Baby-Guard: An IoT-based Neonatal Monitoring System Integrated with Smart Textiles

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***Abstract*—A rising number of preterm babies demands innovative solutions to monitor them in the Neonatal Intensive Care Unit (NICU) continuously. NICU monitors various kinds of vital signs. Among them, there is a strong demand for an accurate and sophisticated technology to monitor respiration rate (RR) and detect critical events such as apnea. Existing solutions for RR monitoring either rely on the indirect measurements from thoracic impedance or other invasive techniques posing discomfort and risk of infections to babies. Also, multiple wire loops lying around babies hinder the delivery of parental and clinical care. Motivated by this need, we have designed an Internet-of-Things (IoT) based smart textile chest belt called "Baby-Guard" to monitor RR and detect apnea. The Baby-Guard is a neonatal wearable system consisting of a sensor belt, a wearable embedded system, and an edge computing device. The sensor belt consists of textile-based pressure sensors and an Inertial Measurement Unit (IMU). The wearable system consists of a microcontroller equipped with wireless connectivity and power management. The edge computing device (ECD) connects with the wearable system through an MQTT networking architecture. ECD hosts signal processing and computing services to extract RR and detect apnea. We conducted simulation experiments using a high-fidelity, programmable NICU baby mannequin. We found an average error of 0.89 BrPM in breathing rate and ~97 percent accuracy in apnea detection. Computation and communication latencies were found to be ~66 and 22 ms, respectively. The Baby-Guard showed potential to be a wireless infant monitoring system in the NICU settings.**

***Index Terms*—Internet of Things, IoT, NICU, Neonatal Care, Health Monitoring, Respiration Monitoring, Smart Textiles**

I. INTRODUCTION

According to the World Health Organization (WHO), annually ~15 million babies are born premature (i.e. before 37 completed weeks of gestation) across the globe [1]. One million preterm babies die before the age of 5 years due to preterm birth and related complications [2]. Preterm babies need continuous monitoring and special care in the Neonatal Intensive Care Unit (NICU) that is a specialized hospital environment that provides monitoring of vital signs such as heart rate (HR), respiration rate (RR), blood oxygen saturation (SpO_2), and other medical parameters of premature babies and babies born with significant health problems [3]. For the medical monitoring, NICUs use conventional sticky electrodes that suffer from challenges such as skin injuries due to adhesives, hassle with long wires, and false alarms due to loosely connected electrodes or drying contacts. Especially, RR monitoring is a big challenge because existing solutions either rely on the indirect measurements of thoracic impedance or other invasive techniques posing discomfort and the risk of infections to babies [4].

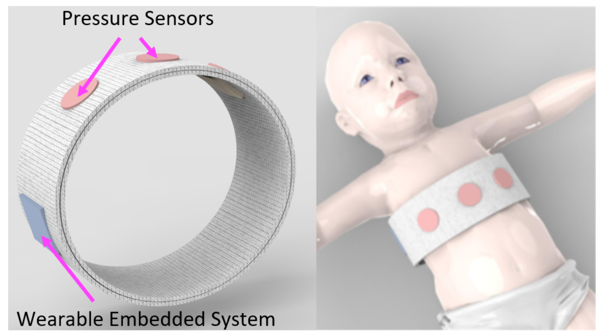

Fig. 1. A Conceptual Diagram of the Baby-Guard

Recent advancements in technologies such as e-textile and Internet of Things can be employed as a solution for the challenges of respiratory monitoring in NICU. To address these challenges, a textile monitoring platform integrated with an IoT-based edge computing architecture called Baby-Guard (providing sensing and computing services) is presented in this paper. Fig. 1 shows a neonatal chest belt made of comfortable smart textiles integrated with textile pressure sensors that are specially designed to detect subtle movements such as expansion and contraction of the chest in preterm babies.

The overall architecture of the Baby-Guard system (shown Fig. 2) consists of two subsystems: 1) a wearable embedded system (designed to acquire and communicate the sensor time-series data from the chest belt) and 2) an edge computing device (designed to receive the time-series data, perform signal processing services, and visualize RR parameters and alarms onto a touchscreen monitor).

