33rd Annual International Conference of the IEEE EMBS
Boston, Massachusetts USA, August 30 - September 3, 2011

Service Oriented Architecture to Support Real-Time Implementation of Artifact Detection in Critical Care Monitoring

Shermeen Nizami, Student Member *IEEE*, James Robert Green, *SMIEEE*, and Carolyn McGregor, *SMIEEE*

Abstract— **The quality of automated real-time critical care monitoring is impacted by the degree of signal artifact present in clinical data. This is further complicated when different clinical rules applied for disease detection require source data at different frequencies and different signal quality. This paper proposes a novel multidimensional framework based on service oriented architecture to support real-time implementation of clinical artifact detection in critical care settings. The framework is instantiated through a Neonatal Intensive Care case study which assesses signal quality of physiological data streams prior to detection of late-onset neonatal sepsis. In this case study requirements and provisions of artifact and clinical event detection are determined for real-time clinical implementation, which forms the second important contribution of this paper.**

I. Introduction

Critical Care Units (CCU), such as Intensive Care Unit (ICU), Paediatric Intensive Care Unit (PICU), and the Neonatal Intensive Care Unit (NICU), provide specialized care and therapeutic support through a host of life saving services and medical devices. Continuous monitoring is used to detect early onset indicators of various pathophysiologies. Different disease conditions, called "clinical events", are detected by analyzing one or more data streams with different acquisition frequencies, lengths and signal quality. For example, some heart rate variability (HRV) analysis approaches require a continuous wave type electrocardiogram signal (ECG) acquired at 500-1000 Hz. Other clinical events such as apnoea can be assessed using oxygen saturation and breathing rates acquired once every second. Although clinical data streams and their associated patterns are known to be generated by underlying patient physiology; it is also an established fact that these data can be corrupted by artifacts [1]-[3]. There are numerous potential sources that introduce artifact at the time of data acquisition including poor skin contact, loose electrodes, muscle activity, power line interference, interference from an electrosurgical unit, and optical crosstalk.

Artifacts in data segments are a source of multiple problems. They can be mistaken for a true representation of patient physiology, in which case subsequent data analysis may lead to false results and misinterpretation of the patient's state. This exposes the patient to risks of incorrect diagnosis, iatrogenic disease and unnecessary therapy or surgery [4]. Some signal artifacts are known to exhibit behaviors that mimic organ malfunction which can lead to severe diagnostic errors [5]. Artifacts increase false alarm rates in patient monitors [6]-[10]. Overall, artifacts compromise quality of service at point of care.

Several research groups have developed techniques for artifact detection (AD) to improve reliability of stream analysis [3], [6], [11]-[15]. However, literature surveyed by the authors reveals that few algorithms have found their way into actual clinical use. This is partly due to the lack of a systematic architecture for self-describing, discovering, integrating and implementing these algorithms into clinically useful workflows. While these techniques have been compared in terms of performance, reliability, robustness and shortcomings, this vast body of literature has not been synthesized to abstract system requirements and provisions for real-time clinical implementation. Requirements define the data necessary at the input of a detection algorithm and provisions define the deliverables at its output. Identification of requirements and provisions is the first step towards real-time implementation of these techniques in clinical environments. This would also contribute towards generalization of the technique for reuse in different clinical settings, for assessing quality of different data streams in the process of detecting different diseases.

Neonatal Intensive Care Units provide specialized tertiary level medical care to pre-term and critically ill term babies. Multiple data sources routinely generate patient information in an NICU. Current research is exposing pathophysiological behaviors that are candidate condition onset predictors for clinically significant events such as late-onset neonatal sepsis (LONS). Therefore, there exists great potential in meaningful integration of neonatal data from multiple sources for automated analysis in real-time. A framework that can detect pathophysiological behaviors in real-time patient data can provide clinicians with timely clinical decision support [16]. Artemis is one such analytical system deployed in real-time NICU settings [17]. However, real-time artifact detection is required to assess signal quality prior to stream analysis for clinical event detection (CED) [16], [17]. This research develops a novel multidimensional service oriented architecture (SOA) to support real-time clinical implementation of AD. It contributes to the larger Artemis system by expanding its existing functionality as detailed in section III-B.

