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On behalf of the e-Health Technical Committee (TC) of the IEEE Communications Society (ComSoc), we wish all our members a very instructive reading of this letter.

The contribution from this edition is coming from Qatar and report on some ongoing activities of Embedded Multicore Systems for Mixed-Critical Internet of Things based Applications.

Members of the e-Health community are invited to contact the author for further information or collaborations.

We also welcome all our members to share their research activities and field experiences through this open newsletter and to open up new opportunities for discussions and collaborations.

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Table of Contents

EMBEDDED MULTICORE SYSTEMS FOR MIXED-CRITICAL INTERNET OF THINGS BASED APPLICATIONS

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I. INTRODUCTION

Internet of Things (IoT) based systems are expected to revolutionize the healthcare domain. The prevalence of continuous health monitoring wearables, and, fast and low-power wireless communication have motivated a shift to connected health models. Connected health is an umbrella term that encompasses a combination of different technologies that enable real-time exchange of health information. In particular, there has been a growing interest in continuous real-time monitoring of chronically ill patients outside the clinical setting. The potential benefits of such systems are enormous, ranging from improving the quality of life of patients and increasing their independence, to reducing unnecessary hospital admission costs [1]. At the same time, allowing healthcare professional to keep an eye on their patients and detect any problematic event.

However, the mixed-criticality nature of remote health exacerbates the weaknesses of IoT based systems. Typically, data from low-power wireless-enabled sensor nodes is collected by a nearby IoT edge-device (hub or gateway) [2]. The gateway routes the data to a cloud, where automatic analysis is performed [2]. Then, useful information is extracted, stored, and visualized for the end user (e.g., physicians or nurses). Some disadvantages of this framework are the high energy consumption due to raw data streaming, big data issues, latency related to cloud computing, and user-privacy [3], [4]. In healthcare systems, where real-time, reliable, secure, and safe core functionalities are of utmost importance; the typical IoT paradigm falls short.

Conventionally, the IoT edge-device is looked at as a simple router between the sensor and the cloud. However, state of the art multicore and heterogeneous platforms offer high, energy-efficient, low-area, and cost-effective computing power [5]. Only recently, such architectures are considered as the potential gateway for critical applications, such as healthcare. They can be used to reconstruct compressed signals in real-time, classify the data locally, encrypt summarized status reports, and deliver them locally to the patient, and remotely to healthcare centers. Additionally, local analytics empower the system in terms of robustness when handling medical anomalies and technical faults. For example, if an Internet connection fault occurs, the system will still be able to deliver diagnostics to the patient, or, sound a local alarm in the patient's household.

In our project, the objective is to put forth a framework that facilitates quick implementation and validation of modular and reconfigurable connected health systems and environments. In addition to providing solutions to challenges of reliability, security, and real-time signal acquisition and processing using embedded multicore platforms. We (i) describe connected healthcare in a general, formal, and model-driven methodology using a standardized modeling language; (ii) develop and optimize compressive sensing, signal classification, pattern-recognition, data-fusion, and encryption techniques in multicore embedded systems; (iii) simulate remote health-scenarios and investigate their real-time power-consumption tradeoffs, classification accuracy, and tolerance to faults; and (iv) create validation tools to ensure the system meets the requirements set-forth by the model.

Using a systematic, model and embedded systems oriented approach, aids in the reduction of system design cost and the effort and time required for re-validation after making changes. Additionally, it introduces a design workflow to fight the ever-increasing technical complexity of IoT systems.

Deploying countries on CEF eHealth digital service infrastructures (eHDSI) are in alphabetical order: Austria, Croatia, Cyprus, Czech Republic, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Luxemburg, Malta, Portugal, Sweden and Switzerland.

In what follows, we provide more details with respect to the scenarios of usage in Section II, the Cyprus' national architecture in Section III, and the validation schemas in Section IV. Section V provides the concluding remarks

II. CASE STUDIES

A. Remote Elderly Monitoring System

The remote elderly monitoring system (REMS) focuses on continuous real-time monitoring and diagnosis of the sensitive demographic of critically and chronically ill seniors. The aim is to enable healthcare providers to monitor the health status of their patients without frequent hospital visits. Such service provides independence for patients and quality of life improvement, instead of frequent hospital visits or nursing homes.