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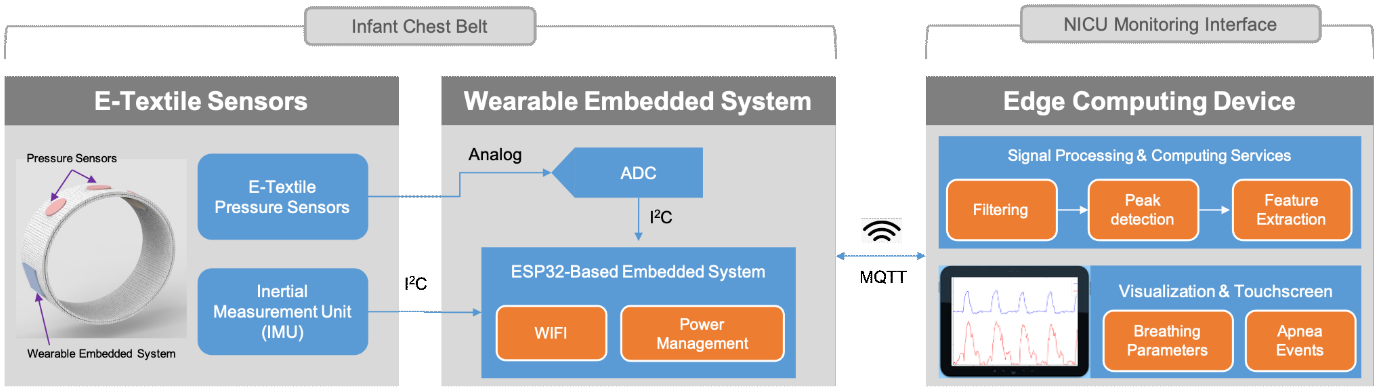

Fig. 2. An overview of the proposed smart textile sensor system for NICU

This paper makes the following scientific contributions:

- Based on the literature survey, Baby-Guard is the first kind of NICU technology that is built upon smart textiles connected with IoT-based edge computing services;
- We designed a textile pressure sensor pad using an industrial embroidery machine. The embroidery design provided more accuracy and reliability to the respiration monitoring by increasing the sensitivity and repeatability of the sensors;
- The location for the pressure sensors was carefully identified on the chest belt such that the subtle chest movements can be captured continuously. This is critical for detecting apnea episodes;
- A local MQTT networking framework was designed and deployed on the edge computing device for real-time data communication;
- Signal processing and computing services such as peak detection, RR calculations, and the detection of apnea episodes were designed and deployed on the edge computing device to offer monitoring and alarm services in NICUs;
- We investigated the performance of the Baby-Guard on a high fidelity NICU training baby mannequin with different breathing rates to evaluate the performance of sensors, computing services, and overall IoT system.

II. Background and State-of-Art

A. Neonatal Intensive Care Unit (NICU)

The NICU admits premature babies who are born before 37 weeks gestation age, mature babies born with birth weight less than 5.5 pounds, and/or full term babies who have serious medical conditions such as breathing difficulties, heart problems, or birth defects [3]. Monitoring physiological signals in NICU is cumbersome and involves handling wires and sticky electrodes. One of the major challenges in NICU medical monitoring is to accurately monitor respiration rate. Particularly, there is no reliable method to detect respiratory rate of preterm babies in NICU. The conventional airflow sensors used for RR monitoring are not well tolerated by preterm babies because this technology is invasive [5]. For this reason, the RR is often monitored indirectly from thoracic impedance measurement. However, such indirect methods are prone to artifact and thus, not clinically accurate [6]. Further, studies have shown that the prevalence of neonatal skin injuries is as high as 43 percent in the NICU [7], [8]. Measurement of thoracic impedance requires sticky adhesive-based electrodes to be placed on the skin of the preterm babies. These sticky electrodes can be harmful to underdeveloped skin of the preterm babies as they can cause skin breakdown, irritation, and stripping [9]. Another disadvantage is that these electrodes are significantly vulnerable to motion artifacts. Baby's cry, holding or moving the baby or other routines of NICU nurses and families can cause artifacts and false alarms [10].

Further, NICU is often filled with long monitoring wires around the babies that creates physical and psychological barriers for nurses and parents to access babies [11], [12]. Such barriers can significantly hinder timely delivery of parental and clinical care. In addition, when the nurses and/or families hold the baby, the movement of wires (that connect the electrodes to the bedside monitors) degrade signal quality and cause lack of accuracy in the output. The long wires makes it harder for nurses to perform routine tasks on babies in NICUs, including changing the diaper or clothes, feeding, and cleaning. For these reasons, there is a need to develop a system that can wirelessly monitor the physiological signals of babies and offer soft, wire-free sensor interfaces that does not hinder the routine operations in the NICU.

B. Internet of Things and Smart Textiles for NICU

Recent advancements in technology can be used to address the challenges of medical monitoring in the NICU. Particularly, IoT-based infrastructure can be deployed in the NICU environment to reduce the number of wires lying around the babies that can lead to improved parental and clinical care delivery. E-textiles can be used in conjunction with the IoT infrastructure to offer a soft and comfortable way to develop medical wearables. The e-textile components can be integrated within different medical wearables related to surgery (e.g. bandages), hygiene (e.g. medical uniforms), drug-release systems (e.g. smart bandages), biomonitoring (e.g. ECG, EEG, EMG, thermal), and therapy/wellness (e.g. electrical stimulation, physiotherapy) [13].