SOA has emerged as a successful solution in many real-

Manuscript received March 26, 2011. This work was supported in part by McGregor's Canada Research Chair and the Natural Sciences and Engineering Research Council of Canada.

S. Nizami and J.R. Green are with Carleton University, Ottawa, Ontario, Canada (email: shermeen@sce.carleton.ca; jrgreen@sce.carleton.ca).

C. McGregor is with the University of Ontario Institute of Technology Oshawa, Ontario, Canada (e-mail: c.mcgregor@ieee.org).

978-1-4244-4122-8/11/$26.00 ©2011 IEEE

world applications. and it holds the potential to facilitate growing demands of automation in healthcare [18], [19]. While the use of SOA in healthcare is constantly expanding, its application in critical care remains an area that requires further investigation [20]. Clinical applications focused on patient and clinician needs require delivery of high quality, reliable and integrated data at point of care. SOA can offer packaged solutions in clinical data analysis applications requiring stringent data quality in critical care settings such as the ICU and Operating Rooms (OR) [18]. The varying needs of a range of CED modules to interface with multiple AD techniques that best suit their requirements of data use and data quality is a problem well suited to the SOA paradigm.

This paper presents a novel application of an SOA to support real-time integration of AD algorithms in clinically applied workflows. AD and CED algorithms published in literature form the business logic that comprises the *services* within this SOA. The objective of the AD framework is to assess signal quality for a range of clinical event detection needs. This paper demonstrates instantiation of the SOA by documenting requirements and provisions of AD and CED services in a LONS case study.

II. Methods and Concepts

In this paper, we have employed *service oriented architecture* as the methodology in developing a component-based system. The fundamental building unit of an SOA is the *service*, which is a modular component encapsulating the business logic or the knowledge base in the distinct context of the application domain [21]. A SOA enables multiple services to access each other using clearly defined protocols called *interfaces*. A component can have multiple interfaces, which can be selectively instantiated at run-time. Three basic types of interfaces are: 1) requirement, 2) provision and 3) configuration [22]. The requirement type interface specifies what the component requires for fulfilling its functional purposes. The provision type interface defines what the component can provide either for another component to function or as a contribution to the system output. The configuration type interface incorporates user-defined functionality. It allows the user to set the component parameters for running a particular application. These interfaces are standardized for use across the SOA with the goal of fulfilling requirements of data acquisition, storage and dissemination. Standardized interfaces allow different services to communicate in the same language regardless of their underlying business logic. An SOA can be developed based on the following set of standards: eXtensible Markup Language (XML), Web Services Description Language (WSDL), and Universal Description, Discovery, and Integration (UDDI) [19].

III. Results

A. Service oriented architecture

The artifact detection SOA design is shown in Fig. 1. It consists of a pool of CED services and another pool of AD services. Each CED service consists of one algorithm to detect one or more diseases or clinical events. Similarly, each AD service consists of one algorithm to detect artifacts in one or more physiological data streams. This research presents a multidimensional framework which, in the context of this research, means that the framework can include multiple CED services using data from multiple streams from multiple patients. Moreover, each CED service can select one or more AD services to pre-process its required data streams. The selection in real-time depends on requirements of the CED and provisions of the AD as well as the availability of data streams and their estimated signal quality. Requirements and provisions of multiple AD and CED services can be defined in a common reference interface, such that any service within the framework can be advertised and discovered through this interface. As shown in Fig. 1, both CED and AD services advertise themselves, i.e., publish their descriptions and access information in a private UDDI framework within this SOA. One way of storing this information is using WSDL , which is used to generate XML documents defining the requirements and provisions of each service. It is proposed that these descriptions be made part of a common reference interface.

