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Multi-level temporal abstraction for medical scenario construction

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SUMMARY

The automatic recognition of typical pattern sequences (scenarios), as they are developing, is of crucial importance for computer-aided patient supervision. However, the construction of such scenarios directly from medical expertise is unrealistic in practice. In this paper, we present a methodology for data abstraction and for the extraction of specific events (data mining) to eventually construct such scenarios. Data abstraction and data mining are based on the management of three key concepts, data, information and knowledge, which are instantiated via an ontology specific of our medical domain application. After a detailed description of the proposed methodology, we apply it to the supervision of patients hospitalized in intensive care units. We report the results obtained for the extraction of typical abstracted pattern sequences during the process of weaning from mechanical ventilation. Copyright © 2005 John Wiley & Sons, Ltd.

KEY WORDS: data abstraction; temporal reasoning; data mining; monitoring

1. INTRODUCTION

In high dependency environments such as intensive care units (ICUs), all clinical, economical and sociological studies, tend to demonstrate the need for computerized assistants that help clinicians in the decision making process. Starting from heterogeneous data, such computerized assistants should rely on efficient real time techniques for data synthesis and automatic recognition of typical scenarios [1].

This automatic recognition of clinical scenes as they are developing is crucial for two main aspects:

- Intelligent alarm detection: it is well known that standard monitoring systems based on alarm thresholds for each individual parameter are very primitive. They, in general,

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introduce noisy pollution instead of real informative events. At the opposite, information fusion for the recognition of high level clinical scenes, representative of acceptable or deleterious situations (scenarios), is highly informative for the clinical staff.

- Computerized guidelines or protocols: the introduction of computerized guidelines or protocols, reflecting a consensual practice, has been proposed to standardize the medical decision making process and to reduce unnecessary variations among practitioners [2]. The recognition of a specific scenario is then a prerequisite to trigger the specific actions plan of a predefined protocol. Similarly, the recognition of a scenario can attest that the clinician is following the expected protocol.

In practice, the construction of such scenarios directly from data or medical expertise is unrealistic. As mentioned in Reference [3], 'Monitoring, [...] with respect to real-world medical environments entails non-trivial data analysis problems. The available data occur at various observation frequencies (e.g. high or low frequency data), at various regularities (e.g. continuously or discontinuously assessed data), and at various types (e.g. qualitative or quantitative data) [...]. Moreover, the observed data include an unexpected high volume of faulty data.'

Because physiological phenomenon are rather slow and data are noisy, clinicians are more interested in the evolution of a parameter (or a set of parameters) over time than in instant parameter values.

In addition to data complexity, we do not dispose of precise knowledge about the normal or abnormal evolution expected for a given patient. In fact, the physician cannot describe in advance the scenarios they would like the system could detect. This difficulty to point out such scenarios can be explained by the fact that:

- each patient is unique and physiological responses to various events are highly variable among individuals,
- for each patient, physiological responses can vary depending of the context (night and day, presence of next of kin...),
- medical decision making can rely on elements not accessible to computers (such as the signs of stress).

Figure 1 illustrates a typical ICU environment where a ventilator assists the patient's ventilation, pumps supply various drugs, and various devices monitor heart or respiratory functions. These devices are connected to the data collector which displays the collected data. Three types of data can be distinguished:

- Analog data: typically raw physiological signals (e.g. ECG);
- Numeric data: depending on the device, specific algorithms (generally not detailed to the user) are applied to provide, from raw signals, values for physiological parameters (e.g. heart rate or tidal volume);
- Symbolic data: typically alarms raised on devices or annotations directly entered into the data collector by the clinician in charge.

Our objective is to extract gradually typical pattern sequences from monitored data. Firstly, abstractions are constructed using knowledge based mechanisms [4]. Then, data mining techniques are used to explore these abstracted sequences and detect regularities, *a priori* unknown, which are eventually considered by clinical experts as representative of a class of

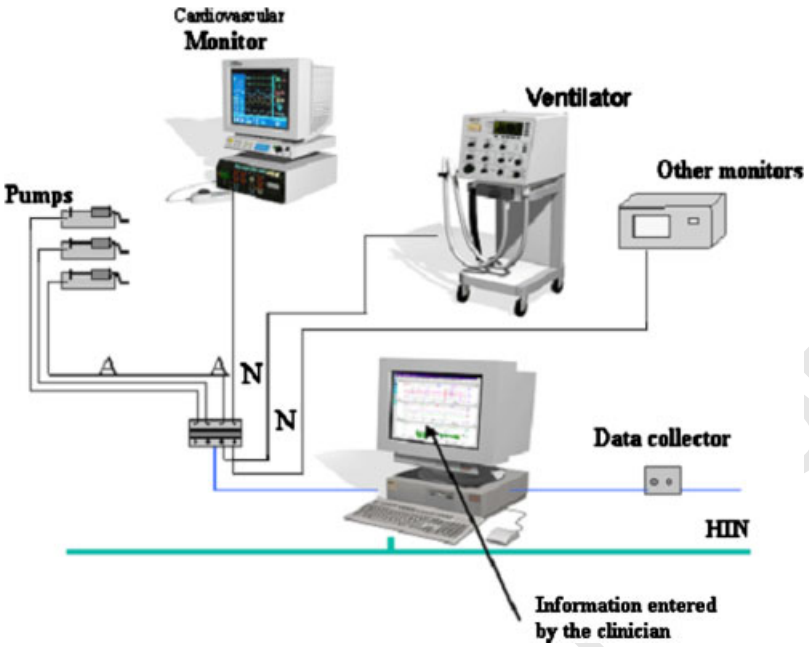

Figure 1. *Dataflow at the patient's bedside*. All data (analog or numeric) coming from monitors are automatically gathered in the data collector. The clinical staff interacts directly with the data collector which is connected to the hospital information network (HIN). A: Analog, N: Numeric.

situations (scenarios) to recognize. Multi-level data abstraction is not straightforward in the ICUs context. It requires the explicit management of information and knowledge and a proper validation of each abstraction step. The validation of the process is strengthened by *a priori* and *a posteriori* control. Prior control consists in taking into account only data considered as reliable. This reliability is based on the manipulation of all the elements available, data, information and knowledge during the process of data abstraction. The *a posteriori* control is ensured by the fact that each step is validated by experts before its use at the next step. For *a posteriori* control, data abstractions should be expressed in medical terms to be understandable by clinicians. For this reason, we built an ontology of the concepts we used. In addition, appropriate visualization tools should help the clinician to browse data and concepts.