REMS consists of three subsystems as illustrated in Fig 1. In the Home subsystem various physiological sign monitoringsensors contentiously transmit data to a gateway. In this implementation, Shimmer wearable sensors are used. Shimmer devices can measure electromyography (EMG), electrocardiography (ECG), respiration, weight, acceleration, torque, and many more physical and physiological signs. They feature Bluetooth low-energy (BLE4) and are equipped with a TI MSP430 microcontroller running tinyOS. The component-based programming language, nesC, can be used within the tinyOS operating system to implement on-node processing algorithms. As for the gateway, the Xilinx Zynq system-on-chip (SoC) platform and the Odroid XU4 are used. The Zynq features a dual core arm processor in conjunction with a field-programmable gate array (FPGA) fabric, and the XU4 is based on the Samsung Exynos 5422 octa-core big.LITTLE processor. These devices open new possibilities for co-and-parallel processing, reducing power and improving efficiency in computationally intensive applications such as security (encryption, compression), data interpretation, classification, and fusion. The reconfigurability of both the sensor and the gateway layers enables the system to fight dynamically

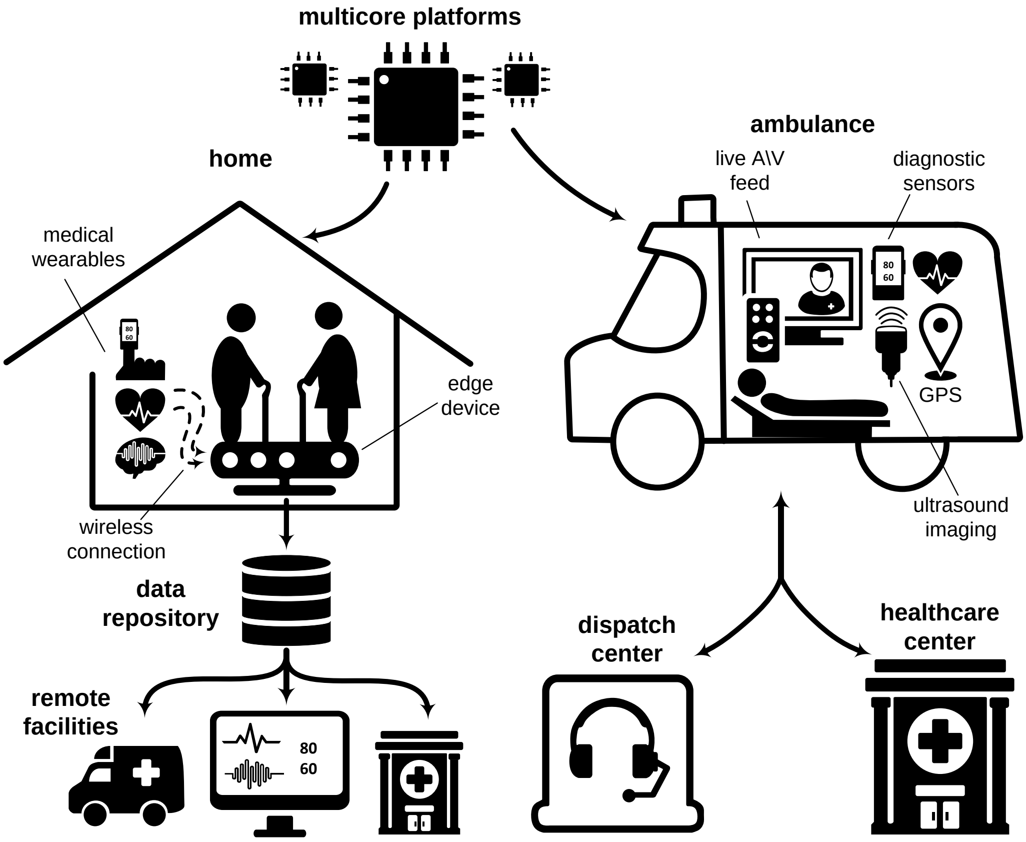

Fig 1. Overview of the remote elderly monitoring system (left) and smart ambulance service (right)

changing environments and allow many scenarios to be tested, optimized for a particular requirement (e.g., real-time analysis, power-consumption), and validated.

