Intelligent Alarm Processing into Clinical Knowledge

Craig B. Laramee*, Leann Lesperance, Don Gause, and Ken McLeod

Abstract— **Alarmed physiological monitors have become a standard part of the ICU. While the alarms generated by these monitors can be important indicators of an altered physiological condition, most are unhelpful to medical staff due to a high incidence of false and clinically insignificant alarms. High numbers of false/insignificant alarms can lead to several adverse consequences such as increased patient anxiety, distraction of clinicians, and decreased efficiency in delivery of care. Furthermore, repeated false/insignificant alarms may increase the chance that healthcare providers ignore clinically significant alarms.**

In this paper we review the current state of intelligent alarm processing and describe an integrated systems methodology to extract clinically relevant information from physiological data. Such a method would aid significantly in the reduction of false alarms and provide nursing staff with a more reliable indicator of patient condition.

I. INTRODUCTION

Modern intensive care units (ICU) are equipped with a large array of alarmed monitors and devices which are used in an attempt to detect clinical changes at the earliest possible moment, so as to prevent any further deterioration in a patients condition.

The effectiveness of these systems depends on the sensitivity and specificity of the alarms, as well as on the responses of the ICU staff to the alarms. However, when large numbers of alarms are either technically false, or true, but clinically irrelevant, response efficiency can be decreased, reducing the quality of patient care and increased patient (and family) anxiety. Previous studies indicate that, in some cases, over 90 percent of the alarms generated are either false or clinically insignificant alarms[1].

Moreover, as the number of monitoring equipment increases, the number of false/insignificant alarms increases [2]. With this increase in the number of alarms it is no surprise that nurses and physicians are frustrated by the flood of noise [3] and in some cases implement their own filtering techniques [4]. ICUs, therefore, are in great need of tools to help clinicians analyze the huge amount of data recorded and to support them in decision making tasks.

II. INTELLIGENT ALARM PROCESSING

Currently, most alarm systems are generally based on threshold crossings, that is, they trigger when the current reading exceeds a preset boundary. This method however, does not account for the natural variation of physiological systems or their highly correlated, non-linear nature. Biological systems composed of large numbers of highly interacting components, giving rise to emergent system behaviors which are not completely understood.

Most quantitative descriptions of physiological systems are made using control theory techniques that were originally developed for linear systems. While these analytical models are useful for simulating general dynamic system behavior, they are not sufficient for diagnosis of a patients physiological condition.

In the past two decades, several advances have been made in the development of intelligent alarm systems that incorporate the complex nature of physiological systems.

Many of these advances have resulted in the identification of *features* or transformations of the raw monitoring data that are extracted to aid in the determination of an alarms clinical relevance. The transformations that define these features can range from relatively straightforward, such as mean or median filtering [5], to quite complex such as translation into temporal episodes [6], trend detection [7], [8], fuzzy similarity-based fractal dimension [9], and multiparameter trend monitoring using wavelet analysis [10]. Feature transformation provides a framework in which to explore statistical relationships among variables and to identify novel combinations that have more diagnostic power than does any individual variable. The benefits of this tremendous flexibility are offset, however, by the complexity of the problem, that is, determining which sets of features are valuable in providing clinical information, and whether they are they consistently predictive across different patients.

Advances in knowledge-based systems have also enhanced the functionality of intelligent alarm systems. Using the knowledge of a domain expert to formulate rules or an expertly classified data set to train an adaptive algorithm has proven useful for intelligent processing of clinical alarms. Expert systems such as neural network [11], knowledge-based decision trees [13], [14] and neurofuzzy systems [15] that encode the decisions of an expert clinician all show significant statistical improvement in the classification of alarms. To utilize these techniques, one needs a training set, that is, a representative population of data that has been correctly classified by a domain expert(s). Clinical expertise is readily available and, as the monitoring and data collection capability of ICUs increases, more information will be available for potential use in improving health care.

In this paper we describe a general, adaptive method to explore features of physiological monitoring data and determine their performance based on information from a domain

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Craig Laramee, Leann Lesperance, Don Gause and Ken McLeod are faculty in the Department of Bioengineering, Binghamton University, Binghamton, NY 13902. * Author to whom correspondence should be addressed claramee@binghamton.edu.

expert for providing clinically relevant alarm information.

III. Integrated Systems Methodology

We present a multiphase process for extracting clinical information from physiological monitoring data and alarm information. The preliminary phase (Phase 0, see figure 1) develops a rule based system based on the opinions of clinical experts. For a given set of n physiological monitoring data $(\vec{x_1(t)}, \vec{x_2(t)}, \cdots, \vec{x_n(t)})$ such as respiratory rate, blood pressure, heart rate, ECG, etc. we extract, from each, a set of m features $(\vec{y_1(t)}, \vec{y_2(t)}, \cdots, \vec{y_m(t)})$. These include, for example, linear combinations and statistical parameter estimates of the raw data as well as other transformations and the untransformed data themselves. In the preliminary phase each of these vector values features $\vec{\mathbf{Y}}$ is examined and evaluated for their value in identifying clinically relevant alarms. The result of phase 0 is an alarm system that integrates physiological monitoring data from multiple systems and coupled with rules determined by a domain expert(s) provides enhanced processing of alarms.