Researchers have also explored smart textile for monitoring the new born babies. Hariyanti et al. designed a wearable fiber optic respiration sensor using optical fiber and integrated it into an elastic material [14]. The sensor was placed on the baby's diaper and the changes in the intensity of light received by the photodiode was monitored to extract the respiration rate. The system was tested on a ventilator machine and performanced with an error of 0.25. Raj et. al developed a RR monitoring system using a 3-axis accelerometer placed on baby's body [15]. The system was compared with direct observation and had a correlation coefficient of 0.974 between measured and observed values of RR.

Researchers have also explored IoT-based infrastructure for monitoring the babies. For example, Jabbar et al. developed an IoT-based baby cradle integrated with sound, temperature, humidity sensors along with auto-swinging support, web camera and musical toy [16]. Data from these sensors was monitored and based on that actions were taken to swing the cradle along with adjusting the cradle temperature and humidity. Researchers have also explored IoT based infrastructure to predict the status of the babies. Fahmi et al. developed an IoT-based smart incubator system for NICU monitoring involving a microphone based system [17]. They trained the algorithm with forty pre-recorded baby voices which were successfully classified into five categories: burping, hungry, sleepy, pain, and uncomfortable to make the system listen to the baby. Researchers have also tried to extend IoT-based services to cloud-based data management and data processing. As an example, Singh et al. developed a system which integrates a Beaglebone and Intel Edison based IoT system with NICU biomedical devices aimed towards cloud-based data management and data analytics [18]. Their system included machine-data integration (MDI), clinical interface for NICU and data analytics engine. Also, Bastwadkar et al. designed a cloud-based big data Health Analytics as a Service (HAaaS) framework to analyze the NICU data in the cloud [19]. They aimed to ease the load of data acquisition on low resource setting NICUs by decoupling the data collection, data acquisition and data transmission components from the software-as-a-service part. The transmitted data was analyzed in Artemis cloud and the results were sent back to the healthcare organization providing HAaaS. Researchers have also used such cloud services designed for patient monitoring to aid the clinical decision making. Ahouandjinou et al. offered a hybrid, intelligent and ubiquitous patient monitoring system called Automatic Detection of Risk Situations and Alert (ADSA) to overcome false alarms and lack of visualization [20]. Their system included several layers to provide support services to healthcare providers aiding clinical decision-making.

In general, most of the existing literature offering IoT-based architectures for NICU monitoring is aimed to utilize machine learning and artificial intelligence based methods to enhance the neonatal monitoring capabilities. Those who used e-textile for baby monitoring, did not integrate such systems with the IoT infrastructure. Many other studies monitored baby voices, temperature, moisture using IoT. However, none of them focused on monitoring vital physiological parameters such as respiration rate while taking advantage of IoT infrastructure. Also, the existing literature added more physical elements (sensors) to the NICU environment and did not focus on reducing the wire complexity in the existing NICU setup. Motivated by this challenges, in our research, we focused on combining smart e-textiles and IoT technologies to offer a novel approach for adhesive-free, wireless, and wearable respiration monitoring technology which can be a promising solution for physiology monitoring in clinical settings such as NICU.

III. Materials and Methods

The Baby-Guard consists of an e-textile pressure sensor pad integrated in a chest belt, a wearable embedded system, and an edge computing device housing signal processing algorithms. The E-textile chest belt is designed to detect chest expansion and contractions during the respiration cycle. The wearable embedded system acquires data from the sensors mounted on the the chest belt and transmits this data wirelessly to the edge computing device that processes the data through a signal processing services and visualizes the resulting parameters.

A. E-Textile Chest Belt for Respiration Monitoring

The e-textile chest belt consisted of a textile base material and Velostat material as sensing element. The Velostat material is a non-woven sheet of polymeric material composed of polyolefins impregnated with carbon black to make it electrically conductive with piezoresistive property [21]. The Velostat material was sandwiched between two layers of textiles. We chose soft-denim material as the textile base. The Velostat material was integrated with the denim fabric using an industrial embroidery machine (ZSK JGVA 0109, ZSK Stickmaschinen GmbH). We used silver-plated conductive threads to integrate Velostat material with base fabric. The signal carrying conductive tracks were also created on the denim fabric using the conductive threads. We used snap-connectors to connect the wearable embedded system with the textile-based sensors. We also integrated an IMU sensor (SEN-13944, SparkFun Electronics) in the chest belt to monitor the chest movement through IMU data as a secondary measure. Also, the IMU data can be useful to identify and remove motion artifacts from the pressure sensor data. However, in the present work, we could not include IMU data in our analysis due to time limitation.