In this paper, we present a methodology for medical scenario recognition based on the gradual construction of multi-level contextual abstractions. The paper is structured as followed. In Section 2, we situate the role of data abstraction and data mining in the global process of knowledge discovery. At first, we describe, by means of an ontology the three concepts used that are data, information, and knowledge. Then, we define data abstraction as a knowledge-based abstraction and explain the importance of an adaptive control. The adaptive control is obtained in two ways:

- Incremental data abstraction process: the gradual construction of abstractions allows adapting abstractions to the dynamics of each parameter.
- Valid abstraction domain construction: this notion is introduced to restrict abstraction to the domain where each parameter can be considered as valid.

In Section 3 we describe in details the abstraction methodology we propose. In Section 4 we present the application context, the weaning of mechanical ventilation, and preliminary results obtained. Section 5 is devoted to discussion.

2. DATA ABSTRACTION AND DATA MINING IN KNOWLEDGE DISCOVERY PROCESS

2.1. Data, information and knowledge in knowledge discovery process

According to Fayyad [5], the process of knowledge discovery via data mining can be divided into five basic activities: selection, pre-processing, transformation, data mining, and interpretation, which are essential to extract useful knowledge from data. The selection step allows to focus, according to pre-defined criterions, on data supposed to be 'interpretable' and with informative potential. The pre-processing concerns treatment of missing and noisy data. The transformation step is useful to define abstractions adapted to the knowledge discovery task. These first three steps represent data abstraction.

The data mining and interpretation steps allow, respectively, to find specific patterns and to select the more relevant ones and extract knowledge. This global process is incremental. According to Fayyad, it can contain loops, in particular the interpretation step can guide all the other steps.

Three concepts are central in this process: data, information and knowledge. These concepts are often confused in the literature. Here, we consider *Data* as the result of an observation or an experiment, *Information* as the result of data abstraction and *Knowledge* as the way by which data and information are handled [6]. Pieces of knowledge cannot be considered as simple elements useful to describe a situation, but as essential elements to construct new information or determine actions to be undertaken [7].

We propose (see Figure 2) a modified version of the process described by Fayyad, to point up the concept of information and the central role of knowledge in the incremental and dynamic processes of data abstraction and data mining in knowledge discovery. Data abstraction is a

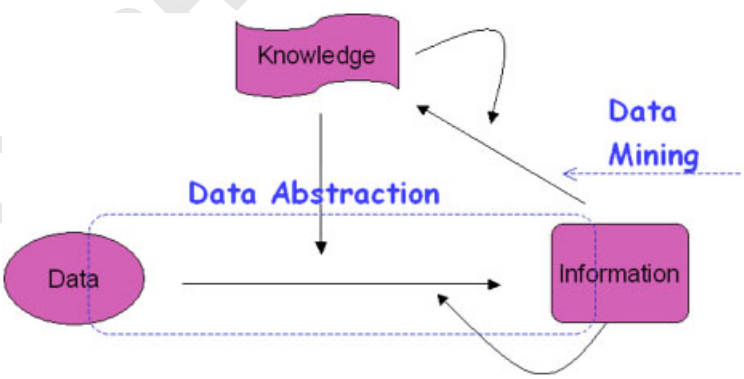

Figure 2. *The data abstraction and data mining processes*. Data abstraction allows the extraction of information from data and is driven by knowledge. Data mining concerns automatic knowledge extraction, knowledge which in turn is used to drive data abstraction and data mining.

complex process: knowledge is required to transform data into information, and this, as early as pre-processing steps [4]. This process has two main objectives (1) the transformation of numeric values, instant-point based, into symbolic values, time-interval based and (2) the generation of several abstracted levels that synthesize parameters evolution. In consequence, it can be considered as a résumé of available data via the creation of information. Knowledge drives the abstraction process. It may emerge from mining process and in turn is used to drive it.

Data, information and knowledge can be refined and instantiated in our medical domain via an adapted ontology.

2.2. *The proposed ontology*

An ontology consists of a set of concepts, relations, and axioms that formalize a domain. It describes how they can or cannot be related to each other. It allows clarifying the domain knowledge structure and provides a more concise representation of this knowledge.

In our context, *Data* are the observed values of a parameter (for instance tidal volume and oxygen saturation). *Information* (see Figure 3(a)) can be supplied or extracted by the data abstraction process. For system supervision, information is essentially represented by temporal objects such as states and events [8]:

- an event is classically defined as an instantaneous change of the system. In our medical context, event represents change or intervention on the system or its environment. We distinguish three types of events: (1) inner events such as changes of a parameter value, (2) outer events (equivalent to intercurrent events such as cares) and (3) alarm on medical devices. Causal links exist between events.
- a state involves the notion of persistence. It represents a time period during which an information is valid (the heart rate being stable during 5 min as an example). States are generated by the data abstraction process. States and events are temporally linked.
- local patterns represent regularities extracted from data and/or information. Local pattern recognition may be used for the detection of specific inner events (see below).

