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NeoWear: An IoT-connected e-textile wearable for neonatal medical monitoring

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ABSTRACT

According to WHO, 15 millions babies are born preterm each year globally. Preterm infant (born before 37 weeks of gestation) are at a significantly higher risk of medical and surgical morbidity in comparison to babies born at term (around 37 weeks). Innovative solutions are warranted to meet the increased requirements of Neonatal Intensive Care Unit (NICU) with rising number of preterm babies. Various kinds of vital signs such as heart rate (HR), respiration rate (RR) or blood oxygen level (SpO_2) are monitored in NICU. Considering the fact the lungs develop in the last few weeks of gestation, preterm babies in NICU demands sophisticated technology to monitor respiration and events related to the respiration. Current technologies rely on the indirect measurements from thoracic impedance or other invasive techniques for RR monitoring. This poses discomfort and risk of infections to babies. Also, the delivery of parental and clinical care is largely impacted by a large number of monitoring cables placed on the babies. To address this requirements, we have developed an Internet-of-Things (IoT) based smart textile chest belt called "NeoWear" to monitor RR and detect apnea events in babies. The NeoWear is a wearable system consisting of a sensor belt, a wearable embedded system, and an edge computing device. The sensor belt comprised of a pressure sensors made of smart-textile and an Inertial Measurement Unit (IMU) to monitor movements. These sensors are connected to a micro-controller equipped with wireless communication capabilities called as a wireless embedded system (WES). The WES wirelessly connects with an edge computing device (ECD) using an MQTT-based IoT networking architecture. ECD is capable to offer signal processing and computing services to detect RR and apnea events. Simulation experiments using a high-fidelity, programmable NICU baby mannequin and five healthy adults were conducted to test the efficacy of the NeoWear System. Our findings shows an average error of 0.89 BrPM in respiration rate measurement and ~97 percent accuracy in apnea detection on baby mannequin. Our experiments also demonstrated that how the movements of the baby mannequin affected the respiration signal during apnea episodes and when breathing rate increased to 40 breaths per minute. In addition, the changes on human respiration data showed a meaningful increase for slow, normal and fast breathing. We also computed computation and communication latencies and they were found to be

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∼66 and 22 ms, respectively. Our preliminary results are promising showing the efficacy of NeoWear to measure respiration and related events for babies.

1. Introduction

Annually ∼15 million babies are born premature (i.e. before 37 completed weeks of gestation) across the globe according to the reports from World Health Organization (WHO) [1]. Approximately one million preterm babies suffer morbidity before the age of 5 years as a result of preterm birth and complications related to the preterm birth [2]. These preterm babies requires to be continuously monitored in the specialized Neonatal Intensive Care Units (NICU). NICU provides services to monitor vital signs of neonates such as heart rate (HR), respiration rate (RR), blood oxygen saturation (SpO_2), and other medical parameters under a specialized hospital environment [3]. For monitoring these parameters, NICUs often use conventional sticky electrodes. These electrodes can cause skin injuries to babies due to adhesives. Also it causes hassle with long wires, and false alarms due to loosely connected electrodes or drying contacts. Specifically, monitoring respiration is challenging because existing solutions uses indirect methods to measure thoracic impedance or other invasive techniques posing discomfort and the risk of infections to babies [4].

Advancement in Smart-textile and IoT technologies draws an attention towards electrodes and a number of wires used in NICU. New solutions can be explored and applied to NICU settings for addressing the challenges of respiratory monitoring in NICU. In this paper, we present a smart textile monitoring platform integrated with an IoT-based edge computing architecture called NeoWear (providing sensing and computing services). Fig. 1 shows a concept diagram of 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 and measure respiration and related events for babies.

NeoWear 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). To the best of our knowledge, NeoWear is the first kind of NICU technology built upon smart textiles connected with IoT-based edge computing services. We developed a textile pressure sensor pad in-lab using an industrial embroidery machine. We carefully identified the location for the pressure sensors on the chest belt such that the subtle chest movements can be captured continuously. Sensor location is important to detect critical events such as apnea episodes efficiently. We developed a local Message Queuing Telemetry Transport (MQTT) networking framework and integrated it with the edge computing device for real-time data communication. We also designed and deployed signal processing and computing services such as peak detection, RR calculations, and the detection of apnea episodes for the edge computing device.

This paper makes the following scientific contributions in the areas of testing the feasibility of NeoWear to monitor respiration and related events of babies:

- We investigated the performance of the NeoWear on a high fidelity NICU training baby mannequin with different breathing rates to evaluate the performance of sensors, computing services, and overall IoT system. Specifically, we applied different movement to the programmable baby mannequin and investigated effects of these movements on the respiration monitoring done using the NeoWear system.
- A comparative analysis was conducted to compare the results of the NeoWear system with the state-of-the-art methods. This comparison showed efficacy of NeoWear system to monitor respiration and related events.
- A study involving human participants was conducted to understand the effects of living situations on the performance of the NeoWear system.

This paper is an extended version of work published in [5]. We extend our previous work by adding the analysis of movement artifacts on the breathing rate. Further, this extension involved study design (involving human participants), IRB approvals, human subject recruitment, human subject on boarding, collecting data from subjects and analyzing the data to evaluate the system. We also show comparison of the proposed system with the state-of-the-art results found in other literature.

2. Background and state-of-art

2.1. 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.

