RMED: A Reconfigurable Architecture for Embedded Medical Monitoring

Homa Alemzadeh, Mushfiq U. Saleheen, Zhanpeng Jin, Zbigniew Kalbarczyk, Ravishankar K. Iyer
Coordinated Science Laboratory
University of Illinois at Urbana-Champaign, Urbana, IL 61801
{alemzad1, msalehe2, zjin10, kalbarcz, rkiyer}@illinois.edu

***Abstract*—In this paper we propose a multi-parameter reconfigurable architecture framework for patient-specific medical monitoring. This architecture is mainly composed of a set of heterogeneous processing engines and flexible communication interfaces, which enable the run-time configuration of the architecture for optimal diagnosis of different diseases. The flexibility of the proposed framework is evaluated by demonstrating two different medical applications for monitoring brain and heart status on an FPGA-based hardware prototype. The evaluated epileptic seizure detection application gains a high detection performance with overall accuracy of 98.52% and sensitivity of 99.47%. For the cardiac ICU monitoring application, the experimental results for detecting abnormality of blood pressure and heart rate in selected patients show a high true positive rate of 94.74%. By applying algorithmic enhancements in the detection scheme, we even achieve early detection of abnormalities in blood pressure in the range of few minutes before standard ICU monitor alarms with a true positive rate of 64%. With a balanced mixture of flexibility, patient-specificity, and detection accuracy at small hardware footprint, the proposed architecture can be an attractive framework for embedded monitoring of a wide variety of medical conditions.**

I. Introduction

Recent technological advancements in miniaturization and integration of sensors, wireless communications, and embedded micro-controllers have enabled the development of intelligent Wearable Health Monitoring Systems (WHMS). Personalized health monitoring devices can be used for early detection of medical conditions and facilitating conventional clinical diagnosis processes. Continuous real-time monitoring of environmental, behavioral, and physiological data can provide in-field diagnostic assessment and alert feedback, either to the patient or directly to the healthcare professionals.

Most of the existing work in this area focuses on the development of wearable biosensors and their integration with personal computing gadgets (such as PDAs and cell phones) for visualization and recording of physiological signals and transmitting the collected data to remote medical servers for in-depth processing. Less attention has been paid to delivering highly dependable real-time diagnosis through lightweight standalone computing devices. Mostly due to performance, area, and energy restrictions, wearable devices are usually equipped with very basic processing capabilities and perform the rather complicated biosignal analysis in an offline manner.

A limitation of existing wearable health monitoring systems is their fixed functionality and lack of functional adaptability. These devices are usually designed for analysis of only a certain type of physiological parameters associated with a specific medical condition, and cannot support multi-parameter analysis techniques for unified clinical reasoning. Multi-parameter medical monitoring [1] can be mostly useful in extreme circumstances and critical environments, such as Intensive Care Units (ICU) [2], battlefields [3][4], and outer space [5], where accurate and complicated diagnostics based on intricate correlated physiological signals analysis is needed. On the other hand, emerging life-critical ubiquitous healthcare applications demand more comprehensive and dependable medical systems. Such systems should automatically adapt to measure specific medical symptoms in response to runtime modifications in system configurations and external circumstances, such as the addition or removal of sensors, mandatory upgrades for fixing bugs, or physical and environmental changes [6][7].

Another important concern in design of wearable medical systems is the battery life. Commercial-off-the-shelf low power microcontrollers (e.g. TI MSP430 [8]) mostly lack the processing capability to support the high degree of computational complexity needed for online and multi-parameter analysis of biomedical signals. On the other hand, although most available DSP solutions (e.g. TI TMS320C54x DSPs[9]) offer both high-performance and power-efficiency, they cannot provide the application-specific customization beyond the DSP domain, demanded for adaptive medical processing.

In this paper, we propose an architecture framework for: (i) performing personalized embedded health monitoring in real-time, (ii) concurrent analysis of various physiological signals for multi-parameter monitoring, and (iii) automatic adaptation to desired diagnostic needs to meet the functionality and performance requirements. By taking advantage of the state-of-the-art sensing and reconfigurable hardware technologies, the resulting architecture, RMED, is prototyped as a single integrated device with the following unique features:

1) *Multi-Parameter Monitoring*: Concurrent capturing and analysis of different physiological signals including EEG, ECG, blood pressure, and heart rate.
2) *Automatic Datapath Reconfiguration*: Integration of an effective set of biomedical signal processing and prognosis techniques into a single datapath that can be automatically configured for monitoring of different medical conditions, such as epileptic seizure detection, and cardiac ICU monitoring.