The REMS data repository is a combination of a cloud-based service and a medical database. Data reports sent by the gateway are stored, and additional analysis is performed. Using medical records and present data, cloud-based analytics can recognize patterns and give healthcare professional a comprehensive overall look at the patients' history and their current status, further personalizing health delivery. Finally, relevant information is visualized, and analytics or emergency alarms are delivered to stakeholders (patient, physicians, pharmacist, ambulance dispatch, etc.).

We dived the mixed-criticality nature of remote health motioning systems into three sub-categories as depicted in Fig 2. Safety-critical indicate requirements, which if not met, may jeopardize the patient or cause serious injury. Mission-critical indicates essential factors for reliable business operation, failure or disruption might result in a negative impact upon the organization, such as the loss of credibility. All criticalities that do not fall under the aforementioned categories are classified as non-critical. Identifying the type and impact of criticalities is the first step in our model-driven approach. Next, we will model REMS subsystems as subsystems and explore the responsibility of each sub-subsystem component in meeting the set criticalities in the context of their function and real-world performance metrics. Then, validation tools will be developed to benchmark the system's performance against the model's requirements, and locate the components where deficiencies occur. Hence, deriving our research and implementation efforts systematically.

In the past year, we investigated compression and machine learning algorithms in pursuit for better reconstruction quality, classification accuracy, and power efficiency. The subspace pursuit (SP) reconstruction algorithm was applied to feature Bluetooth low-energy (BLE4) and are equipped with a TI MSP430

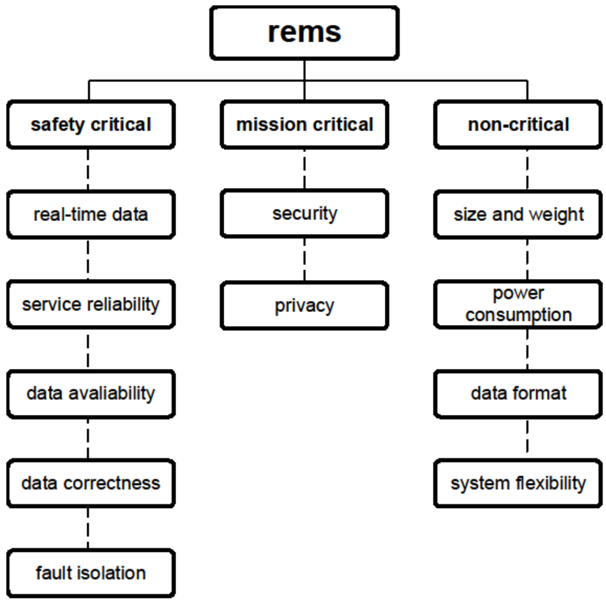

Fig 2. REMS criticalities overview

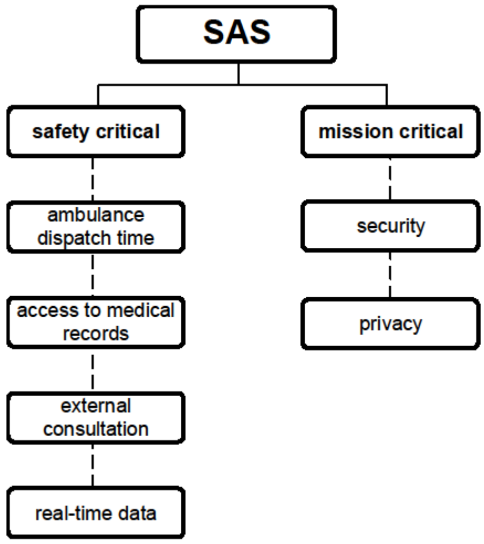

Fig 3. SAS criticalities overview

microcontroller running tinyOS. The component-based programming language, nesC, can be used within the tinyOS acceleration, ECG, and EEG signals. Acceleration and ECG signals were retrieved with sufficient information to permit classification. Physical falls were detected with 91.7% accuracy using the extended nearest neighbor (ENN) with a signal compression factor of 0.35. And, heart arrhythmia was recognized with an accuracy of 99.3% using both K-nearest neighbor (KNN) and EEN with a signal compression factor of 0.25. Efforts relating to EEG signals were focused on improving the reconstruction quality. First, the joint sparsity of EEG signals was exploited, and we found that measuring four or eight EEG channels simultaneously leads to an improvement in reconstruction quality. Second, a signal dependent sparsifying bases and signal structure dependent sparsity estimation were developed; leading to a better signal quality and energy compaction.