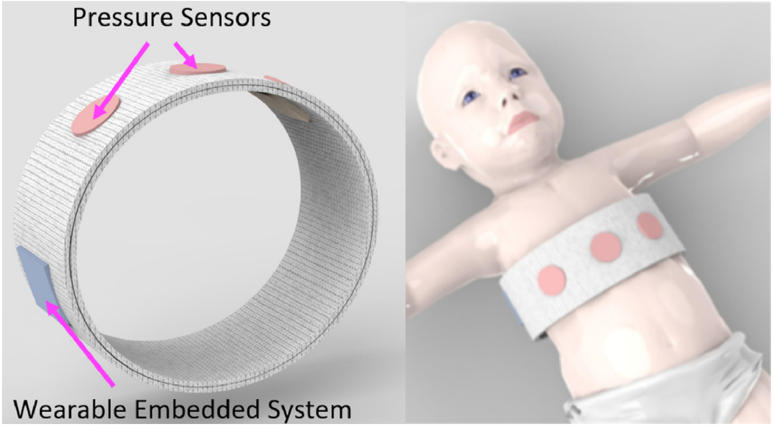

Fig. 1. A conceptual diagram of the NeoWear.

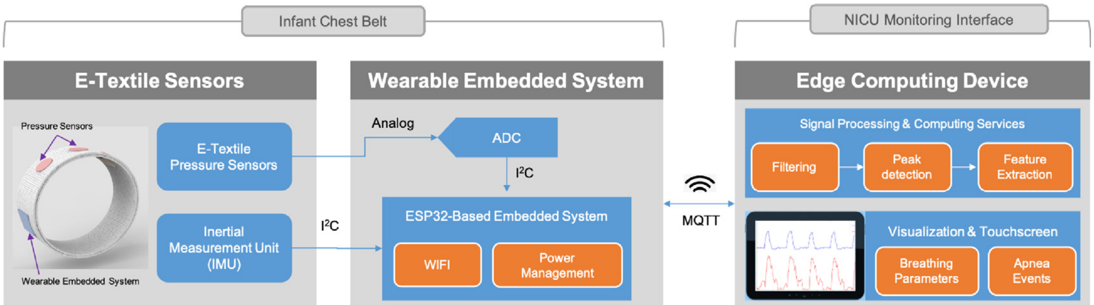

Fig. 2. An overview of the proposed smart textile sensor system for NICU.

Particularly, there is no reliable and user-friendly 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 [6]. 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 [7]. Further, studies have shown that the prevalence of neonatal skin injuries is as high as 43 percent in the NICU [8,9]. 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 [10]. 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 [11].

Further, NICU is often filled with long monitoring wires around the babies that often create physical and psychological barriers for nurses and parents to access babies [12,13]. 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) could degrade signal quality and cause lack of accuracy in the output. The long wires make 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 new 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.

2.2. Internet of things and smart textiles for NICU

Recent advancements in technology can potentially 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) [14].

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 [15]. 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 breaths per minute (BrPM). Raj et al. developed a RR monitoring system using a 3-axis accelerometer placed on baby's body [16]. The system was compared with direct observation and had a correlation coefficient of 0.974 between measured and observed values of RR. Chen et al. developed a smart vest including Polydimethylsiloxane–Graphene (PDMS–Graphene) sensors for respiration signal; textile-based dry electrodes for ECG signals; and IMU sensors. They compared their PDMS–Graphene sensor with PSG and calculated r value as 0.977 [17]. Roudjane et al. designed a t-shirt with spiral fiber antenna sensors to monitor respiration rate by sensing the changes on thoracic volume [18]. They compated their system with spirometry as the gold standard. They found the error as ± 2 bpm. Rossol et al. developed an algorithm to detect respiration rate from camera footage [19]. To record the respiratory movements, they used micromotion and stationarity detection (MSD) method. They also compared their algorithm with hospital standard and found a good correlation with r equals 0.948.

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 [20]. 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 (crying, calm etc.) of the babies. Fahmi et al. developed an IoT-based smart incubator system for NICU monitoring involving a microphone-based system [21]. 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 [22]. 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 [23]. 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 [24]. Their system included several layers to provide support services to healthcare providers aiding clinical decision-making. Lorato et al. offered a system which monitors the RF pixels in thermal videos and classifies the respiration rate according to them [25]. They tested their system on 9 infants and reached 73% sensitivity for sensing the obstructive apnea. Lorato et al. also offered another method to classify the short cessation of breath to detect longer apnea [26]. They tested their algorithm on 5 babies with 91 annotated cessations of breathing. Their algorithm detected the cessation of breath with 93% accuracy. Lee et al. developed an algorithm which detects the apnea from chest impedance monitoring [27]. They offered a new algorithm which removes the cardiac signal from the chest impedance to provide more robust monitoring of apnea. Monasterio et al. offered an algorithm which is based on multimodal analysis framework using electrocardiogram, impedance pneumogram and photoplethysmographic signals to reduce the false alarms for apnea [28]. They tested their algorithm on 27 neonatal babies and achieved 100% accuracy on the training set and 90% accuracy on validation set. Uddin et al. developed an algorithm which detects the sleep apnea from nasal airflow and pulse oximetry [29]. They tested their algorithm on 988 polysomnography records. Their results showed an agreement between estimated and scored apnea where the correlation coefficient is 0.95.

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, and 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.

3. Materials and methods

The NeoWear 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 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.

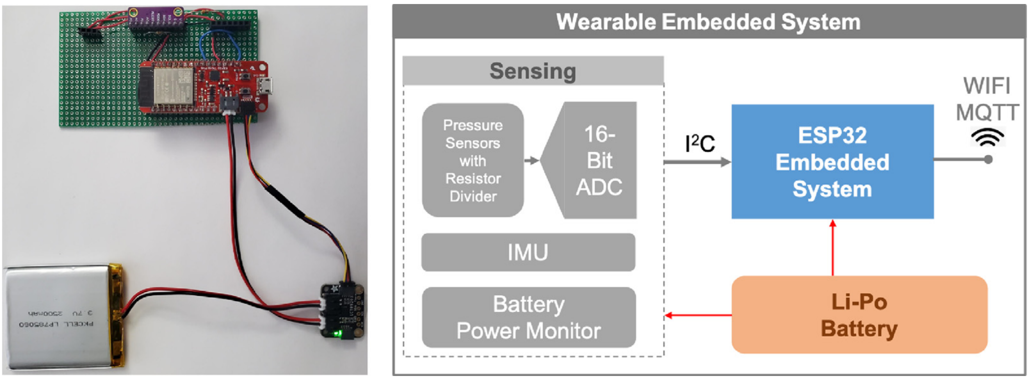

Fig. 3. Wearable embedded system.