Fig. 1 shows step wise discovery and integration of the two services. A user, in this case a clinician, accesses the framework through a computer. The configuration interface allows the clinician to set operational parameters such as available data streams, their frequencies, and requirements of signal quality. The CED service sends these operational requirements to the service broker through its requirement interface in step 1. The broker searches the UDDI in step 2 for an appropriate AD service whose provisions interface matches the requirements of the CED service. Once a suitable AD service is found from the pool of AD services in the UDDI registry, the broker connects the CED service to the appropriate AD service in step 3. In step 4, the AD service provides its service description written in WSDL to the requesting CED. The CED service would parse the XML-based WSDL document in step 5 and accepts service provisions of the AD in step 6. This step is the confirmation of the connection between the services, also known as service composition. It is followed by framework instantiation in step 7 where data starts to flow for patients

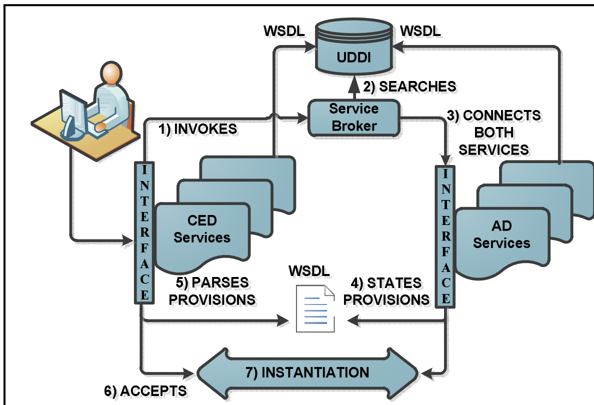

Fig. 1. SOA for artifact detection. All communication and data transfer is in XML.

for whom the CED is configured to operate. In step 7 both services commence XML-based two-way messaging and data transfer through their interfaces. Various communication protocols such as Simple Object Access Protocol (SOAP) and Representational State Transfer (REST) can be employed to enable this data exchange.

B. *Case Study*

This SOA is being developed for integration with the Artemis data analytics system. The Artemis framework is currently deployed with the ability to capture neonatal patient data in real-time [17]. An SOA approach to capture physiological data from patient monitors within Artemis was described in [23], where physiological data streams are made available through the Physiological Log service. These data streams can be channeled to individual and independent invoking CED and AD services. Services are composed prior to run-time, after which bidirectional data exchange takes place between these services through their interfaces. In general, CED services for different diseases will have different needs in terms of data types, length, frequency and quality. The contribution of this research is the definition of the requirements and provisions interfaces of the invoking AD and CED services in the context of a late-onset neonatal sepsis (LONS) case study. These definitions describe the required data stream attributes as well as the outputs provided by these services at run time as depicted by Fig. 2. This case study is the first step towards identification of requirements and provisions interfaces of individual services. In future work this approach shall be expanded to fully develop a common reference interface for this SOA.

LONS is one of the clinical events under research in Artemis. The incidence of LONS in NICUs worldwide varies between 11% and 53% [24], resulting in an average neonatal death rate of 45% [25]. Research has shown that reduced baseline and variability in heart rate can serve as a predictor of LONS [26]. In this case study, we propose a CED service called LONS - HRV, where the algorithm calculates a number of HRV metrics over 5 minutes of ECG data. Downward trends in these metrics observed over 24 hours act as LONS prognosis tools. This service requires a certain quality of the ECG signal at its input. In case the quality of the ECG signal deteriorates LONS-HRV is capable of analyzing the pulse plethysmograph (PPG) to extract the pulse rate (PR) and can evaluate HRV metrics based on it. In this framework, the LONS-HRV service would invoke an AD service to assess the quality of the ECG acquired from the patient monitor. We have found the ADAPIT algorithm published by Yu *et al.* to be quite suitable as an AD service for this case study [3]. Its advantages include modularity, independence from data collection hardware and ease of modification in case one source of waveform data becomes unavailable.