B. Smart Ambulance System

The smart ambulance system (SAS) aims to improve ambulances dispatching and patient localization speed. Also, it capitalizes on the inherit en-route time by delivering patient diagnostics from the ambulance to emergency clinicians. The SAS ambulance houses a similar technology to the Home subsystem from the previous section. However, in addition to diagnostic sensor, the ambulance has imaging and therapeutic equipment such as ultrasound machines, a general positioning system (GPS) to keep concerned individuals up to date with its location, and is equipped with video/audio (AV) capabilities for the emergency medical technician (EMTs) to consult with clinical experts.

Instead of going through a data repository, the ambulance directly communicates with the remote facility where the data is displayed and recorded for physicians to assist and give instructions, pre-diagnose, and prepare the emergency room adequately. The ambulance dispatch center tracks the locations of all ambulances, receives emergency calls and reports, and dispatch ambulances with the fastest expected arrival time.

The attended workflow for SAS is as follows:

i. The subject calls the ambulance service and provide information about the incident.
ii. The ambulance dispatch center operator locates the subject and the closest ambulance and dispatches it.
iii. The operator finds the nearest hospital to the subject and connects the ambulance's SAS to the hospital's SAS.
iv. The ambulance arrives at the incident location and collects information about the criticality of the patient, provides the hospital with diagnostic

measures while en-route, and takes instructions and preparation steps from physicians over a live AV feed, if necessary.

v. The hospital keeps track of the ambulance location and makes early diagnostics and preparations.

Figure 3 illustrates SAS criticalities. Ambulance dispatch time, real-time monitoring, access to records, and external consultation are identified as safety-critical. Because, the time-of-arrival to the incident location, data validity, and the ability for EMTs to get assistant from experts are all detrimental to the patient's welfare. Meanwhile, a secure and private telecommunication between the ambulance and healthcare facility is mission-critical as the organization's credibility relies on accommodating the stringent privacy regulations on sensitive patient data and medical records.

III. CONCLUSION

Connected health models, especially continuous remote health monitoring, face many bottlenecks when considering the common IoT system framework. Meanwhile, multicore heterogeneous architectures can offer competent edge devices capable of retrieving and analyzing signals in real-time. In the implementation of REMS and SAS, the focus is placed on exploiting such platforms to address limitations within the IoT paradigm. They are used to reconstruct compressed signals, detect anomalies, and implement security and robustness measures. Additionally, a modular-model-drive design approach is followed; potentially reducing implementation cost and revalidation and recertification efforts, and providing a tool-kit to fight system complexity.

ACKNOWLEDGMENT

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Call for Papers

The IEEE Conference on Biomedical and Health Informatics (BHI) 2018 and the IEEE Conference on Body Sensor Networks (BSN) 2018, two premier flagship venues in the area of mHealth, health analytics and wearable computers, will be co-located this year along with the Health Information Management Systems Society Annual Conference (HIMSS) 2018. Our joint event will take place in Las Vegas, Nevada, USA, 4-7 March 2018.

The joint organization will provide a unique forum to showcase novel sensors, systems, signal processing, analytics and data management services. The presentations will offer the latest findings of researchers on efficient and innovative signal acquisition, transmission, processing, monitoring, storage, retrieval, analysis, visualization and interpretation of multi-modal signals including physiological, biomedical, biological, social, behavioral, environmental, and geographical data.

The joint program will feature world-renowned keynote speakers from academic research institutions, government agencies and industry, with seminars outlining the future direction for research in the area of biomedical and health informatics and body sensor networks.

Authors are invited to submit full papers (4 pages) and short abstracts (1 page) presenting innovative research as outlined under the topics of interest for each conference.

Special sessions and workshops offering focused presentations on cutting edge research topics will be organized by experts in the field.

Awards for the best paper and poster will be presented at the conference. Authors of a set of papers and presentations, selected by the peers, will invited to submit an extended version of the paper to a special issue of the IEEE Journal of Biomedical and Health Informatics, the flagship engineering journal in this area

BHI-BSN Important Dates

Full Papers
Submission Due - Nov 6, 2017
Decision Notification - Dec 10, 2017
Final Paper Submission - Jan 15, 2018

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We are looking forward to seeing you in Las Vegas!

Conference Website: https://bhi-bsn.embs.org/2018/#