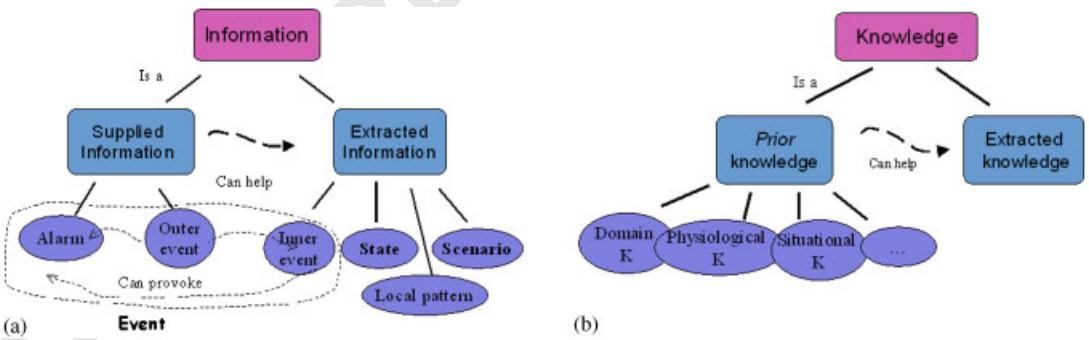

Figure 3. *Information and knowledge ontology*: (a) Information ontology. Event and state represent, respectively, a change in the system and a system property which lasts over time. Some events are provided by the clinical staff or the medical devices. Local patterns are regularities detected in the data and/or information. State, local patterns and events are used to build scenarios that can eventually be automatically detected; (b) Knowledge ontology. Knowledge can be extracted or given *a priori* to the system.

- a scenario is the representation of the temporal links between states and events. It can be represented using a temporal constraints graph [8].

Similarly to information, *knowledge* can be supplied or extracted (see Figure 3(b)). Prior knowledge is essentially expert knowledge provided in the form of classification rules and causal relations between parameters and is context dependent. Extraction of specific pattern sequences allows the definition of scenarios representative of specific situations that can be recognized in the future. Once they are validated by medical experts as representative of specific normal or abnormal situations, extracted patterns or regularities expressed in the form of association rules constitute new knowledge elements that guide actions that need to be undertaken.

2.3. Data abstraction

According to the Webster dictionary, to abstract signifies 'isolate, mentally separate an element, an object property in order to considerate them separately'.

2.3.1. Knowledge-based abstraction. Data abstraction is a knowledge-dependent process that builds abstractions in the domain parameters space at several levels of temporal granularity [4].

However, this process is not as obvious as it seems. Sowa notes (mentioned in Reference [9]): 'The set of features. . .seem almost obvious once they are presented, but finding the right features and categories may take months or years of analysis. The proper set of categories provides a structural framework that helps to organize the detailed facts and general principles of a system. Without them, nothing seems to fit, and the resulting system is far too complex and unwieldy.'

Several systems have been proposed for medical data abstraction that can be distinguished by the way they use knowledge and information. In Reference [10], the authors propose a methodology for extraction of local trends from a stream of ICU data. Trends are calculated by linear regression in a temporal window, called characteristic span, whose the size depends on the parameter dynamics. Standard deviation gives a local stability index. Qualitative notions such as 'increasing' and 'decreasing' or being 'steady' and 'unstable', are obtained directly by trend versus stability plan partitioning. The partitioning requires the introduction of *prior* knowledge to fix thresholds. Based on the definition of typical trends templates, TrenDx [11] allows their automatic recognition in monitoring patient data. In VIE-VENT [3], an open loop system for the supervision of neonatal mechanical ventilation, knowledge and extracted information are combined. Shahar [4] has studied in depth the implication of knowledge in temporal abstraction mechanism. Following this author, three types of abstraction are distinguished: horizontal abstraction (in respect of time), vertical abstraction (in respect of parameter) and oblique abstraction or trends (linking time and parameter) that rely on knowledge-based mechanisms (see Figure 4). Horizontal abstraction changes the temporal validity associated to a property. Four temporal abstraction mechanisms are considered for this purpose. *Temporal interpolation* links a point stamped property over a time interval (notion of state or property persistence over a time interval). *Prolongation by continuity* creates one state starting from two consecutive states when a given property is valid. *Aggregation* concerns the concatenation of consecutive states where a property is not continuously valid but valid at least over a fraction of them. *Forgetting* [12] removes non-relevant, redundant or out of date information.

Vertical abstraction performs a change in parameter space. In this case, three abstraction mechanisms are distinguished [9]. *Qualitative abstraction* is the symbolic classification of numeric data (for example, respiratory frequency $\in \{10, 25, 35\}$ cycles/min $\rightarrow$ {low, normal,

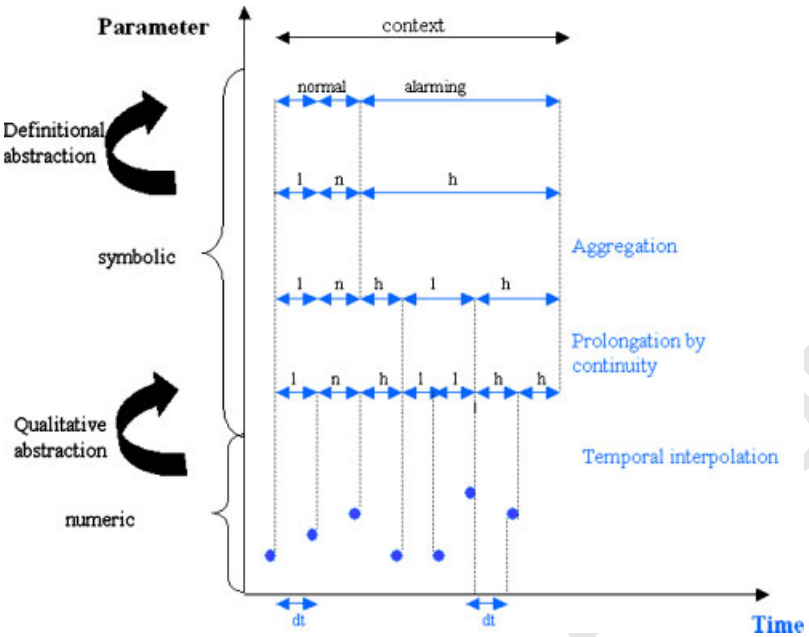

Figure 4. *Knowledge-based abstractions from* [4]. Vertical abstraction performs a change in parameter space. Temporal abstraction performs a change in time space. In order to interpret numeric data, several abstracted levels are gradually built based on contextual domain knowledge.

high}). *Definitional abstraction* is based on essential, necessary features of a concept (as an example, low respiratory frequency and low tidal volume and low end tidal PCO2 cause apnea or disconnection). *Generalization* is a subtype hierarchy (for example, rapid desaturation is a subclass of alarming situation).