3.1. 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 [30]. 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. The objective of the IMU data was also to identify and remove motion artifacts from the pressure sensor data.

3.2. 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 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 allowed us to sample the IMU and pressure sensor data at 125 Hz.

3.3. 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 [31] discussed in this manuscript (i.e., NeoWear). MQTT is also used to secure the information, e.g. the private and sensitive information of the patients [32,33].

Since the MQTT protocol (using the current communication library [34]) requires payload to be sent as an unicode character array, the pressure sensor data and IMU data was converted into a comma separated value (CSV) formatted character array (the values in the array separated with comma) [35]. 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 125 Hz [34]. The payloads were received by the edge computing device which runs a Mosquitto MQTT broker service [36]. As shown in Fig. 4, the Raspberry Pi hosted the MQTT broker and collected data from MQTT client which was running on the WES.

3.4. Edge Computing Device (ECD)

The 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 [37]. The comma separated value array payloads are decoded to UTF-8 and

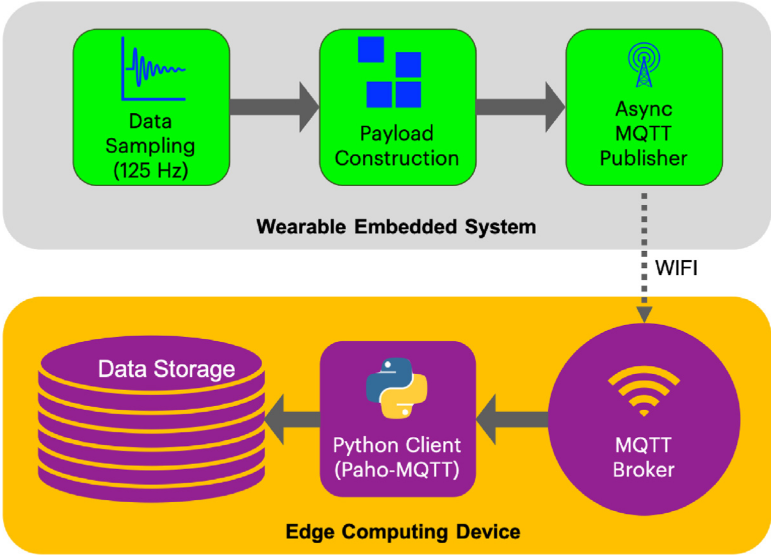

Fig. 4. MQTT communication architecture.

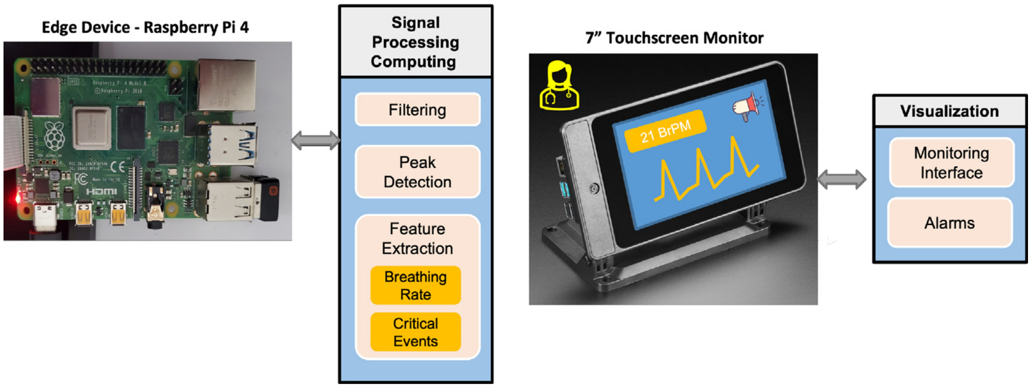

Fig. 5. Edge computing device.

appended to a python list object which was 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 movement and high frequency noise. We used a moving average filter to remove the noise from the signal. We chose moving average filter in our architecture due to its simplicity considering the implementation on the embedded system. 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.
- Peak Detection: The breathing process, inhalation and exhalation, generated peaks in the data. Each breathing movement corresponded to one breathe. We employed an adaptive peak detection algorithm to detect these peaks in the pressure data using windowing. The algorithm finds the local maxima in the signal and finds peaks in the window according to the local maxima [38].
- Feature Extraction - Extraction of Instantaneous RR: The instantaneous respiration rate was extracted by computing the time difference between two successive peaks. The equation mentioned below was used for calculation (T is the time difference between two consecutive peaks. $RR = 60000/T$
- Detection of Apnea Episode: Apnea can be defined as cessation of breathing. The apnea detection was based on the instantaneous respiration rates. After the instantaneous RR was calculated, a threshold was set. The RR values below the threshold were detected and labeled as apnea by the algorithm.