The ADAPIT service inputs four data streams, two of which are continuous wave (CW) types, i.e., the ECG and PPG (**ECG-CW** and **PPG-CW**), and two are parametric, i.e., heart and pulse rates (**HR, PR**). ADAPIT is a data fusion algorithm which avails the redundancy in these signals; it also has motion artifact filtering capabilities. At its output it provides a QI ranging from **MinNumValue** = 0 to **MaxNumValue** = 3 for every 7 seconds of continuous wave data. Signal quality requirements for LONS - HRV can be user set. For example, no more than 35% of the 5 minute window of analysed ECG data can have a quality index (QI) of less than 3. Table I states requirements of LONS-HRV service in terms of stream type, frequencies and quality. The QI is a signal quality requirement of LONS-HRV and a provision of ADAPIT service. ECG-CW and PPG-CW are data type requirements of LONS-HRV and provisions of the Physiological Log services. Fig. 2 is a graphical representation of the AD and CED requirements and provisions interfaces identified for runtime in this case study. We have added a new variable at the provisions interface of ADAPIT, called **AnalyzeSignal**. It specifies which stream should be analysed with the given QI values and available streams, these have been derived using ADAPIT QI determination rules [3]. It may take up any one of the string values shown in Table I fourth column. If the accumulated QI for the 5 minutes data segment is lower than the user set requirement (e.g., QI = 3) then the provision output of LONS-HRV is a low signal quality flag (LSQF), otherwise it will evaluate HRV metrics. **MessageFrequency** is stream frequency that is required by LONS-HRV to operate and is a provision of the Physiological Log service. This requirement can be user set depending on the output frequency of the patient monitor and granularity of analysis.

XML documentation for data exchange between these two services through their interfaces is shown in Fig. 3. An **AD-Packet** with a **PacketFrequency** of once every 7 secs is sent from ADAPIT provisions interface to LONS-HRV requirements interface. It consists of two **AD-Data** data types. These are **QI** and **AnalyzeSignal** as shown in Table I and described above. The ADAPIT algorithm has been validated with a PPG-CW frequency of 91 Hz [3]. In the

TABLE I
REQUIREMENTS OF LONS-HRV SERVICE

QI	Available signal		AnalyzeSignal	Message Frequency (Hz)
	ECG-CW	PPG-CW		
3	Yes	Yes	ECG-CW	500
2	Yes	No/Yes	ECG-CW	500
1	No/Yes	Yes	PPG-CW	91
0	No/Yes	No/Yes	None	0

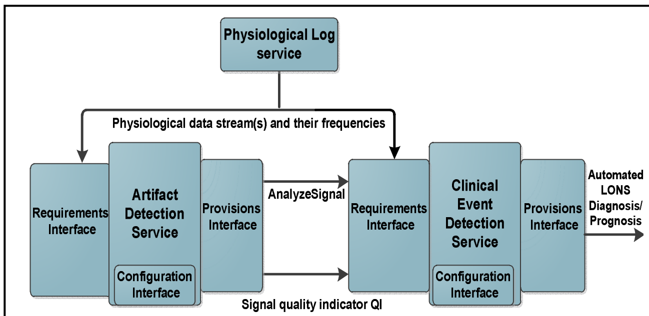

Fig. 2: Framework instantiation in the LONS case study

```
<AD-Packet>
   <PacketFrequency>0.143</PacketFrequency
   <PatientID> NICUBED01</PatientID>
   <DeviceID1>0099</DeviceID1>  <!-- ECG and HR acquisition device-->
   <DeviceID2>0079</DeviceID2>  <!-- PPG and PR acquisition device-->
   <SendTime>11:13:42</SendTime>
   <AD-Data>
      <MessageID>QI</MessageID>
      <MinNumValue>0</MinNumValue>
      <MaxNumValue>3</MaxNumValue>
      <NumValue>3</NumValue>
   </AD-Data>
   <AD-Data>
      <MessageID>AnalyzeSignal </MessageID>
      <StringValue>ECG-CW</StringValue>
   </AD-Data>
</AD-Packet>
```


Fig. 3. XML document for data exchange between ADAPIT provisions and LONS-HRV requirements interfaces.