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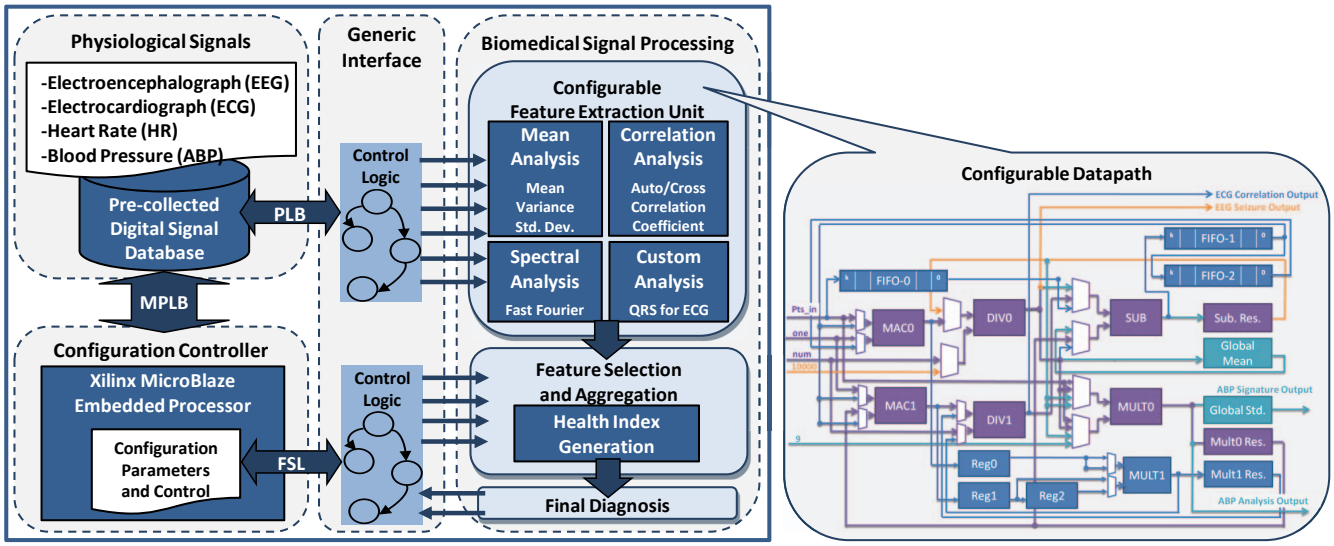

Fig. 1. RMED Architecture Framework with Configurable Datapath prototyped on an FPGA platform

3) *Reusing Computational Basic Blocks*: Identifying a set of heterogeneous computational blocks shared by different processing algorithms and modularizing them as fairly simple basic blocks that can be efficiently reused by a configurable controller to achieve a reasonable tradeoff between performance, hardware cost, and power consumption.

II. Architectural Overview

Our proposed architecture framework for embedded medical monitoring, prototyped on a commercially available FPGA platform, is illustrated in Figure 1. The inputs to the system are different types of vital physiological signals collected by biomedical sensors (e.g. EEG/ECG electrodes, accelerometers, and pulse oximeters). In the initial prototype the input signals are pre-stored as high-precision data in a digital database and are passed into processing engines through a generic interface.

The Configuration Controller is responsible for dynamically capturing the configuration parameters from the user and environment and passing them to the computational units. In the current prototype, the configuration controller is implemented as software running on top of an embedded processor on the FPGA platform. The configuration parameters can be sent at run time to the reconfigurable hardware through the generic interface that is tightly integrated with the processor. These parameters indicate the desired detection scheme, the source and destination of the data to be processed, and different configurations for real-time signal processing. The Generic Interface is implemented as a state machine that controls concurrent data transfer through communication links (FSLs) and processor buses (PLBs) and enables simultaneous computation and analysis of physiological signals.

The main parts of this architecture are biomedical signal processing units, which are responsible for extracting different features from the set of measured signals. In the initial prototype, the Feature Extraction Unit is designed by statically identifying a common set of signal processing techniques shared by different biomedical processing schemes, such as Mean Analysis, Spectral Analysis, Correlation Analysis, as well as custom analysis techniques, such as QRS and heart beat detection for heart activity investigation. These heterogeneous processing blocks are modularized as hardware basic blocks that can be reused in a reconfigurable datapath, shown in the right part of Figure 1.

The reconfigurability of feature extraction units allows real-time selection of a suitable set of analysis and computation techniques and their dynamic reconfiguration to perform specific medical diagnostic tasks. Examples demonstrated by previous works include: (i) a combination of the spectral and correlation analysis blocks can be used to compute a coherence metric in detecting cognitive decline [10], (ii) a seizure detection scheme can be implemented by performing local variance computation using the mean analysis block [11], and (iii) as part of ECG analysis, combining QRS and correlation analysis blocks can detect irregularity in heart beats [12]. This flexibility in feature selection is provided by the Feature Selection and Aggregation block.