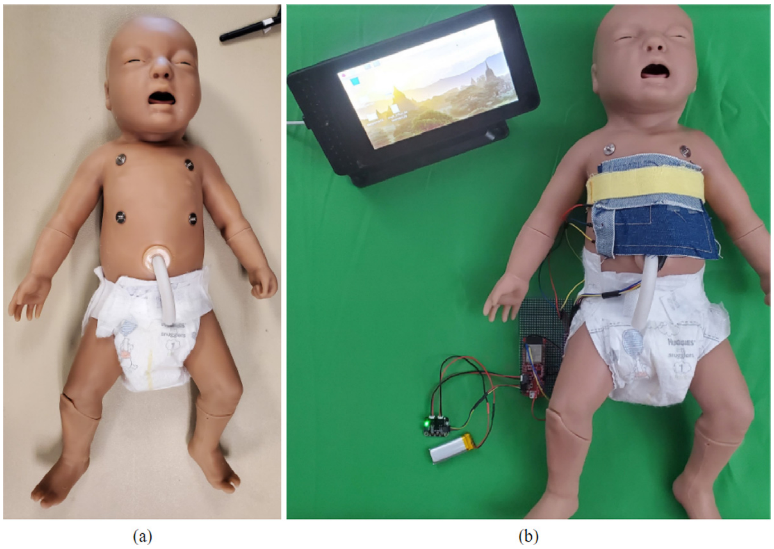

Fig. 6. (a) Tory — the high-fidelity mannequin and (b) e-textile sensor placement on Tory.

4. Experimental setup and procedure

Our aim was to design a respiration monitoring system that can monitor the respiration of premature babies in the NICU and detect critical episodes such as apnea. 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). We also conducted experiments with healthy adults to monitor the respiration of humans.

4.1. Experimental setup

4.1.1. Experiments on baby mannequin

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 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).

4.1.2. Experiments on healthy adults

The chest belt mentioned in Section 3.1 was re-designed and adjusted for healthy adults to fit the adult size. From our experiments with the baby mannequin, we realized that the placement of the sensors is important. The sensors need to be on the middle and two sides of the chest as shown in Fig. 7 and they must be on the same place for every participant. It is known that every adult has different sizes of the chest area. For this reason, we designed the chest belt that can be adjusted to different chest sizes. To place the sensors on the same place among different participants, we decided to adjust the length of the fabric between the sensors. To sense the movement of the thoracic area, the chest belt was placed under the chest as shown in Fig. 7. The data were collected from five participants with three different body sizes (1 extra large, 2 large, 2 medium) The participant demographics was discussed in Section 4.2.4.

4.2. Experimental protocols

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

4.2.1. Variations in breathing rates (Baby mannequin)

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.

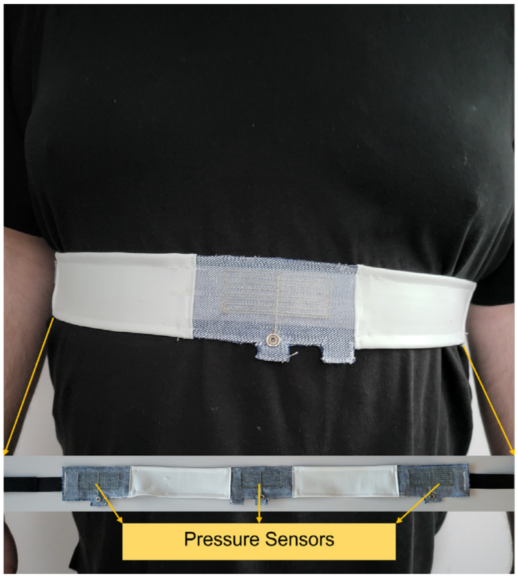

Fig. 7. Chest belt for adult data collection.

Table 1
Experimental protocol for variations in breathing rates.

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	

4.2.2. Critical event detection (Baby mannequin)

Apnea is a critical event when a baby stops breathing for some period of time, minimum of 20 seconds [39]. 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.

4.2.3. Extraction of movement noise (Baby mannequin)

To analyze the noise coming from the movements, Tory was programmed to perform arm movements. In experimental protocol, three different breathing rate (35, 40 and 45) and apnea simulation was used with and without the movement. The movement periods was labeled by using a switch. The switch sent value "1" when there was a movement and value "0" when there was no movement. Details are shown in Table 2.

4.2.4. Participant characteristics for healthy adults

Table 3 shows the participant characteristics. We included five healthy participants (P.1–P.5, Mean(SD) = (29.4 ± 6.37) years) in our study involving 2 male and 3 female participants. The participants were recruited locally. The study protocol was approved by the University of Rhode Island Institutional Review Board (protocol number is 1785106-6).

Table 2
Experimental protocol for movement noise.

Experiment	BrPM	Movement	Duration (min)	Total duration (min)
Variations in breathing rates	35	No	5	40
	35	Yes	5	
	0	No	5	
	0	Yes	5	
	40	No	5	
	40	Yes	5	
	45	No	5	
	45	Yes	5	

Table 3
Participant demographics.

Participant	Gender	Age	Chest size
P. 1	Male	38	Extra large
P. 2	Female	34	Large
P. 3	Male	30	Large
P. 4	Female	25	Medium
P. 5	Female	20	Medium

4.2.5. Experimental protocol for healthy adults

In this study, we aimed to monitor the changes in human respiration. To distinguish the different respiration rates, a breathing protocol similar to Tory was followed. Participants were asked to come to the lab. Then the chest belt was put on their chest. Participants then asked to perform 10 deep breaths (∼45 s), 10 normal breaths (∼35 s), 10 fast breaths (∼15 s) while they are standing. The whole experiment took ∼105 s.

5. Results and discussions

5.1. 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.

5.1.1. Preprocessing of the raw signal — Baby mannequin

The changes in the output of the pressure sensors was successfully captured in our experiment. The raw signal coming from the pressure sensors (shown in Fig. 8(a)) was filtered using a moving average filter to remove the unwanted noises. Fig. 8(b) shows the filtered signal. As can be seen from Fig. 8, 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.

5.1.2. Preprocessing of the raw signal — Healthy adults

The raw signal coming from the pressure sensors (shown in Fig. 9(a)) was filtered using a moving average filter to remove the unwanted noises. Fig. 9(b) shows the filtered signal. As can be seen from Fig. 9, the moving average filter was able to remove the noise artifacts from the raw signal.