2.3.2. Adaptive control of data abstraction. Data abstraction process should be carefully controlled to bring reliable information in an efficient way: a low abstraction level, close to the level of data, is too informative to be efficiently used, whereas a high level can lead to an irreversible loss of informative data. Moreover, the data abstraction process, to be valid, has to rely on reliable parameter values. It may happen that due to noise in the acquisition process, or external disturbances, the parameter shows erratic and non significant values. We therefore restrict the abstraction process to operate on so-called 'valid abstraction domain', i.e. domains where the parameter behavior is considered as valid.

Then, reliability and adaptability are ensured by:

- Modelling the abstraction process as the incremental building of new information: The gradual construction of abstractions allows adapting abstractions to the dynamics of each parameter.
- Bringing specific knowledge and information to early control and adapt abstraction process according to the dynamic of each parameter.
- Interacting early with clinical experts to validate each step.

2.4. Data mining

Mining is the next step in the process of knowledge discovery: 'it consists of applying data analysis and discovery algorithms that, under acceptable computational efficiency limitations, produce a particular enumeration of patterns (or models) over the data' [5].

We search for relations we can represent as association rules such as 'If parameter 1 is unstable during 20 min BEFORE parameter 2 becomes unstable THEN a specific event occurs' which ties states and events with temporal constraints.

Two central questions can be raised: (1) In general, data mining algorithms generate a set of association rules. Therefore, which measure can be introduced to assess the information power of these rules and then to select the more informative ones? (2) When we consider the availability of medical expertise, time is always short. Therefore, which data mining techniques can be used to manage time?

2.4.1. Informative power of association rules. Generally, five measures are used for ranking the usefulness and utility of discovered rules. The measures for association rules such as '$X \rightarrow Y$' are (P corresponds to probability values):

- support: $\text{supp}(X \rightarrow Y) = P(X, Y)$
- confidence: $\text{conf}(X \rightarrow Y) = P(X, Y)/P(X)$
- interest: $\text{intr}(X \rightarrow Y) = P(X, Y)/(P(X)P(Y))$
- conviction: $\text{conv}(X \rightarrow Y) = P(X)P(\neg Y)/P(X, \neg Y)$
- reliability: $\text{rel}(X \rightarrow Y) = P(X, Y)/P(X) - P(Y)$

In order to refine rules ranking, several authors propose additional measures. The causal relations ($X \rightarrow Y$) and ($\neg Y \rightarrow \neg X$) are similar and the descriptive relations ($X \rightarrow Y$) and ($X \rightarrow \neg Y$) are opposite. This leads Kodratoff [13] to introduce a confidence measure:

- $\text{conf}(X \rightarrow Y) = P(Y/X) - P(\neg Y/X)$ for a descriptive relation,
- $\text{conf}(X \rightarrow Y) = 1/2(P(Y/X) + P(\neg X/\neg Y)) - P(\neg Y/X)$ for a causal relation.

Note that a possible temporal delay between the relation attributes is not taken into account.

Because data mining techniques are various (classification, clustering ...), 17 measures, classified according to techniques used are presented in Reference [14], for ranking the knowledge discovered. Quantitative measures based on statistical significance, coverage or confidence, do not always indicate the relevance and usefulness of the knowledge that is discovered. To be selective, Hildermann *et al.* [14], propose five principles that a measure has to fulfill for being relevant.

2.4.2. Temporal relationships discovery. Discovering frequent episodes in temporal sequences is well studied in the literature (see [15] for a review). Generally, temporal sequencing is defined a *priori*. Recently [16], the problem of learning rules about temporal relationships from labelled time intervals was studied. The authors define a new rule semantic based on a sliding window: 'Given a randomly selected sliding window that contains an instance of the premise pattern, then with probability p this window overlaps a sliding window that contains the rule pattern'. P defines the support of the rule: higher is the support, higher is the quality of the rule. They obtained good results about the quality of the extracted rules. However, the methodology was only tested on simulated data.

In References [17,18], the authors describe a method for transforming real time series values into symbolic representations (the time axe is divided into intervals with the same length, and a symbol is given to each interval). This new representation was used for searching motifs in each parameter separately using on a probabilistic approach.

In Reference [19], the authors searched for multi-parameter rules. Starting from haemodialysis data, they tried to discover rules such as 'IF Trend of parameter 1 is decreasing BEFORE State of parameter 2 is High THEN dialyse fails'. They searched for rules about co-occurrences of states or trends such as 'IF Trend of parameter 1 is decreasing AND State of parameter 2 is High THEN dialyse fails'. A standard confidence measure was used and did not seem to be optimal.

In our medical context, we chose to explore the search for co-occurrences of states and events and the use of confidence measure for ranking causal relations [13].

3. DATA ABSTRACTION AND DATA MINING AT WORK

In this paragraph, we detailed the methodology we applied for the automatic supervision of medical ventilation.