B. Wearable Embedded System (WES)

The WES comprised a microcontroller unit with wireless communication capabilities, an analog-to-digital converter (ADC), and a signal conditioning circuit (Fig. 3). In our application, we chose an ESP32-based microcontroller (Sparkfun Thing Plus, Sparkfun Electronics) to design the wearable embedded system. The board came with in-built WiFi communication capabilities for wireless data transmission. The

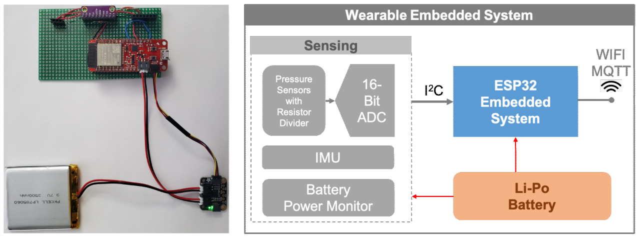

Fig. 3. Wearable Embedded System

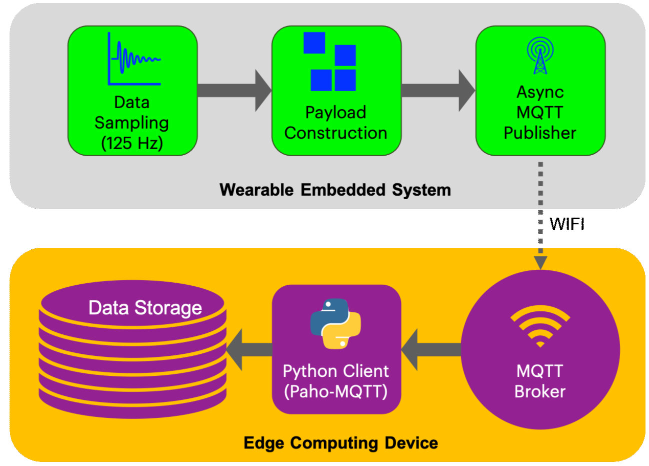

Fig. 4. MQTT Communication Architecture

pressure sensors were integrated with the WES using a 16-bit ADC (ADS1115, Adafruit). Since piezoresistive pressure sensors change their resistance as the pressure is applied, we used a resistor divider circuit as an interface between pressure sensors and the ADC to scale the analog signals. We also interfaced the IMU sensor with WES through I^{2}C communication protocol.

The ESP32 board is programmed using Visual Studio Code - Platform IO software. The program allows us to sample the IMU and pressure sensor data at 125 Hz. The maximum respiration rate for the babies can be 60 breaths per minute (BrPM), so a sufficient sampling frequency must be 120+ Hz. We chose 125 Hz as sampling frequency for respiration monitoring. In the presented research, IMU signals were not used. However, we plan to use IMU data to detect and remove motion artifacts and enhance signal quality.

C. MQTT data communication

Message Queuing Telemetry Transport (MQTT) is a subscribe-publish messaging protocol that is commonly used in IoT applications. The lightweight nature and minimal memory usage enables MQTT clients to be utilized in resource-constrained settings such as wearables [22]. Since the MQTT protocol requires payload to be sent as an unicode character array, the pressure sensor data and IMU data was converted into a CSV formatted character array [23]. We chose Async-MQTT client library due to its non-blocking MQTT publish method which allows the ESP32-based WES to send sensor payloads over WiFi at 125Hz [24]. The payloads were received by the edge computing device which runs a Mosquitto MQTT broker service [25]. As shown in Fig. 4, the Raspberry Pi hosted the MQTT broker and collected data from MQTT client which was running on the WES.

D. Edge Computing Device

The edge computing device (ECD) was a Raspberry Pi based portable computing system running on an quad core ARM processor. The ECD is equipped with built-in wireless communication capabilities. Particularly, we used the MQTT connection shown in Fig. 4 to link the ECD with the WES. A client python script uses the Paho-MQTT library to receive incoming payloads in the base topic to which WES device publishes [26]. CSV payloads are decoded to UTF-8 and appended to a python list object which is then stored as a CSV file every two seconds. A portable 7" LCD screen (Fig. 5) with SmartiPi Touch 2 Case was used as a tabletop monitor to display the data graphs, breathing rates and critical events. The signal processing computing services included filtering, and feature extraction as discussed below.

