministry of Science and Technology under the Project Nos. DPI2006-06624, ENE2009-10280, and ENE2004-07335.

[1] J. Vega, G. A. Rattá, A. Murari, P. Castro, S. Dormido-Canto, R. Dormido *et al.*, Proceedings of the IEEE International Symposium on Intelligent Signal Processing, 2007, pp. 949–954.
[2] M. Ruiz, E. Barrera, S. Lopez, D. Machon, J. Vega, and E. Sanchez, Fusion Eng. Des. **71**, 135 (2004).
[3] J. González, M. Ruiz, E. Barrera, J. M. López, G. de Arcas, and J. Vega, Service-oriented architecture of adaptative, intelligent data acquisition and processing systems for long-pulse fusion experiments, Fusion Eng. Des. 85, 274 (2010).
[4] P. C. de Vries, M. F. Johnson, and I. Segui, Nucl. Fusion **49**, 055011 (2009).
[5] B. Cannas, A. Fanni, P. Sonato, M.K. Zedda, and JET-EFDA, Nucl. Fusion **47**, 1559 (2007).
[6] G.A. Rattá, J. Vega, A. Murari, G. Vagliasindi, M.F. Johnson, P.C. de Vries, and JET-EFDA, Nucl. Fusion **50**, 025005 (2010).
[7] A. Murari, G.Vagliasindi, P. Arena, L. Fortuna, O.Barana, M. Johnson, and JET-EFDA, Nucl. Fusion **48**, 035010 (2008).
[8] J. M. López, M. Ruiz, E. Barrera, G. de Arcas, and J. Vega, Rev. Sci. Instrum. **79**, 10F335 (2008).
[9] F. Detering, B.D. Blackwell, M. Hegland, D.G. Pretty, K. Nagasaki, and S. Yamamoto, ANZIAM J. **50**, C729 (2009).
[10] A. Murari, T. Edlinton, J. Brozozowski, E. de la Luna, P. Andrew, G. Arnoux, F. E. Cecil, L. Cupido, D. Darrow, V. Kiptily, J. Fessey, E. Gauthier, S. Hacquin, K. Hill, A. Huber, T. Loarer, K. McCormick, M. Reich, and JET-EFDA, Fusion Eng. Des. **82**, 1161 (2007).