3.1. The available elements

Several elements were at our disposal:

3.1.1. Raw physiological data. Waveforms (ECG, systemic arterial pressure and SpO_2) were delivered by the cardiovascular monitor (Datex 1606, Finland). Airway flow and pressure signals were measured via sensors. The Biopac MP100 and its companion software AcqKnowledge (Biopac, Santa-Barbara, Canada) were used for signal acquisition at a sampling rate of 100 Hz. The extraction of the physiological parameters was done cycle by cycle and then re-sampled at 1 Hz to be processed by the techniques we used [20]. Data included physiological parameters and device settings. Physiological data comprised respiratory data such as Respiratory Rate or blood gases (SpO_2) and cardiology data such as heart rate.

3.1.2. Extracted information. In order to qualify parameter variation and therefore to better control the data abstraction process, symbolic trends were computed for every parameter, with associated characteristic periods. Following Reference [10], trends and standard deviation were used to qualitatively partition the parameter space. Trend was computed using linear regression on a window whose size was determined according the dynamics of the parameter under study and called 'characteristic span'. When computed in that way, trend is comparable to a derivative. It is then possible to reconstruct filtered data by integration of trend values. At any time and according to the characteristic span, the value of the parameter and its trend, characterized by the slope of the regression line, were given. The standard deviation was used as an index of stability. We used the partioning of the trend versus stability plan (or more precisely regression coefficient versus standard deviation) to determine the predefined categories (increase, decrease, steady, unstable) [10]. 'Unstable' corresponds to a high standard deviation reflecting extremely noisy signals. 'Steady', 'increasing' and 'decreasing' correspond to a low

standard deviation (stable condition) and to a regression coefficient respectively close to zero, one, minus one.

3.1.3. Prior knowledge. Three kinds of *prior* knowledge were available:

(1) Situational knowledge (knowledge about intercurrent events): at the patient's bedside, an observer qualified each device alarm in terms of false positive, false negative, true positive and true negative and annotated event occurrences. According to clinicians the following events have been considered: modifications concerning drug therapy (addition, suppression, increase and reduction of drugs with vasoactive or sedative effects), modification concerning ventilator settings, blood or plasma filling, investigations such as EEG, thorax X-ray, blood gas sampling, presence of any person at the beside (nurses, doctors, physiotherapist, family), calibration procedures of the monitors, arterial line flush, clinical observations such as movements or anxiety. Alarms that occurred during the observation period were annotated using the following definitions: a true positive alarm was an alarm occurring when a parameter was outside the normal limits AND a medical or a technical action was taken. A false positive alarm was defined when a parameter was outside the limits, leading to no therapeutic action. A false negative alarm occurred when an action was taken, corresponding to any problematic situation, while no alarm was raised on any devices (see Figure 8).

(2) Physiological (causal knowledge) consists in temporal or causal relations between physiological parameters (such as if Volume Tidal high and Respiratory Rate high then Minute Volume high);

(3) Clinical knowledge was used to transform numerical values into symbolic parameters.

3.2. Information and knowledge handling through data abstraction

Fusion of knowledge and information is central in our approach. Our data abstraction methodology divides each step into four sub-steps:

Sub-step 1: Is devoted to the description of the parameters on which abstraction operates, the abstraction methods (mean calculation, merging time intervals, etc) used;

Sub-step 2: Corresponds to the identification of the *prior* knowledge and/or extracted information necessary to drive the abstraction;

Sub-step 3: Focuses on the definition of the domain where abstraction is valid (abstraction validity domains), in terms of constraints operating on raw data, abstracted data and knowledge;

Sub-step 4: Corresponds to the control step by step by the clinician of the abstraction process via a graphical interface. Note that the introduction of new information also contributes to the explanation of the expertise.

3.3. Two types of data abstraction

We distinguish simple and complex temporal abstractions [21]:

- simple abstraction builds a symbolic data descriptor on a time interval that characterizes a state (as stable or unstable), or a trend (as increasing or constant). It is constructed directly from raw data.
- complex abstraction tries to establish temporal relations between intervals constructed from previous simple or complex abstractions steps [21]. Such relations are also called local

patterns; they are used to characterize typical events such as a disconnection from the ventilator for instance.

3.3.1. Simple abstraction for state construction. The objective of the simple abstraction process is to determine the state of an individual parameter, for example 'HR stable for 30 min' in order to get closer to the clinician's discourse. We restrict the abstraction process validity domain to domains where the parameter behavior is considered as valid. Validity domains are based on the notion of stability: if a parameter is marked as unstable, we consider its numeric values as no valid. Several steps have been necessary to determine validity domain.

(1) *Parameter labeling in terms of stable or unstable*. This step qualifies each measured value in terms of stable or unstable. Stable is refined in 'steady', 'increasing' or 'decreasing' (see Figure 5(a)).

Sub-step 1:

Elements: raw values.

Description: raw values.