NICU, it is usual to acquire ECG-CW at a **MessageFrequency** of 500 Hz, hence there will be 500 data values sent to these services each second by the Physiological Log service.

To the best of the authors' knowledge, this SOA approach to build an AD framework is unique. Patient monitors comprise of simple hardware and software linear filters to reduce the impact of artifacts by pre-processing individual data streams [1]. However, no approach has been previously described in the literature for post-processing multiple data streams with the objective of dynamic integration of multiple AD and CED algorithms or services in real-time.

IV. Conclusions and Future Work

This paper has presented novel SOA based integration of artifact and clinical event detection in real-time critical care monitoring. Framework instantiation is demonstrated by means of a late-onset neonatal sepsis case study.

This research forms part of the larger Artemis project where we are proposing a new platform for real-time multi-dimensional patient monitoring leading to early clinical event detection and prognosis. Through future research, a common reference model shall be developed for AD interfaces to support real-time clinical implementation of multiple algorithms to detect artifacts in multiple physiological data streams. The framework shall be integrated with Artemis and instantiated using real-time data to simultaneously detect multiple diseases in critical care settings, including apnoea and intraventricular haemorrhage in neonatal populations.

The multidimensional framework proposed in this research shall enable dynamic discovery of optimal service composition which can lead to improved accuracy and reliability in clinical event detection as opposed to isolated use of static AD and CED algorithms found in literature.

References

[1] G. Takla, J. H. Petre, D. J. Doyle, M. Horibe and B. Gopakumaran, "The Problem of Artifacts in Patient Monitor Data During Surgery: A Clinical and Methodological Review," *Anesth. Analg.,* vol. 103, pp. 1196-1204, November 1, 2006.

[2] N. McIntosh, "Intensive care monitoring: Past, present and future," *Clinical Medicine,* vol. 2, pp. 349-355, 2002.

[3] C. Yu, Z. Liu, T. McKenna, A. T. Reisner and J. Reifman, "A Method for Automatic Identification of Reliable Heart Rates Calculated from ECG and PPG Waveforms," *Journal of the American Medical Informatics Association,* vol. 13, pp. 309-320, 2006.

[4] C. Chase and W. J. Brady, "Artifactual electrocardiographic change mimicking clinical abnormality on the ECG," *Am. J. Emerg. Med.,* vol. 18, pp. 312-316, 2000.

[5] M. Ma´rquez F and e. al, "Common electrocardiographic artifacts mimicking arrhythmias in ambulatory monitoring," *Am. Heart J.,* vol. 144, pp. 187-197, 2002.

[6] S. Charbonnier and S. Gentil, "On-line adaptive trend extraction of multiple physiological signals for alarm filtering in intensive care units," *Int J Adapt Control Signal Process,* vol. 24, pp. 382-408, 2010.

[7] C. L. Tsien, "Event discovery in medical time-series data." in *Proc AMIA Symp.* 2000, pp. 858-862.

[8] A. Aboukhalil, L. Nielsen, M. Saeed, R. G. Mark and G. D. Clifford, "Reducing false alarm rates for critical arrhythmias using the arterial blood pressure waveform," *J. Biomed. Inform.,* vol. 41, pp. 442-451, 2008.

[9] G. D. Clifford, A. Aboukhalil, J. X. Sun, W. Zong, B. A. Janz, G. B. Moody and R. G. Mark, "Using the blood pressure waveform to reduce critical false ECG alarms," *Computers in Cardiology,* vol. 33, pp. 829-832, 2006.

[10] A. Otero, P. Félix, F. Palacios, C. Pérez-Gandía and C. O. S. Sorzano, "Intelligent alarms for patient supervision," in *IEEE International Symposium on Intelligent Signal Processing*, 2007.