- Filtering: The raw data acquired from the chest belt includes high frequency noise. We used a moving average filter to remove the noise from the signal. The moving average filter was delay adjusted with window size of 15 samples for different breathing rate detection and 200 samples for critical event detection.
- Feature Extraction - Extraction of Instantaneous RR: The breathing process generated peaks in the data as shown in Fig. 7. The feature extraction included a peak detection from the pressure data. We employed an adaptive peak detection algorithm to detect these peaks in the pressure data using windowing. Subsequently, we computed the time difference between two successive peaks to compute the instantaneous respiration rate.
- Detection of Apnea Episode: The apnea detection was based on the instantaneous respiration rates. After the instantenous RR was calculated, a threshold was set. The RR signal which are below the threshold were detected and labeled as apnea by the algorithm.

IV. Experimental Setup and Procedure

Our aim was to design a respiration monitoring system that can monitor the respiration of premature babies kept in the NICU and detect critical episodes such as apnea in these babies. To evaluate the performance of such a system, we designed a physical simulation experiment setup using a high fidelity programmable baby mannequin named Tory (Tory S2210, Gaumard Scientific Company Inc.) shown in Fig. 6 (a).

A. Experimental Setup

The baby mannequin Tory was borrowed from the Simulation Program at the Women and Infants Hospital. Tory is a life-like mannequin and is typically used in training NICU nurses. Tory can be programmed to offer physical simulations

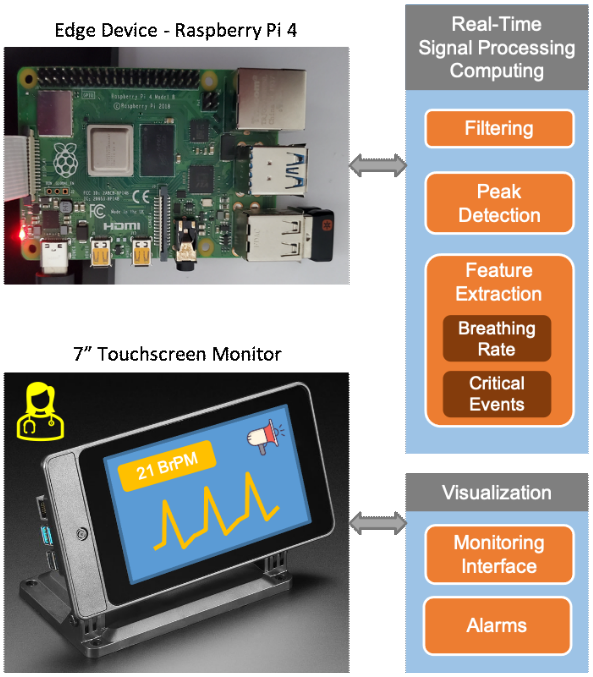

Fig. 5. Edge Computing Device

of chest/limb movements and apnea episodes. The chest belt was placed on Tory as shown in Fig. 6 (b). Tory was programmed using a software called UNI to simulate different breathing rates (number of breaths per minute), breathing types (normal and periodic breathing which includes random changes in breathing rates) and duration (time duration for simulation).

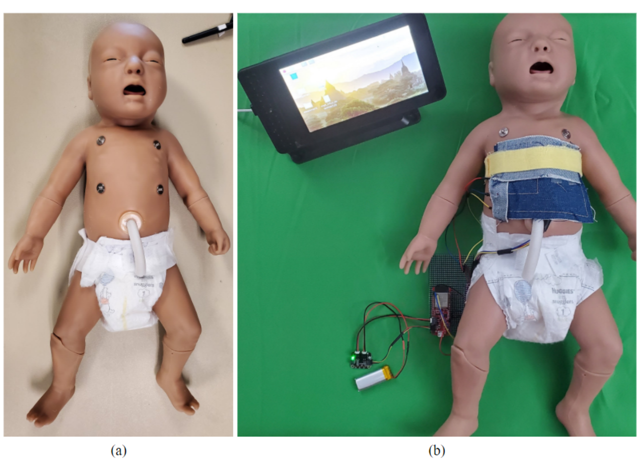

Fig. 6. Experimental Setup (a) Tory - the high-fidelity mannequin and b) e-textile sensor placement on Tory.

B. Experiment Protocols

To evaluate the system, we developed a set of experimental protocols as following:

1) *Variations in breathing rates:* To simulate slow, normal and fast breathing, breathing rates from 20 BrPM to 60 BrPM were applied to Tory incrementally. Particularly, we chose to simulate 20, 35, 40, 45, 60 BrPM scenarios ranging from low breathing rate to highest breathing rate often seen in newborns.

2) *Critical event detection:* Apnea is a critical event when a baby stops breathing for some period of time, minimum of 20 seconds [27]. It is utmost essential to detect this event that could lead to death or major medical condition to the baby. To simulate the apnea episodes in our experiments, the breathing rate was programmed to simulate 0 BrPM and applied to Tory between 35, 40 and 45 BrPM breathing rates. Details of each experiment protocols are indicated in Table 1.

