Computer/human structural coupling for data interpretation

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We work on the design of computerized systems that support experts during their complex and poorly formalized data interpretation process. We consider interpretation as the process by which high level abstracted information is attached to data. We assume that a computer could efficiently helps an expert in such a process via a structural coupling (Maturana and Varela, 1994) based on their interactions. Enaction appears as a stimulating source of inspiration for the design of such systems. Our approach is applied to the exploration of physiological time series acquired from patients in intensive care unit (ICU).

Time series interpretation for ICU monitoring systems

Nowadays in ICU, monitoring systems have high level of false alarm rates (Tsien et al., 2000) essentially because they rely on simple threshold-based methods and do not take into account the richness of the information contained in physiological parameters records. A patient record is a long, high frequency, multivariate time series data. Classical monitoring improvement techniques are focused on algorithms at a numerical level (Tsien et al., 2000; Calvelo et al., 2000). On the contrary, we propose that symbolic abstraction could bring *useful* information to data, providing a better understanding of these still poorly formalized data but also, and more deeply, a new approach for monitoring based on dynamic anomaly detection.

A multivariate time series is the trace of the physiological patient time course. Two types of information could be discovered: 1) events that could occur and 2) relations (causal or temporal) between events that highlight the patient state evolution. Then, two sorts of information should be explored: symbols and relations between symbols. A symbol is an abstraction of the data-level signature of an event. For time series exploration, a signature is a fuzzy pattern in the data. When a segment matches such a fuzzy pattern, it is associated with the corresponding symbol. The exploration of the time series data should reveal what the important events are and then build the corresponding signatures. With this information numerical time series are translated into symbolic time series. A relation between symbols is a trace of the event's dynamic. A relation brings contextual information on symbols that are implicated in it. A scenario will be a relevant, *i.e.* frequently or rarely observed in patients' states evolutions, complex set of relations between several symbols.

Clinicians have difficulties to define the signatures of relevant clinical events and the various significant patterns attached to them. Moreover, the identification of pertinent relationship between them reveals to be a complex combinatorial task. The aim of our work is to assist, using computer, clinicians in their deep exploration of physiological data to *discover* the useful information, events and signatures, which can be eventually introduced in a new generation of monitoring systems.

Human & Machine structural coupling: An enactive approach

We advocate for a structural coupling between a clinician and a machine to benefit from their complementarities. A clinician is able to take into account of a large context of a specific patient's data record and has a global view on the data. A machine is able to treat a large amount of patients' cases and performs a numerical analysis on the data. Our goal is enables this structural coupling based on enaction theory. The clinician and the machine are both considered as agents that could perceive and modify their environment and have mutual interactions.

Varela et al. (1993) define an enactive system as a system that builds the world while it is built by it. We transpose this definition to the case of a world of time series data. An agent modifies its representation of the data along the exploration process. Enaction theory leads us to consider two design constraints: 1) each agent builds its own representation independently of the other, and 2) interactions are only possible through the data. In the structural coupling paradigm, interactions made through the shared time series data guide agents to congruent representations. Our approach share some similarities with the talking heads of Steels (2003) that interact about the shared perception of geometrics figures and build abstract representation in the form of a shared lexicon in an emergent way.

Course-of-action centered design (Theureau J., 2003) proposes to implicate users in a system's construction before its exploitation phase. We propose here to design systems that evolve during their exploitation. In our approach, the processing evolves depending on the agent experience, *e.g.* past processing of data and past interactions with the others agents.

System architecture

Figure 1 shows the system architecture. Three successive steps are considered, which consists in extracting meaningful segments of data (Segmentation step), transforming them into symbolic signatures (classification step) and finally associating them to form temporal scenarios (learning step). Each step is performed in a bottom-up way, in order that new information emerges based on lower-level processing. In parallel, lower-level information is revised considering new upper-level information (feedback). It ensures the global knowledge consistency. At each step, the clinician is included in a two ways circular information flow that represents mutual man-machine interaction through the data. An interactive annotation task is the supporting task of mutual interaction for the two first steps.

We have developed algorithms for each step and the complete system is currently under implementation. The symbolic time series transformation is under evaluation.

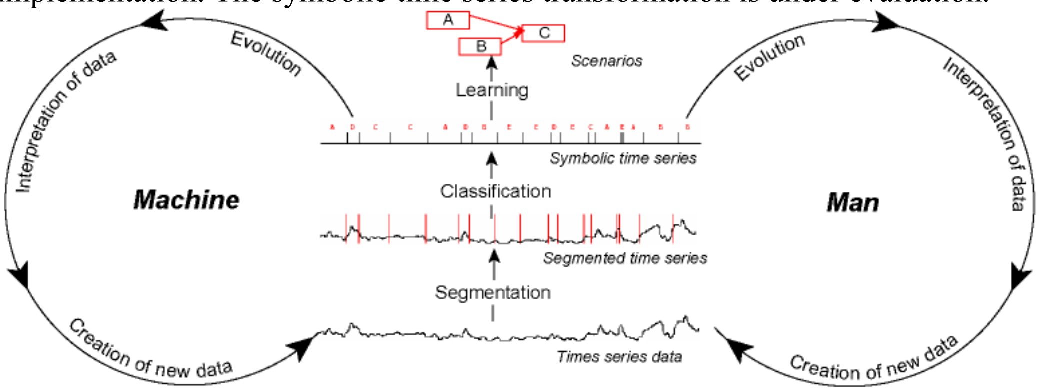

Figure 1: Interactive time series interpretation system.

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