To reduce the rate of false positives and provide a higher accuracy, our real-time monitoring system supports a patient-specific detection scheme instead of using generic population-based techniques. In this approach, for a period of time (learning phase) the normal bounds of the physiological signals of the patient are extracted and aggregated to build a signature of the normal characteristics of an individual. This patient-specific signature, called "Health Index", is used later during the online active monitoring phase for diagnosis of abnormalities. The feature selection and aggregation unit computes the unified health index by selecting appropriate features based on the target detection scheme and aggregating them with appropriate weights.

The Final Diagnosis stage is where the online active monitoring and diagnosis happens. The real-time extracted features

are classified into normal and abnormal categories based on continuous checking of features against the precomputed health index and estimating the stability of the patient's status over time and understanding how they deviate from patient's normal bounds. The final diagnosis results are provided either as new parameters to the configuration controller for further processing or as medical reports for professional review.

In the current prototype of the architecture, we focus only on the configurable feature extraction unit and present example detection schemes that do not use feature aggregation and health index generation.

III. Application Scenarios

This section presents the algorithmic background for two example applications that are evaluated using our framework for real-time monitoring of brain and heart status.

A. Epileptic Seizure Detection

The various automatic seizure detection techniques reported in the literature use different kinds of computation-intensive statistical techniques. For EEG-based epileptic seizure detection, we use a technique based on variance analysis presented in [11]. In this work, the sample entropy and variance-based feature extraction techniques are evaluated in terms of accuracy and hardware implementation overhead. The results show that local variance analysis gains a high level of accuracy (99.2%) compared to other techniques and does not impose large amount of complexity and hardware overhead.

The detection performance of the seizure detection scheme in terms of sensitivity, specificity, and overall accuracy is reported for 80 data sets of seizure and non-seizure EEG data. The results show that using a variance-based feature extraction technique accompanied with a basic threshold-based classifier provides a high rate of sensitivity (99.47%) and overall accuracy (98.52%) in detection [11].

B. Cardiac ICU Monitoring

We choose a cardiac ICU (Intensive Care Unit) set-up as an example scenario for demonstrating the applicability of multi-parameter patient-specific abnormality detection schemes.

The cardiac ICU computation flow is based on a mean analysis technique and starts by generating the normal signature of the patient being monitored. For a given period of alarm-free observations, called "global window", the normal signature for a specific signal is obtained by computing the mean (μ_g) and standard deviation (σ_g) values of the collected sample data over that observation period. In the active monitoring stage for much smaller sized non-overlapping time windows, referred as "local windows", the local mean (μ_l) of the newly collected data is computed to suppress local variability in the data. Finally, the absolute difference (error) of the local mean and the global mean ($\delta = |\mu_l - \mu_g|$) is computed and compared against the global standard deviation. Any absolute error more than 3 times the global standard deviation is classified as an indication of an abnormal observation. This is based on the observation that blood pressure (ABP) and heart rate (HR) signals are approximately normally distributed [2] and therefore almost all their data samples (99.7%) should reside within the $\pm 3\sigma$ range of the μ.

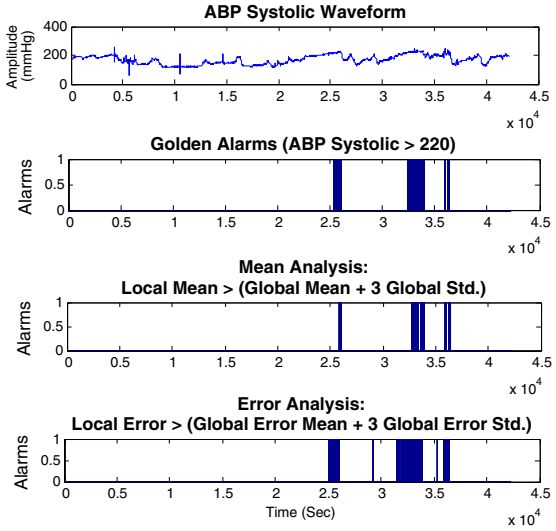

Fig. 2. Abnormality Detection and Comparison for ABP Data - Mean Analysis and Error Analysis

To verify the algorithm outlined above, a multi-parameter ICU database, called MIMIC from PhysioNet [13], is used. Figure 2 shows the results of applying the above algorithm on the arterial blood pressure (ABP) systolic data stream of patient #211 in the database. The results are shown for an observation period of about 9 hours (32188 sec) where the first 4.2 hours (15000 sec) are used to generate the normal signature and the rest of the time is actively monitored with a local window size of 1 sec. As shown in the figure, the number of alarm events generated when the ABP crosses 3σ are comparable to the number of annotated golden alarm events obtained directly from the database. This is similar to the case when the algorithm is applied on the HR data stream of patient #230 with a global window size of 15000 sec. The results of ABP and HR data confirm the applicability of our algorithm for cardiac ICU monitoring.