TABLE I
EXPERIMENTAL PROTOCOLS

Experiment	BrPM	Duration (min)	Total Duration (min)
Variations in Breathing Rates	20	5	59
	20 to 35	1	
	35	15	
	35 to 40	1	
	40	15	
	40 to 45	1	
	45	15	
	45 to 60	1	
	60	5	
Apnea	35	1	9
	35 to 0	1	
	0	1	
	0 to 40	1	
	40	1	
	40 to 0	1	
	0	1	
	0 to 45	1	
	45	1	

V. Results and Discussions

A. System Evaluation

One of our aims was to evaluate the feasibility of our system to capture the respiration rate using the chest belt and the edge computing system with satisfactory accuracy level. For this, we deployed signal processing algorithms on the edge computing device. This section describes the performance of various signal processing algorithms.

1) *Preprocessing of the Raw Signal:* The changes in the output of the pressure sensor was successfully captured in our experiment. The raw signal coming from the pressure sensors (shown in Fig. 7 (a)) was filtered using a moving average filter to remove the unwanted noises. Fig. 7 (b) shows the filtered signal. As can be seen from Fig. 7, the moving average filter was able to remove the noise artifacts from the raw signal. The Signal to Noise Ratio (SNR) was found to be 10.79 dB for raw signal and 11.79 dB for the filtered signal. The moving average filter was able to improve the SNR by 10 percent. Since a higher SNR number means clearer signal, the preprocessing ensured good quality signal for further processing.

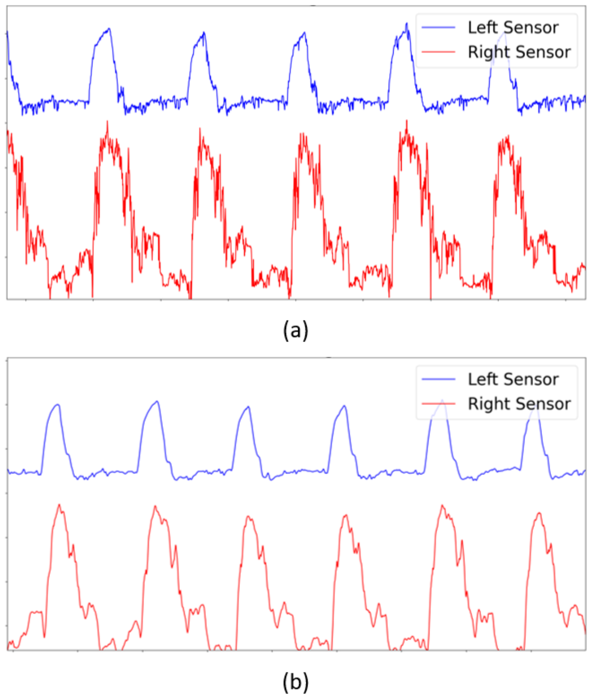

Fig. 7. Pressure data coming from the sensors. (a) Raw data and (b) Filtered data

2) Respiration Change Detection: The ECD was enabled to compute breathing rate from the pressure sensor data. We used a peak detection algorithm (described in Section III.D) to capture the respiration peaks from the filtered data. The outcome of the peak detection algorithm is shown in Fig. 8. Based on the peaks found by the peak detection algorithm,the

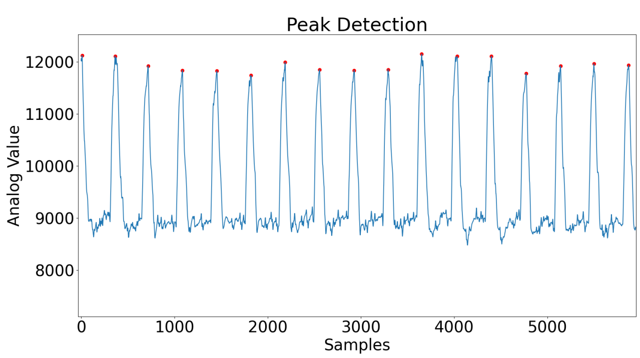

Fig. 8. The Outcome of Peak Detection Algorithm

ECD extracted the respiration rate by computing the inter peak interval. According to our experimental protocol (discussed in Section IV.B.1) five different RR were simulated using Tory. We computed Mean Absolute Error (MAE, shown in Table II) between the measured RR and the simulated RR. We could find from MAE and Fig. 9 that the respiration rates measured using the ECD were closely matching with the simulated RR values.