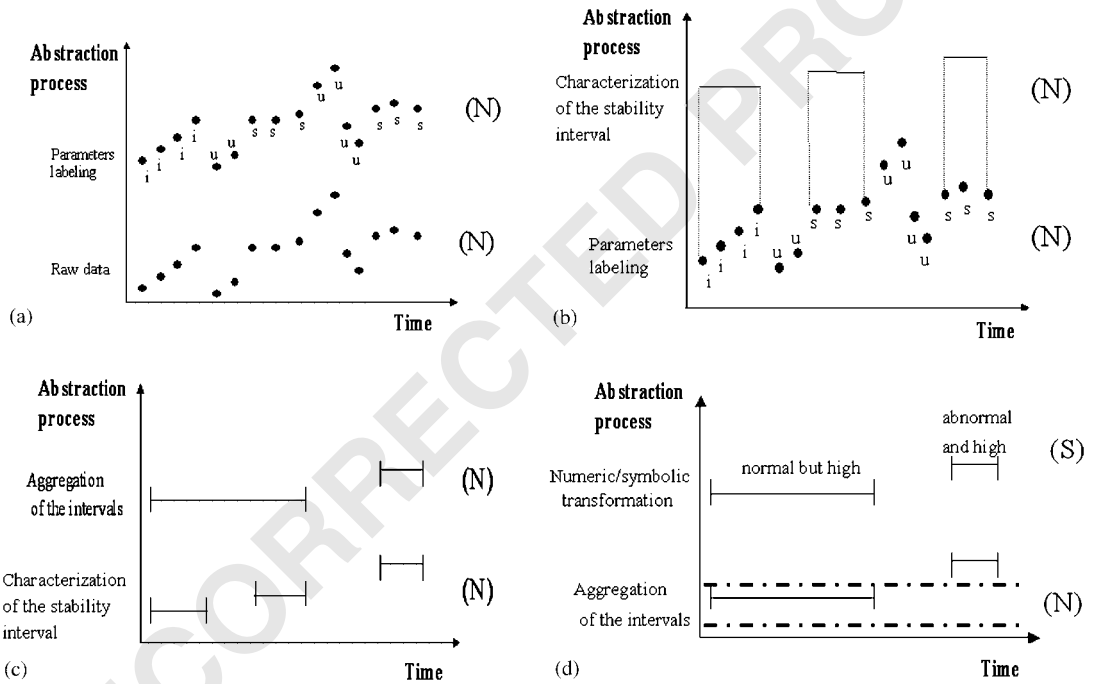

Figure 5. *Abstraction process*: (a) Abstraction process (1/4). Starting from raw data, each parameter is finally labeled as increasing (i), steady (s), unstable (u). N: Numeric; (b) Abstraction process (2/4). Abstractions using trend information. i: increasing, s: steady, u: unstable, N: numeric; (c) Abstraction process (3/4). The first two segments have been aggregated since the gap between them is smaller than their lengths, the difference between their means is weak and the variation of the raw data during this gap is below a threshold of precision but these conditions are not satisfied for the following 1; (d) Abstraction process (4/4). N: numeric, S: symbolic. The dotted lines are the thresholds of the parameter normality. Between, below and above, these two thresholds, the parameter is considered respectively, as normal, too low and too high. When the parameter is close to the thresholds but into the strip, we add the notions of 'normal but high' and 'normal but low'.

Operation: the counting of the number of moving windows, used to assess stability that contain a given measured value.

Sub-step 2:

Elements: extracted information: trend, characteristic span.

Prior knowledge: a measured value is considered as stable if it is qualified more often as stable than as unstable.

Sub-step 3:

Each measured value is qualified in terms of stable or unstable. The objective is to define the abstraction domain validity as a succession of measured values considered as stable (see the technical details for more details).

Sub-step 4:

The obtained results are displayed and validated by the clinician.

Technical details. Because trend is calculated on a moving temporal window, each measured value can be used for several trend calculations and then be considered many times as steady, increasing, decreasing or unstable. We consider a value as stable and use it for mean calculation if it is qualified as stable 1.5 times more than as unstable. This empirical value was validated by the clinicians. Stable is eventually refined as 'steady', 'increasing' or 'decreasing' based on the more frequent symbol.

(2) *Using trends to control data abstraction: characterization of the stability interval by the mean and the standard deviation of the values labeled as stable*. The purpose of this step is to perform a first abstraction, controlled by the trend characteristics resulting in the computation of time intervals called segments, where the mean is computed for each considered parameter (see Figure 5(b)).

Sub-step 1:

Elements: raw parameter values.

Description: raw values.

Operation: mean.

Sub-step 2:

Extracted information: trend, stability factors and characteristic span.

Prior knowledge: abstraction is valid when a parameter remains stable for a period of time.

Sub-step 3:

The mean and standard deviation are computed for each parameter based on their valid abstraction domains. These domains are identified based on the extracted information (step 2) and *prior* knowledge.

Sub-step 4:

The obtained results were displayed and validated by the clinician.

(3) *Using prior knowledge to control data abstraction: aggregation of the intervals according to temporal relations, mean values or raw data variations*. The purpose of this step is to perform a second abstraction, controlled by *prior* knowledge about parameter temporal variations resulting in the computation of refined time intervals (e.g. refined segments and adjusted mean values) (see Figure 5(c)).

Sub-step 1:

Elements: parameter segments (e.g. temporal segments where the mean has been previously computed).

Description: mean values, segment length and temporal interval between segments.

Operation: concatenation and mean.

Sub-step 2:

Prior knowledge: two kind of heuristic rules are used in this process. The first kind (a classical heuristic) checks the segment length, inter-segment interval and the gap between the segment means, considering the raw data standard deviation. The second kind controls that the parameter variation is below a given threshold or above this threshold but for a limited time period corresponding to the characteristic span supplied by Calvelo *et al*. [10]. The threshold for these rules is fixed by the clinician and depends on the precision of the measured data on which the parameter relies.

Sub-step 3:

The data abstraction process consists in concatenating the segments under interest and computing their mean values.

Sub-step 4:

The obtained results were displayed and validated by the clinician.

(4) *Numeric/symbolic transformation of these final segments*. The purpose of this step is to transform the quantitative values of segments into qualitative values such as 'normal', 'unstable', 'normal but high', 'abnormal and high', 'normal but low', 'abnormal and low'. All this information is attached to temporal intervals (see Figure 5(d)).

Sub-step 1:

Elements: parameter segments (e.g. temporal segments where the mean has been previously computed).

Description: mean values, segment length and temporal interval between segments.

Operation: classification

Sub-step 2:

Prior knowledge: thresholds given by experts define a normal zone in which the parameter is considered as normal. Starting from these thresholds (a, high threshold and b low threshold), we refined labels as 'normal but high' (α) and 'normal but low' (β). These thresholds are, respectively, the mean between the sup (respectively, inf) normal value and the mean between the 2 thresholds given by clinicians ($\alpha = (a + (a + b)/2)/2$ and $\beta = (b + (a + b)/2)/2$).