[11] S. Asgari, M. Bergsneider and X. Hu, "A robust approach toward recognizing valid arterial-blood-pressure pulses," *IEEE Transactions on Information Technology in Biomedicine,* vol. 14, pp. 166-172, 2010.

[12] S. Charbonnier, G. Becq and L. Biot, "On-line segmentation algorithm for continuously monitored data in intensive care units," *Biomedical Engineering, IEEE Transactions on,* vol. 51, pp. 484-492, 2004.

[13] J. A. Quinn, C. K. I. Williams and N. McIntosh, "Factorial Switching Linear Dynamical Systems Applied to Physiological Condition Monitoring," *Pattern Analysis and Machine Intelligence, IEEE Transactions on,* vol. 31; 31, pp. 1537-1551, 2009.

[14] P. Yang, G. Dumont and J. Ansermino, "Sensor Fusion Using a Hybrid Median Filter for Artifact Removal in Intraoperative Heart Rate Monitoring," *J. Clin. Monit. Comput.,* vol. 23, pp. 75-83, 2009.

[15] E. Walls-Esquivel, M. F. Vecchierini, C. Héberlé and F. Wallois, "Electroencephalography (EEG) recording techniques and artefact detection in early premature babies," *Clinical Neurophysiology,* vol. 37, pp. 299-309, 2007.

[16] M. Stacey and C. McGregor, "Temporal abstraction in intelligent clinical data analysis: A survey," *Artif. Intell. Med.,* vol. 39, pp. 1-24, 2007.

[17] M. Blount, M. R. Ebling, J. M. Eklund, A. G. James, C. McGregor, N. Percival, K. P. Smith and D. Sow, "Real-time analysis for intensive care: Development and deployment of the artemis analytic system," *IEEE Engineering in Medicine and Biology Magazine,* vol. 29, pp. 110-118, 2010.

[18] G. Juneja, B. Dournaee, J. Natoli and S. Birkel, "Service Oriented Architecture Demystified," Intel Press, Intel Corporation, 2007.

[19] J. Hurwitz, *Service Oriented Architecture for Dummies, 2nd Edition.* Indianapolis, IN: Wiley Pub., Inc, 2007.

[20] C. McGregor and J. M. Eklund, "Next generation remote critical care through service-oriented architectures: Challenges and opportunities," *Service Oriented Computing and Applications,* vol. 4, pp. 33-43, 2010.

[21] T. Erl, *Service-Oriented Architecture Concepts, Technology, and Design.* Indianapolis, IN: Prentice Hall Professional Technical Reference, 2005.

[22] S. De Cesare, M. Lycett and R. Macredie , *Development of Component-Based Information Systems.* Armonk, N.Y. : M.E. Sharpe, c2006.

[23] R. Kamaleswaran, C. McGregor and J. Percival, "Service oriented architecture for the integration of clinical and physiological data for real-time event stream processing," in *Engineering in Medicine and Biology Society, Annual International Conference of the IEEE,* 2009, pp. 1667-1670.

[24] O. K. Helder, J. Brug, C. W. N. Looman, J. B. van Goudoever and R. F. Kornelisse, "The impact of an education program on hand hygiene compliance and nosocomial infection incidence in an urban Neonatal Intensive Care Unit: An intervention study with before and after comparison," *Int. J. Nurs. Stud.,* vol. 47, pp. 1245-1252, 2010.

[25] J. R. Moorman, D. E. Lake and M. P. Griffin, "Heart rate characteristics monitoring for neonatal sepsis," *Biomedical Engineering, IEEE Transactions on,* vol. 53, pp. 126-132, 2006.

[26] M. P. Griffin, D. E. Lake, T. M. O'Shea and J. R. Moorman, "Heart rate characteristics and clinical signs in neonatal sepsis," *Pediatr. Res.,* vol. 61, pp. 222-227, 2007.