In our analysis, we observed that higher breathing rates are more susceptible to noise. Since Tory's chest movements are dependent on automated signals coming from software, the height of the chest increases as the respiratory rate increases. For this reason, the chest pushes the pressure sensors and creates separate pressure change independent from actual respiration. Also, we have noticed the software simulated breathing rates were not exactly followed by the Tory's hardware. We found loss of breathing simulation events (on Tory's Hardware) in the normal breathing setting, which may lead to additional noise in the data and errors in benchmarking.

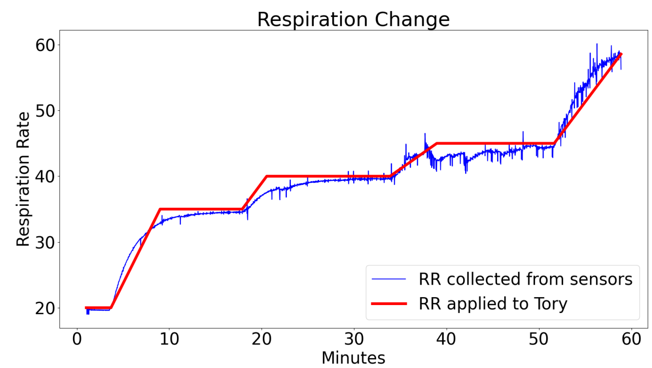

Fig. 9. Comparison of RR applied to Tory and RR collected from sensors

TABLE II
ERROR MEASUREMENT IN DIFFERENT BREATHING RATE CONDITIONS

Breathing Rate	Mean Absolute Error
20	0.32
35	0.88
40	0.95
45	1.43

3) Critical Event Detection - Apnea: Apnea can be defined as cessation of breathing. We aimed to detect respiration related clinical events such as apnea using the ECD. For this, Tory was programmed to simulate apnea events. We employed an apnea detection algorithm on the ECD (discussed in Section III.D). This algorithm successfully detected apnea episodes. Fig. 10 shows the comparison between the apnea detection done by the ECD and the simulated apnea episodes. We computed accuracy, sensitivity and specificity for the apnea detection. The accuracy, sensitivity, and specificity values were found to be 96.94, 96.53, and 100, respectively. Overall, we could see a good agreement between the simulated apnea episode and detected apnea episode. To increase the accuracy of apnea detection algorithm and distinguish motion events and apnea events, we are planning to perform experiments on simulating the baby motion and apnea at the same time and include IMU sensor data in the algorithm.

B. IoT Performance Evaluation

1) Communication Latency: Latency is one of the important aspects related to IoT infrastructure. The performance of the IoT infrastructure depends on the responsiveness of a