Sub-step 3:

The data abstraction process consists of classifying the parameter segments.

Sub-step 4:

The obtained results were displayed and validated by the clinician.

3.3.2. Complex abstraction for event construction. The objective of complex abstraction process is to detect data patterns that can eventually be recognized as events. For example, the event 'sensor disconnection' is an outer event that can be detected by a change in some parameters. This event is an important cause of false alarms. An important inner event to detect early is 'desaturation' which induces a drop in SpO_2 parameter. These events have been chosen because of their clinical impact, frequency of occurrences and diagnosis reliability.

Another event was studied that we called 'spike'. It is a rough variation of a parameter on a short time interval. It is a simple inner event that does not linked to any outer event or a clinical event.

Complex abstraction consists in four sub-steps.

Sub-step 1:

Elements: parameter segments (e.g. temporal segments where the mean was previously computed).

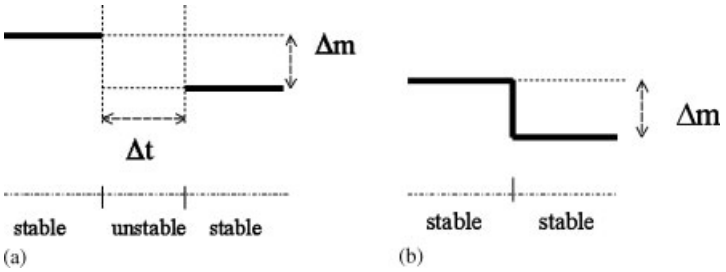

Figure 6. *Two specific patterns*: (a) temporal gap Δt separates two stable periods (bold lines); (b) meeting of two stable periods. A difference Δm between their mean values can be measured.

Description: mean values, segment length and temporal interval between segments.

Operation: classification.

Sub-step 2:

Prior knowledge: it consists in knowledge about the parameter behaviour for these events. It checks the segment length, inter-segment interval and the gap between the segment means, according to predefined patterns models.

Sub-step 3:

The data abstraction process consists of classifying the patterns according to their characteristics.

Sub-step 4:

Validation. There are two steps of validation concerning the detection and the interpretation of events. The obtained results are displayed and validated by the clinicians by reference with the annotations taken during the patient monitoring.

Technical details:

We study two patterns that differ according to two thresholds on time delay and variations means. A first pattern is based on unstable zone. When the parameter is considered as unstable, we search for some relations between time and variation of the means during stable zones around the unstable zone. This pattern is represented in Figure 6(a) when Δt (time interval between two stable zones) and Δm (difference between the means of the two stable zones) are high, it corresponds to an unstable parameter change. When Δm is low, it corresponds to an artifact. A second pattern does not comprise an unstable interval (see Figure 6(b)).

These patterns applied to SpO_2 parameter can be used to recognize a desaturation since a 'desaturation' implying an important decrease in SpO_2 that can be unstable (first pattern with Δt and Δm high) or stable (second pattern). The first pattern with a low Δm applied to this parameter can be used to recognize a sensor disconnection. It corresponds to an abrupt change although the parameter values do not change before and after disconnection. This pattern applied to other parameters can be used to detect spikes.

3.4. Data mining: search for relations between abstractions

Firstly, we searched for relations such as '{VT abnormal high} causes {fR abnormal high}'.

For the temporal aspect, similarly to Reference [19], we looked at co-occurrences of states by calculating the temporal overlaps between them. We defined the support of the relation as the temporal states overlaps, and the support of the premise and conclusion of the relation as the corresponding state duration.

Prior and conditional probabilities were defined, respectively, as the support of the corresponding relation divided by the total duration of observation and by the support of the relation premise. Based on the same principle, we searched for relations with conjunction of states as premise.

We considered two types of measures for rules ranking, the standard confidence and the causal confidence [13].

4. PRELIMINARY RESULTS

4.1. Clinical context

Our methodology for data abstraction and data mining has been used in the context of weaning from mechanical ventilation. Weaning is the period when the clinician tries to gradually withdraw the mechanical assistance. This is a crucial period. A too fast decrease of the assistance can cause an excessive fatigue for the respiratory muscles and an additional stress for the patient. On the other side, continuing mechanical ventilation has negative physiological, psychological and economical impacts [22] and leaves the patient vulnerable to the complications of ventilation. Clinical data used in this study were acquired based on a specific weaning protocol. This protocol is composed of three parts. During the first hour, the patient is in classical ventilation, during the following two hours the patient breathes by himself on a T-piece and then on spontaneous ventilation. At any time during the last two periods, the patient can be placed back on artificial ventilation. At each step, physiological data are recorded and a medical assistant annotates all meaningful alarming situations. This procedure lasts 4 h even in case of weaning failure. At the end, weaning is considered as a success if the patient can breathe without assistance for 24 h. This protocol was approved by our local ethical committee. Only patients who fulfil specific pre-weaning criteria are included into this protocol. We collected data on eight patients corresponding to three failures and five successes of the protocol.

Based on the weaning protocol, the automatic extraction of patient states typical patterns can lead to (1) a better understanding of the physiological effects due to weaning, and (2) the prediction of weaning failure or success by recognition of specific scenarios as they are developing. In the latter case, the total duration of the weaning could be reduced. This work is part of a global French project called OSSCAR for the optimization of medical strategies from cardio-respiratory signals in intensive care and anesthesia.

4.2. Data abstraction

An illustration of the proposed methodology is given in Figure 7. The graph at the top shows simple and complex abstractions for several cardio-respiratory parameters (heart rate, respiratory rate, tidal volume, minute volume, oxygen saturation (derived from pulse oxymetry SpO_2) and systolic arterial pressure). The graph at the bottom corresponds to some events annotated by the observer.