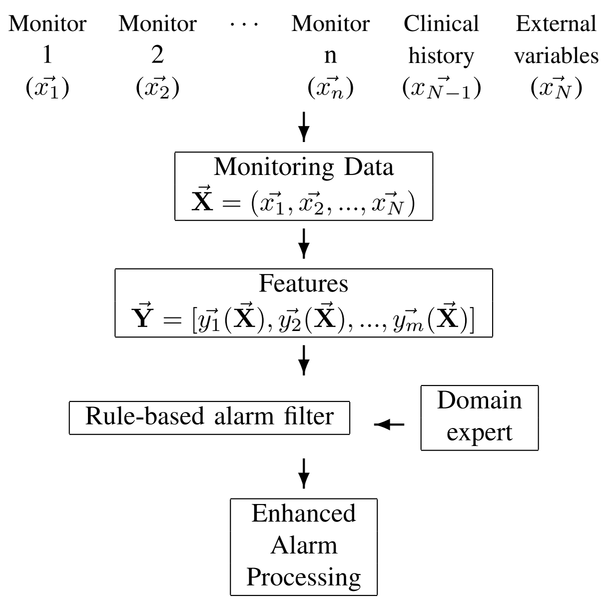

Fig. 1. Phase 0 of Intelligent Alarm Processing Scheme. A rule-based system to evaluate features for their value in identifying clinically relevant alarms.

In the second phase (Phase 1, see figure 2) the number of features extracted from the monitoring data is extended $(\vec{y_1(t)}, \vec{y_2(t)}, \cdots, \vec{y_m(t)}, \vec{y_{m+1}(t)}, \cdots, \vec{y_M(t)})$ to include a larger variety of *potentially* valuable features. For example, results of fractal, phase space, graph and reconstructability analysis are included in this extended set of features as well as novel features to be developed using evolutionary approaches. The value of each of these extended features is determined by their contribution towards correct classification of a training set as determined by an R-category linear classifier operating in a Phi-space $\vec{\Phi} = [\vec{\varphi}_1(\vec{\mathbf{Y}}), \vec{\varphi}_2(\vec{\mathbf{Y}}), ..., \vec{\varphi}_k(\vec{\mathbf{Y}})]$ [16]. The Phi-transformation provides a mechanism by which non-linear discriminant functions in the feature space are transformed to linear functions in the Phi-space via a family of real, single-valued, linearly independent functions $\vec{\varphi}_i$ (e.g. rth order polynomial). The result of phase 1 is an intelligent system that integrates physiological monitoring data and alarm information from multiple systems with knowledge from domain experts to identify clinically relevant features of the physiological monitoring data for the determination of real alarms. Moreover, the adaptive and extensible nature of this system permits improved identification of clinically relevant (and potentially novel) features of physiological monitoring data through iterated application and expert review (phase 2).

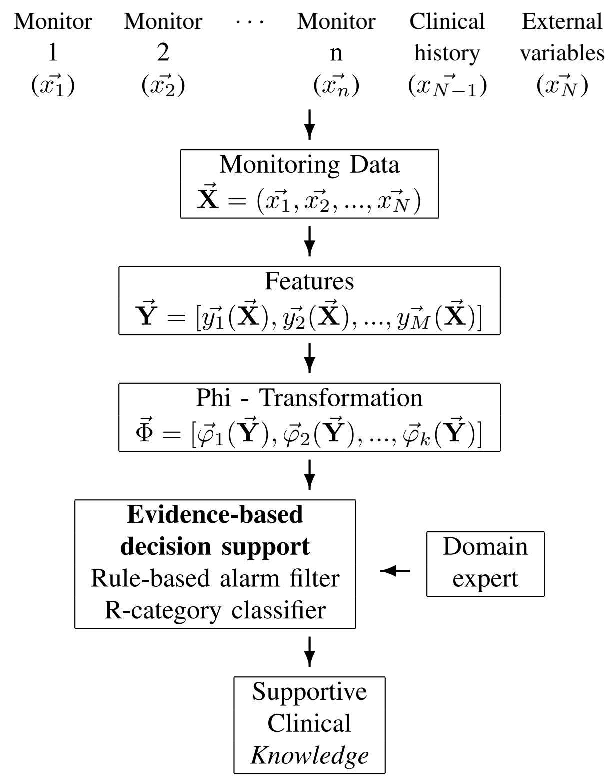

Fig. 2. Phase 1 of Intelligent Alarm Processing Scheme. Features are evaluated for their contribution towards correct classification of a training set as determined by an R-category linear classifier operating in a Phi-space.

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[1]Any opinions, findings, conclusions or recommendations expressed are those of the authors and do not necessarily reflect the views of the New York State Office of Science, Technology and Academic Research.

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