5.1.3. Respiration change detection — Baby mannequin

The ECD was enabled to compute breathing rate from the pressure sensor data. We used a peak detection algorithm (described in Section 3.4) to capture the respiration peaks from the filtered data. The outcome of the peak detection algorithm is shown in Fig. 10. Based on the peaks found by the peak detection algorithm, the ECD extracted the respiration rate by computing the inter peak interval. According to our experimental protocol (discussed in Section 4.2.1) five different RR were simulated using Tory. We computed Mean Absolute Error (MAE, shown in Table 4) between the measured RR and the simulated RR. We could find from MAE and Fig. 11 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. It can be seen from Fig. 11, the feature extraction algorithm was not able to calculate 60 BrPM episode. 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.

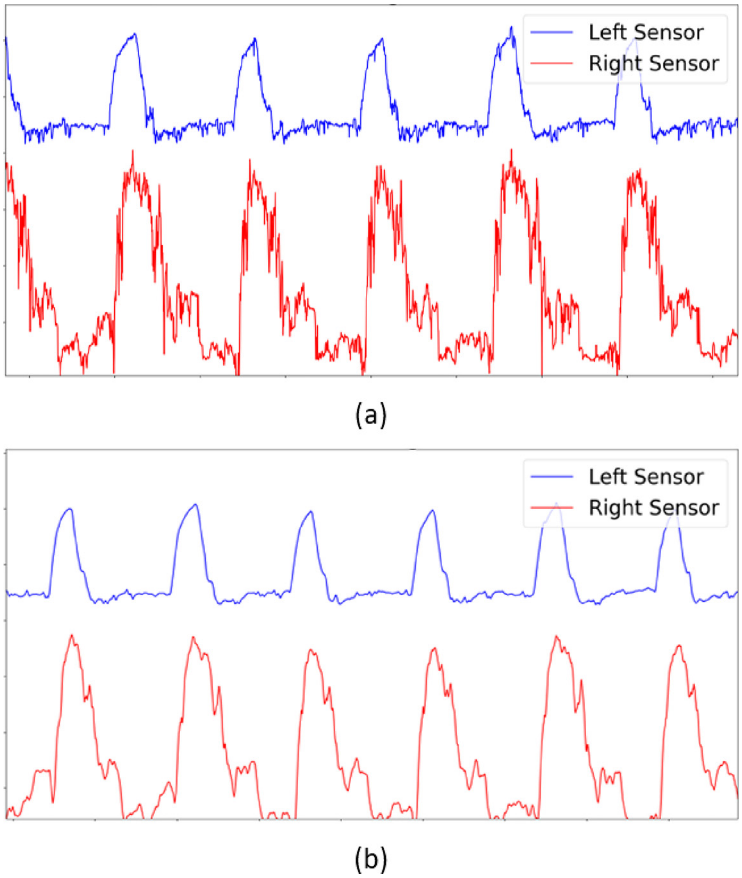

Fig. 8. Pressure data coming from the sensors on Tory. (a) Raw data and (b) Filtered data.

Table 4
Mean absolute error.

Breathing rate (BrPM)	Mean absolute error (BrPM)
20	0.32
35	0.88
40	0.95
45	1.43

5.1.4. Respiration change detection — Noise analysis

According to our experimental protocol(discussed in Section 4.2.3), three different RR including the movements were simulated using Tory. Fig. 12 showed that the respiration rates measured using the ECD were closely matching with the simulated RR values.

We also observed that the movement noise affected the apnea episode and 40 BrPM breathing rate mostly. When we checked the log file provided by Tory's software, it was seen that the movement during these episodes created instant movements (which was shown as shallow breathing in the log file) and these movements caused the increase in between 10–15 (apnea) and 25–30 (40 BrPM) minutes when they corresponded with movement.

5.1.5. 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 3.3). This algorithm successfully detected apnea episodes. Fig. 13 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

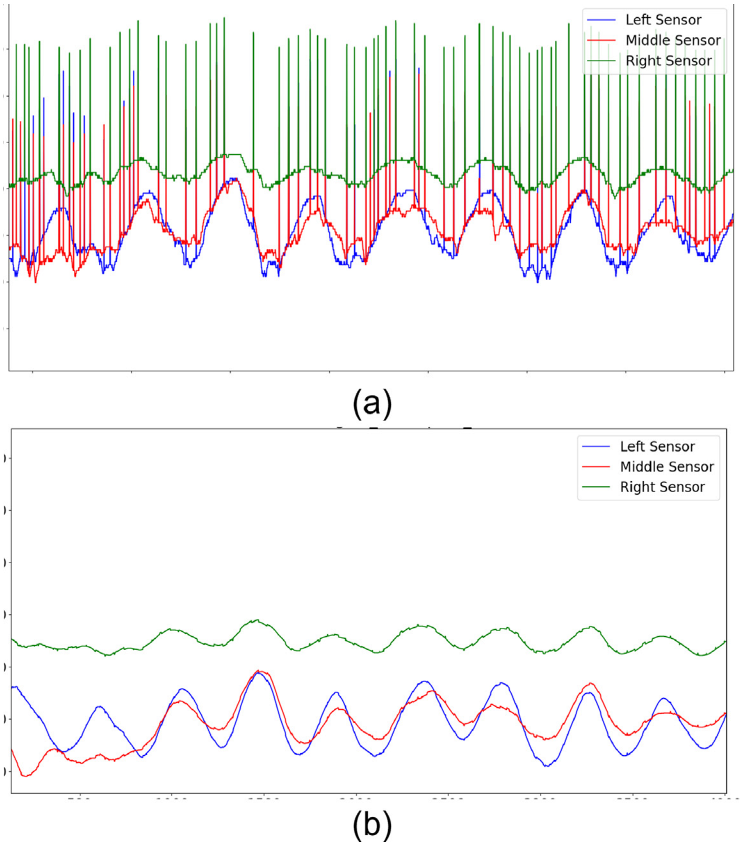

Fig. 9. Pressure data coming from the sensors on healthy adults. (a) Raw data and (b) Filtered data.