A posteriori, the comments by three physicians were: at time 2080 s, there was a transient modification that can be related to a tracheal suction. Our abstraction process detected an SpO_2 disconnection (event a in Figure 7). The same event was detected at time 7000 s lasting longer than the previous one, followed by a true episode of desaturation starting around 7600 and ending 8600. Our abstraction process detected a desaturation (event b in Figure 7.). However, disconnection at time 7000 was not identified. It was aggregated with the start of desaturation.

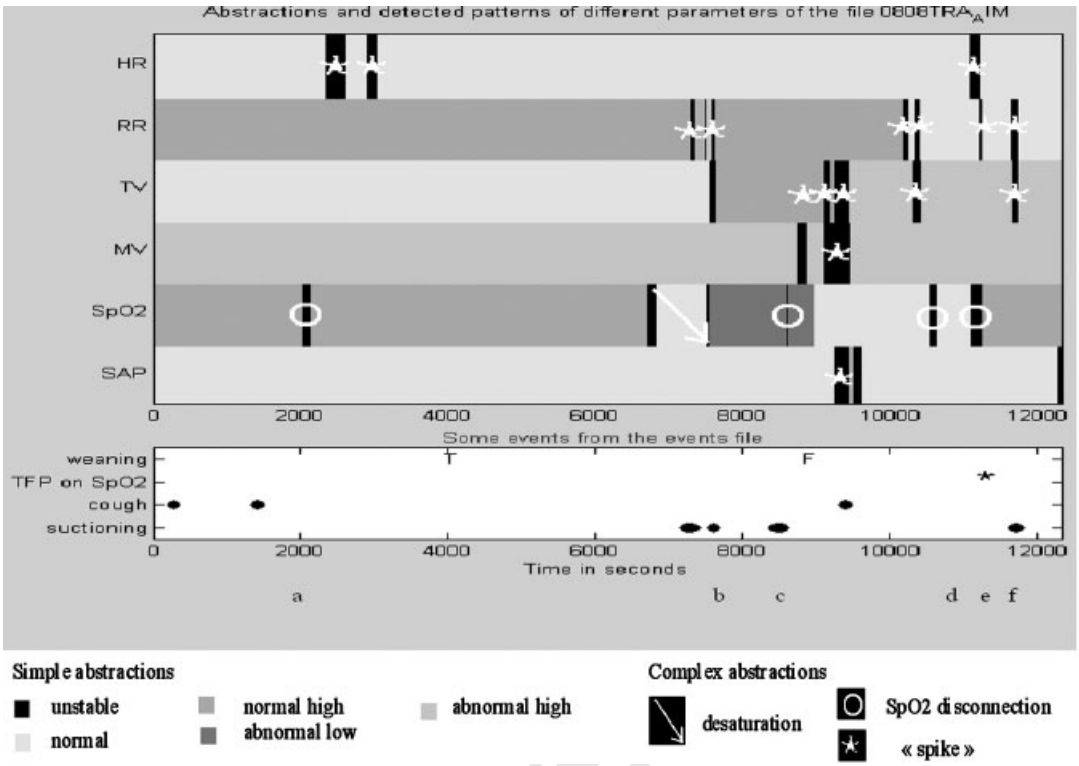

Figure 7. *Abstractions and real events*. Events file: on the row 'weaning', 'T' corresponds to the moment when the patient started to breath by himself on a T-piece and 'F' corresponds to 'failure', the patient was replaced on mechanical ventilation. 'TFP on SpO_2' signifies a technical false alarm on SpO_2, as a general rule, it corresponds to a disconnection. Notice the events file is not exhaustive. a, b, c, d, e and f indicate the events detected by our abstraction process.

The end of the desaturation episode is detected as a disconnection (see c). Two others episodes of disconnection around 10 600 and 11 200 were detected (d and e).

We observe that 'spikes' on respiratory parameters (RR, TV and MV) can correspond to suctioning (b, f), a more precise study of this relation is in progress.

4.3. Association rules

Some details of the results are presented in Table I. Following discussion with medical experts, it appears that only the first rule is correct, the second has no clinical interest and the third is false. Causal confidence measure allows rejecting the third rule, the lowest value measure, but fails to separate the first and the second rules.

5. PERSPECTIVES AND CONCLUSION

In our methodology, we distinguish two coupled steps, data abstraction and data mining relying on prior and extracted knowledge.

Table I. Example of rules ranked using two measured.

Rules	Confidence	Support	Causal confidence
1	0.64	720	0.45
2	1	4342	0.5
3	1	1146	−0.41

Note: Rule 1: 'RR abnormal low → SpO_2 unstable'. Rule 2: 'RR normal → SpO_2 normal high'. Rule 3: 'SpO_2 normal high → RR unstable'. The confidence measure is comprise between 0 and 1 contrary to causal confidence [13] between −1 and 1. Formulas for confidence, support and causal confidence calculations are reported in the text.

A multi-level data abstraction is a prerequisite for scenario construction. Data abstraction is defined as an incremental process, combining data, information and knowledge in numerous different ways. Abstraction reliability is reinforced by interactions with clinical experts to validate each abstraction step. Results obtained on ICU data are encouraging. Applying this methodology on a large data set will allow its refinement and strengthen its validation.

Starting from data abstraction, we searched for relations between them based on co-occurrences. Searching for interval based temporal rules is an open NP-complete problem [19]. The search for co-occurrences of states could be a rapid and easy to implement alternative. However, it is not properly taken time into consideration, in our context. In particular, the duration of the conclusion of the rule is not take into account in the probabilities calculus. We used standard and causal confidence measures for rules ranking. The mitigated results we obtained indicate that measures and support definition are not appropriated. The use of an appropriate definition for the support and measure of temporal rules should be introduced. Moreover, clinical situations are characterized by a set of parameters, rarely by a single one. A conjunction of conditions should appear as premises of association rules.

Due to the importance of these aspects in medical applications, future work should be focused on solving these problems.

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