We have also investigated an enhanced version of the above algorithm based on an error estimation technique. The extended algorithm is outlined as follows:

1) In the learning phase, for the global window g, we compute the mean of the samples (μ_g), errors ($\delta_g = |g - \mu_g|$), mean of errors (μ_{δ_g}), and standard deviation of the errors (σ_{δ_g}).
2) In the online active monitoring phase, we take a small (e.g., 1 sec) local window l, and compute the mean (μ_l) and error ($\delta_l = |\mu_l - \mu_g|$) for that local window.
3) Finally, an anomaly will be marked for a local window duration if $\delta_l > (\mu_{\delta_g} + 3 \times \sigma_{\delta_g})$. (This is based on the assumption that the δ values are normally distributed.)

This enhancement in the algorithm enables early detection of abnormalities in blood pressure within a few minutes before

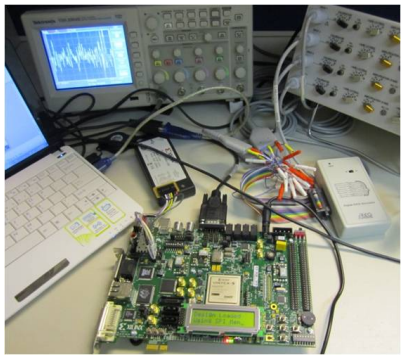

Fig. 3. RMED Prototype on Xilinx Virtex-5 FPGA Platform

"golden" ICU monitor alarms in selected patients, as shown in Figure 2 for patient #211. Using an initial global window (g) of 25000 seconds, the error estimation method detects the first alarm event at time 25036 seconds, where the monitor detects it at time 25429 seconds, indicating an early detection of 6.5 minutes. Considering alarms in close proximity clustered as single alarm events, similar predictive outcomes are observed for the remaining alarm events for this patient. However, compared with the mean analysis method, the error analysis algorithm suffers from a relatively higher number of false positives. In order to reduce false alarms and reflect the significant changes in global trend over longer periods of time, we are working on a modified version of global window that will be a sliding window instead of a fixed one.

The performance of the cardiac ICU monitoring scheme using mean analysis and error analysis techniques is evaluated for 4 different patients — 2 with ABP and 2 with HR abnormalities — over an average observation period of about 12 hours. Using the mean analysis method, out of the total 19 cases of abnormal events annotated for that period, 18 events were correctly classified as abnormal, indicating a true positive rate of 94.74%. For the error analysis algorithm, the average early detection time length (*time of golden alarm - time of computed alarm*) was 4.03 minutes. Out of the 25 alarm events observed among these patients, 16 were correctly detected as abnormal, indicating a true positive rate of 64%.

IV. Experimental Evaluations

This section presents the experimental results for implementing the seizure detection and cardiac monitoring schemes using RMED architecture, prototyped based on a Xilinx Virtex-5 XC5VFX70T FPGA (Figure 3).

Table I reports the module-level hardware cost and power consumption of the developed RMED prototype, excluding memory overheads. Our prototype introduces very little hardware overhead by utilizing only around 17% of FPGA logic cells (from which 25.05% is for interface and reconfigurable detection modules) and there is still a large space available on the FPGA for incorporating more functionalities. The interface and detection modules consume only around 0.73 mW of dynamic power while the the majority of power (99.48%) is consumed by Microblaze control and communication parts.

TABLE I
Prototype Hardware Footprint and Power Consumption

Resource Type	Reconfigurable Modules	Generic Interface	MicroBlaze Ctrl/Comm.
Slices	366 (16.98%)	174 (8.07%)	1378 (63.94%)
Slice Reg	665 (21.19%)	371 (11.8%)	1607 (51.22%)
LUTs	1026 (28.19%)	354 (9.72%)	1735 (47.67%)
Power (mW)	0.67 (0.47%)	0.06 (0.04%)	140.52 (99.48%)

V. Conclusions

This paper presents a reconfigurable architecture framework – RMED – for embedded analysis of multiple physiological sensor streams in different medical monitoring scenarios. The proposed architecture is based on integration of a common set of biomedical signal processing techniques. These techniques are implemented as a reconfigurable datapath that can be efficiently customized by the user through a dedicated interface. An FPGA-based hardware prototype is developed and then verified using two example application scenarios, epileptic seizure detection and cardiac ICU monitoring. In conclusion, the reconfigurable architecture presented here provides a promising tradeoff between flexibility (configurability), performance (high detection accuracy), and cost (low hardware overheads) for embedded medical monitoring and can be scaled to support a wider range of application scenarios.

VI. Acknowledgment

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