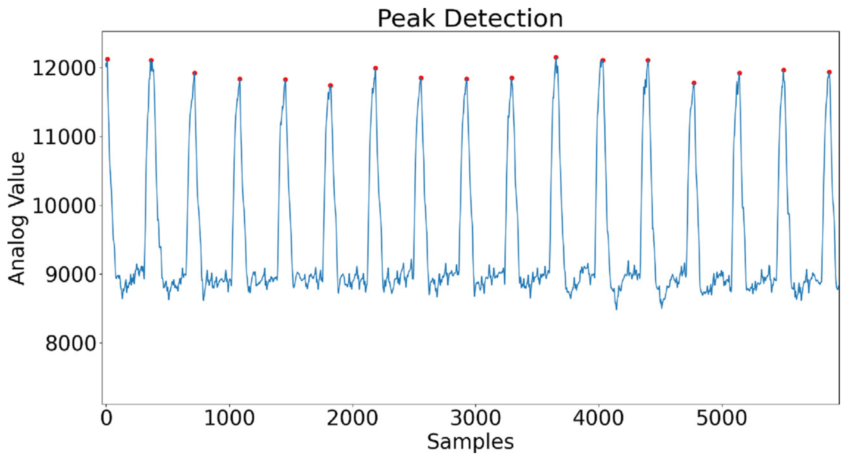

Fig. 10. The outcome of peak detection algorithm.

to perform experiments on simulating the baby motion and apnea at the same time and include IMU sensor data in the algorithm.

5.1.6. Respiration change detection — Healthy adult

According to our experimental protocol (discussed in Section 4.2.5) three different breathing types were collected from five participants. The breathing rates were calculated according to the total time for performing 10 breaths. It is obvious that the breathing rate is not constant on human as it does on the baby mannequin as can be seen in Fig. 14. For this

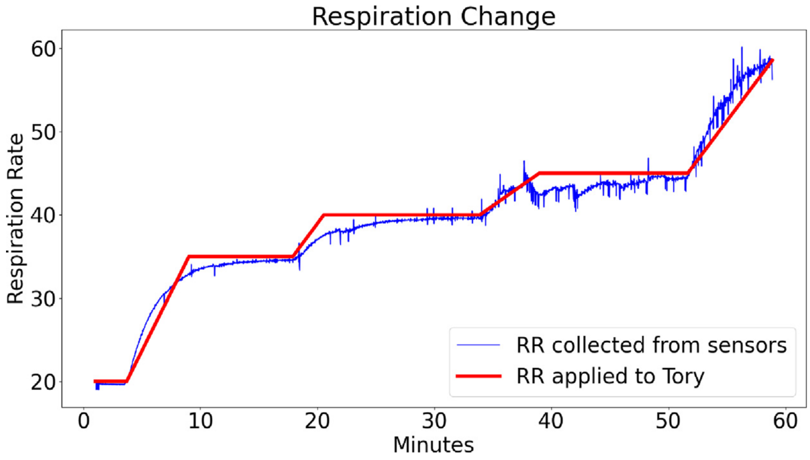

Fig. 11. Comparison of RR applied to Tory and RR collected from sensors.

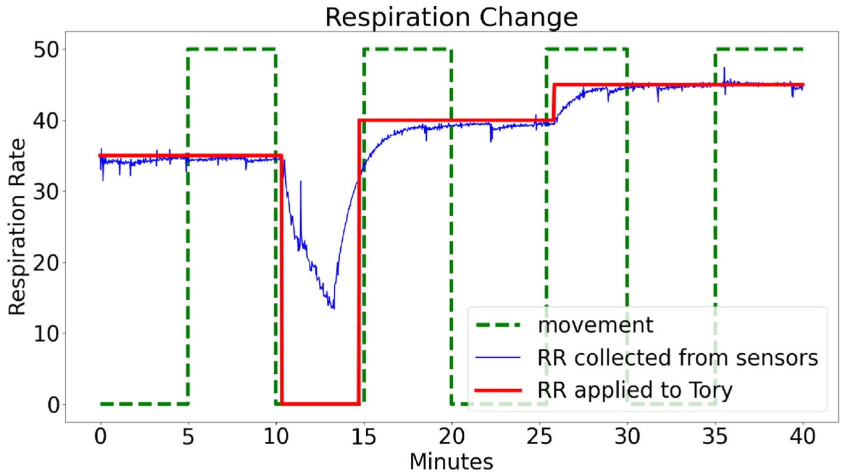

Fig. 12. Comparison of RR applied to Tory and RR collected from sensors (with movement).

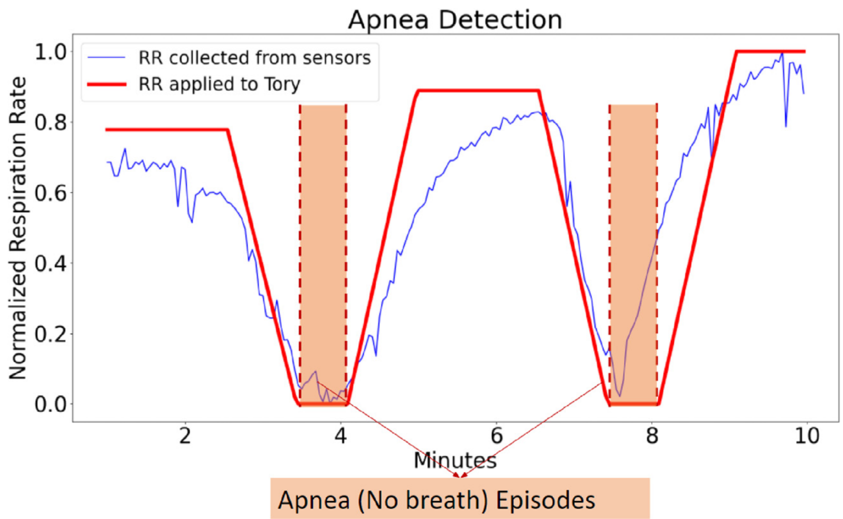

Fig. 13. Comparison of simulated apnea events and apnea detected by the ECD.