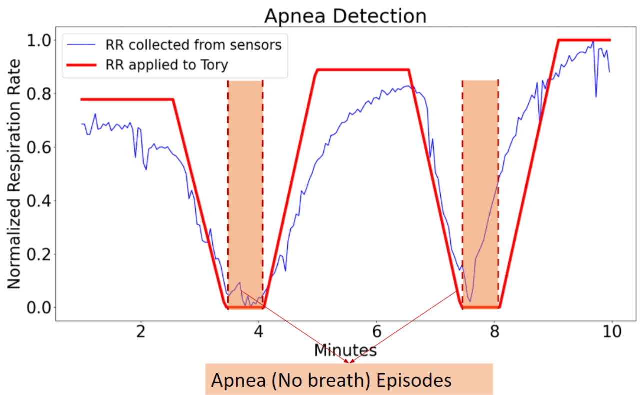

Fig. 10. Comparison of simulated apnea events and apnea detected by the ECD

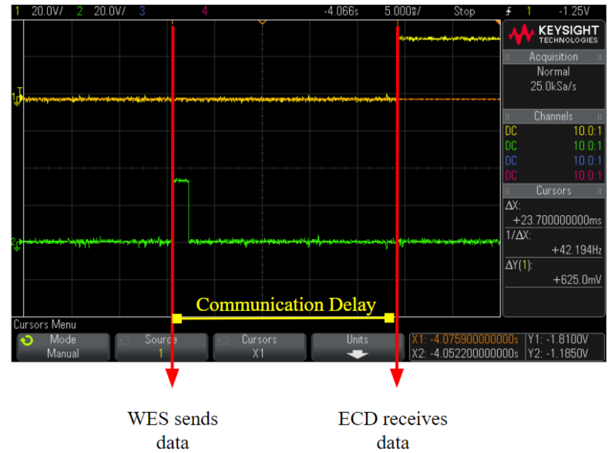

Fig. 11. Communication delay between ESP32 and Raspberry Pi

system or network. Higher amounts of latency can lead to delayed responsiveness and degrade the system performance. Particularly, in mission critical applications such as NICU, we need to measure and optimize the latency to identify the critical events in the NICU and generate timely-alarms. In our case, the communication latency refers to the time delay between the time when data is sent from the WES (ESP32 board) and the time when the data is received by ECD (Raspberry Pi). To calculate this time difference, a digital output pin on ESP32 board was assigned to become high (provides 3.3V output) when the data was sent. Also, on Raspberry Pi, a digital output pin was assigned to become high when the data was received. Those two pins were connected to two different channels of a digital oscilloscope. When those pins turned high, the signals were captured by the oscilloscope and the time difference between them was calculated as shown in Fig. 11 The average communication latency was found to be 22.33 milliseconds for the data to reach from the WES to ECD. It is acceptable to monitor the normal breathing events but needs to be improved to monitor time-critical events such as apnea. In addition, it should be considered that when the number of channels increases, the probability of more latency also increases demanding better optimization techniques.

2) Computational Latency: In our present research, we aim to detect critical events related to respiration rate, such as apnea. The detection of such critical events depends on the collection and processing of RR data. High amounts of processing time can lead to delays in the detection of apnea and may result in severe medical repercussions. Particularly in our case, the computational latency refers to the time difference between the time when the data processing begins and the time when it ends. To calculate the computational delay, a time stamp was saved at the beginning of data processing, another time stamp was saved at the end of data processing and the difference between those time stamps was calculated. The computational delay was found 0.669 seconds for processing 2-seconds data (250 samples) and 67.9 seconds for processing 1-hour data (438600 samples). In addition to data length, the complexity of algorithm also effects the computational latency. It can be seen that more complex algorithms will take more time to compute.

3) Battery Performance: Since the Baby-Guard is a wireless system operated on a battery, it is essential to know how long the battery can run the system on a single charge. We wanted to make sure that the battery will last long enough to give sufficient time to run the WES for at least one shift of Nursing i.e. 8 hours. The Baby-Guard was powered by a 3.7V 2500mAh LiPo battery shown in Fig. 3. The battery consumption of the system was monitored during the experiment and the battery status was sampled every 10 second by the WES, then sent to the ECD. For 70 minutes continuous data collection, the battery percentage dropped from 3.7 V to 3.43 V. Fig. 12 shows the battery voltage change. Ideally, the battery lasts approximately 2 days on a single charge based on the present hardware configuration.

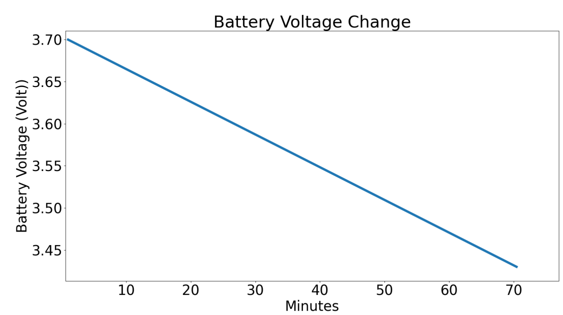

Fig. 12. Battery Performance

VI. Conclusions and Future Work

In our present work, we have designed an IoT enabled e-textile-based respiration monitoring platform called Baby-Guard. We developed a wire-free sensor belt, a wearable embedded system, and an edge computing device. We evaluated the performance of the Baby-Guard system using a high-fidelity baby mannequin called Tory. Our preliminary results are promising and show the potential of the Baby-Guard system to be used as a tool to monitor vital physiological parameters such as respiration rate in the NICU.

The initial promising results also lead us to make more experiments on the comparison between traditional sensing systems for respiration monitoring. The system will be tested with existing solutions to evaluate its accuracy and reliability.

One of the limitations of our current work is the integration of IMU sensor within the signal processing computing services. We collected data from pressure sensors and IMU. We have included an IMU as a secondary measure to detect respiration rate and critical episodes such as apnea and IMU data can also help to detect and remove motion artifacts from pressure sensor data. In future, we plan to work on the IMU data and define the noise profile from the data of motion artifacts. This will improve our algorithm to provide quality data and synchronise the critical event detection using IMU and pressure sensor data to improve the accuracy of the system.

Also, to provide more reliable apnea detection, we will upgrade our data processing with a sliding window detection algorithm. This algorithm will create a window according to the base signal and compare the data inside the window based on the threshold. We are also planning to create a supervisor algorithm that will monitor the outcome of the instantaneous peak detection algorithm. According to the number of missing peaks, the system will create different alarms. These alarms will be incorporated in the GUI using an Apnea Detection Bar that will be a colored display to offer alarm severity.

In the future, we are interested in conducting a thorough fault tolerance analysis on hardware system, software and firmware, networks, and power sources since NICU is a mission-critical operation with a minimum margin for failures and errors, especially when time-critical events like apnea need to be handled.

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