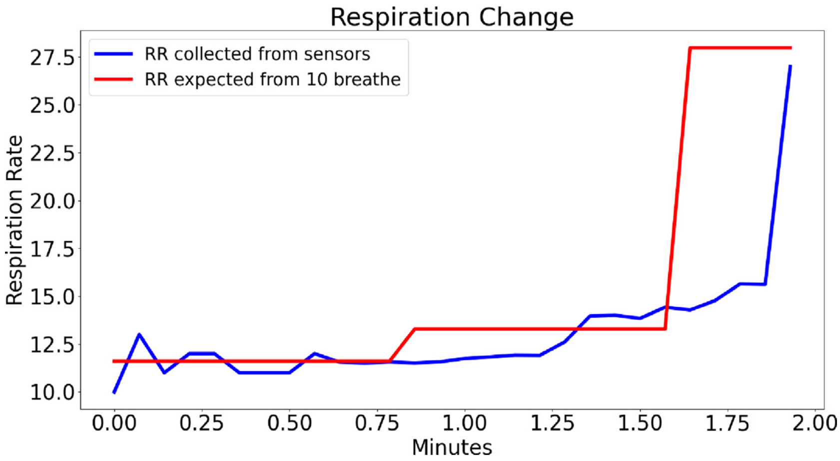

Fig. 14. Comparison of RR expected from 10 breaths and RR collected from the sensors.

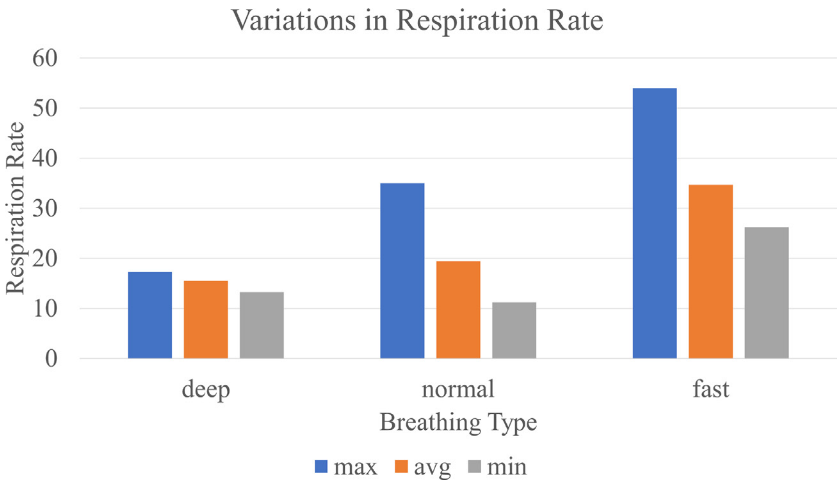

Fig. 15. Average values of different breathing types.

reason, the maximum, average and minimum values were calculated for each participant. The average of those values were shown in Fig. 15.

During the data collection, we realized that the data contained sudden spikes. Since the conductive thread is not insulated, the small movements coming from the human body creates those spikes and causes noisy signal. For this reason, we realized that extracting the RR from no-breathe signal was really hard and needed more sensitive algorithm. In addition, it was seen that the data collection code lagged while publishing 125 Hz data and caused data loss. For this reason, we reduced the sampling rate to 64 Hz for human data collection.

5.2. IoT performance evaluation

5.2.1. 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 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 3.3 V 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. 16. The communication latency for the data to reach from the WES to ECD was tested

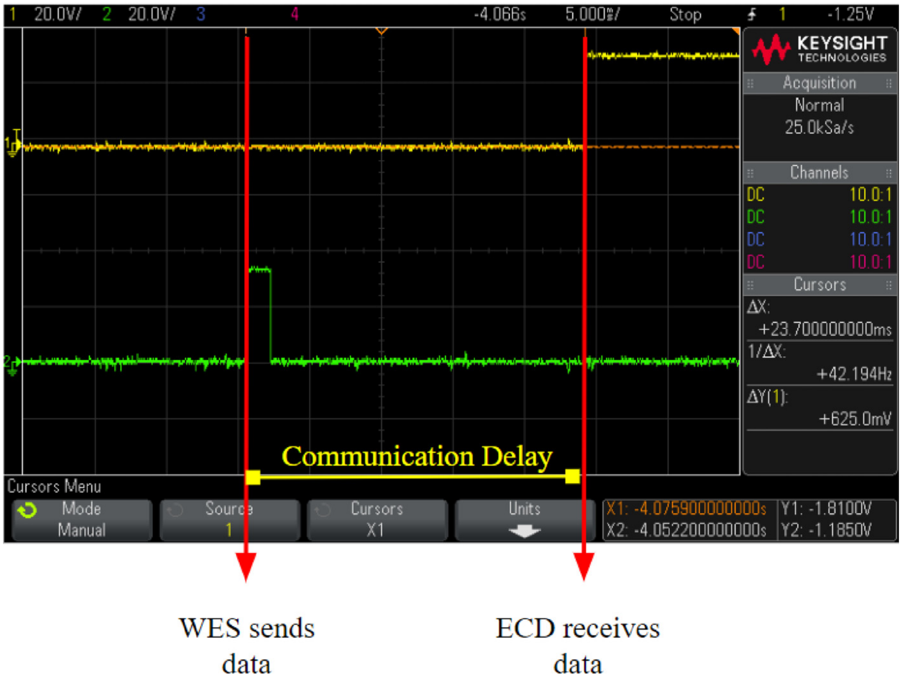

Fig. 16. Communication delay between ESP32 and Raspberry Pi.

four times. The maximum latency was 27.80 ms while the minimum latency was 15.22 ms. The average communication latency was also found to be 22.33 ms. 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.

5.2.2. 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 edge computing device receives data every 2 s in a batch of 250 samples for Tory and 128 samples for healthy adults (resulting from updated sampling rate of 64 Hz). The ECD processes this data at every 2 s intervals. To estimate the average processing time, all the batches were combined (resulting in 438 600 samples) and processed. The computational delay was found 0.669 s for processing 2-s batches (250 samples) and 67.9 s for processing combined batches (438 600 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.

5.2.3. Comparison with state-of-the-art

We also compared the efficacy of our system with existing literature. For this, we compared the accuracy, sensitivity and specificity of our study with the state-of-the-art. Table 5 shows the comparison between previous studies and our study.

As can be seen from Table 5, our system performed better than the state-of-the-art as far as the sensitivity, specificity and accuracy are concerned. The studies mentioned in the state-of-the-art mostly focused on developing more robust algorithms to extract the respiration rate from external sensors such as thermal cameras [25,26], chest impedance [27], electrocardiogram [28,29]. During our literature survey, we noticed that, to accurately measure the respiration events, a robust sensing mechanism is as equally important as the robust algorithm. Following this, we created the respiration sensing belt and the data collection/processing setup in our lab. Further, we also learned from our literature survey that indirect measurement methods (such as thermal cameras [25,26], electrocardiogram [28,29] etc.) to measure respiration might not be the best choice to capture critical events such as Apnea. Thus, in our design we chose to measure the chest movements using pressure sensors to capture the respiration related events. We have also incorporated IMU in our chest belt to improve the system performance with further developments. Also, we gave attention to the fact that the long

Table 5
Comparison between state-of-the-art.

Study	Accuracy (%)	Sensitivity (%)	Specificity (%)
Cay et al. (This Study)	96.94	96.53	100
Lorato et al. [26]	93.16	76.32	94.39
Lee et al. [27]	90.64	86.68	91.5
Lorato et al. [25]	94.35	73.39	98.26
Uddin et al. [29]	90.7	98.9	60
Monasterio et al. [28]	90	86	91

duration respiration monitoring in real-life settings would require a solution which is user-friendly and easily adoptable. Thus, we chose to use an e-textile-based solution to create our system which does not need any adhesive to stick to the body [27] and it is comfortable enough to be used for long hours for unobtrusive respiration monitoring. Further, the algorithms that we designed for our system to compute respiration and detect apnea were also tailored to suit our sensor characteristics such as amplitude, noise and range of the output signal.

As a result of our design choices, Table 5 shows that on-body sensors which are dedicated to the respiration rate monitoring offer better accuracy than the other sensors which are used to extract the respiration rate as the secondary measurement. Overall, we found that our system (NeoWear) takes advantage of in-lab designed sensors, data acquisition system which is dedicated to respiration rate extraction as the primary measurement, and edge computing device which works in harmony with each other to offer better results compared to other literature.

6. Conclusions and future work

In our present work, we have designed an IoT enabled e-textile-based respiration monitoring platform called NeoWear. We developed a wire-free sensor belt, a wearable embedded system, and an edge computing device. We evaluated the performance of the NeoWear system using a high-fidelity baby mannequin called Tory. Our preliminary results are promising and show the potential of the NeoWear 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 for human data collection. We collected data from pressure sensors and IMU in the experiments with baby mannequin. We have included the IMU sensor as a secondary measure to detect respiration rate and critical episodes such as apnea. IMU data was also used to detect the motion artifacts from pressure sensor data. The results showed that our system could detect the movement and the noise coming from the movement could be removed from the respiration signal. Since our experiments with baby mannequin shows promising results, in future, we plan to add an IMU sensor to the adult chest belt. We will analyze the IMU data coming from human and define the noise profile from the data of motion artifacts. This will improve our algorithm to provide quality data and synchronize the critical event detection using IMU and pressure sensor data to improve the accuracy of the system.

Another limitation that we faced was the drawback of MQTT because of low-power system and high sampling rate. We realized that increased distance with low-power settings and the high sampling rate caused data loss and increased the latency on MQTT connection. To overcome this limitation, the sampling rate was decreased. This demands further investigations to explore different communication methods for NeoWear in future.

In real-life settings such as hospitals, authors have conducted pilot focus-group studies involving hospital NICU visits and interviewing nurses to understand the requirements. The NeoWear setup is designed around the idea that a nurse can monitor multiple babies under his/her observation. Understanding developed from nurses' interviews showed that each nurse can handle up to 5 babies in a single room. The current NeoWear setup is designed to handle one node (i.e., WES) in the current settings. However, this setup can be expanded to add more nodes (multiple WESs) by expanding the MQTT based protocols. Further, in future, security mechanism can be integrated in the MQTT protocols to ensure the confidentiality and integrity of information.

In addition, we observed that the baby mannequin Tory has limitations on the higher breathing rates ($\geq$45) due to his mechanical system. The mechanical system is not following the simulated respiration rate exactly. However, NeoWear focuses on detection of critical event i.e., Apnea which is 0 BrPM. Thus, the current interest of the NeoWear system is focused more towards lower respiration rate compared to higher respiration rate. In future, application of NeoWear can be extended to explore critical conditions related to higher respiration rate.

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.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Gozde Cay reports financial support was provided by Republic of Turkey Ministry of National Education.

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Data availability

The authors are unable or have chosen not to specify which data has been used.

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