A Step Towards Design and Validation of a Wearable Multi-Sensory Smart-Textile System for Respiration Monitoring

Dhaval Solanki[1], Gozde Cay[1], Md Abdullah Al Rumon[1], Vignesh Ravichandran[1], Kunal Mankodiya[1]

[1]Electrical, Computer and Biomedical Engineering Department, University of Rhode Island, Kingston, RI, USA

dhaval_solanki@uri.edu

Authors Contributed Equally

Abstract— **Among many advancements in wearable technology, there is a strong demand to develop wearable smart textiles for monitoring respiration in daily life settings. The existing methods for respiration monitoring are not sufficient to monitor the respiration events continuously in real-life settings and are not validated extensively. Motivated by this need, we developed a wearable multi-sensory smart-textile system called "RespWear" for accurate and reliable respiration monitoring in daily life settings. RespWear consists of a textile pressure sensor belt (to monitor the chest movements related to breathing) and a wearable data acquisition system. The wearable data acquisition system supports wireless communication to offer unobtrusive monitoring of respiration. The data collected from the sensor belt was sent to a recording device via ESP-Now respiration rate analysis. We recruited 4 participants (2 female and 2 male) to validate the RespWear for monitoring different respiration rates (number of breaths per minute) and different postures (standing, sitting, and bending). An OptiTrack IR camera system was used as a gold standard to validate RespWear performance. Results showed that RespWear had an excellent correlation (r-value = 0.836) with the data collected using OptiTrack camera system for the respiration rate calculation. These findings showed that the RespWear can be a good candidate for being a wireless, wearable respiration monitoring system in daily life settings.**

Keywords— Respiration, Wearable, Smart-Textile Sensor.

I. Introduction

Recent technological advancements enable noninvasive monitoring of health in real-life settings, allowing insights into diurnal health changes. Monitoring physiological parameters such as heart rate, blood oxygen level, and respiration is gaining popularity for maintaining good health and wellbeing, especially after the COVID pandemic. Among these physiological parameters, respiration monitoring is under-recognized despite the fact that it could be used to evaluate various health conditions such as asthma, apnea, bronchitis, and emphysema, along with complications that affect the critical systems such as the nervous system, excretory system, and cardiovascular system [1-4]. Monitoring respiration can be useful to diagnose the disease as well as monitor the effects of the treatment/interventions on the patients.

Reports indicate that respiration can be linked to emotions such as happiness, surprise, sadness, anger, stress, and fear [5-8]. This link between respiration and human emotions can be useful to prevent mental disease and improve the mental health of the patients [9]. Also, human emotion recognition can be useful in psychological studies such as investigating consumer and social trends [10]. Besides, emotions are also used to study driver safety [7]. It can also be useful in virtual reality-based clinical interventions [11-13] and in investigating cognitive and learning processes [14]. Further, respiration is widely used to train athletes and improve their performance [15].

There are several methods to monitor respiration. These methods can be divided into two main categories, namely, contact-based and noncontact-based methods. Contact-based methods involve acoustic-based methods [16-18], Airflow-based methods [19-22], Chest/Abdominal movement detection [23-26], Oximetry Probe (SpO_2) based method [27-28], and ECG-based method [29-33]. Noncontact-based methods involve Radar Based Respiration Rate Monitoring [34-36], Optical Based Respiration Rate Monitoring [37-40], Thermal sensors, and thermal imaging-based respiration monitoring [41]. Non-contact methods offer the opportunity for monitoring the user's respiration events without hindering their movements. However, these non-contact methods are limited to lab-based setup. Besides, it raises concerns related to patient safety, electromagnetic interference with medical equipment, etc. On the other hand, contact-based methods are more reliable and can be used in daily life settings. However, there is a tradeoff between the type of the sensors, the application area (clinical or experimental), and the wearability aspect. The existing methods are not sufficient to monitor respiration and related events continuously in real-life settings and are not validated extensively. Motivated by this, we propose to develop and validate a smart-textile-based respiration monitoring system comprising of textile-based sensors and a data acquisition module. We conducted a validation experiment using the gold standard motion capture system.

In our current work, a smart textile pressure sensor was designed with an industrial embroidery machine to monitor chest movements. The pressure sensor pads were carefully integrated into a chest belt to cover both the upper and lower chest area. The presented system also comprises a wearable wireless data acquisition system. The system was validated for different breathing rates and for different postures (standing, sitting, bending). The effect of postures on the efficacy to monitor respiration rate was analyzed. The system was compared with data collected using an IR motion camera system. Our findings suggest that the proposed system can be a reliable respiration monitoring solution for in-home, clinical, and research settings.

II. SYSTEM DESIGN

We designed the RespWear system which consisted of (A) In-house developed textile-based pressure sensors, (B) A chest belt, housing the pressure sensors, and a wearable data acquisition unit to record respiration data wirelessly.

A. *Design of the Pressure Sensors*

The respiratory cycle (inhalation and exhalation) causes movement in the entire chest area. The magnitude of movement varies from person to person including the differences in gender, body dimensions, height, and structure. Therefore, to achieve accurate respiration detection, the entire chest area needs to be monitored. The embroidered pressure sensors were created using Velostat material (that changes its resistance when pressure is applied to it) and conductive thread. Breathing causes movement of the chest which can be used to create pressure on the Velostat material using a chest belt. This pressure changes the resistance of the Velostate material. To record the resistance changes, a silver-coated conductive thread was embroidered on a denim fabric using an industrial technical embroidery machine (ZSK Embroidery Machines). The Velostat material was sandwiched between the two pieces of denim fabrics (Fig. 1). Six sensor pads were created to monitor respiration.

B. *Design of the chest belt*

The chest belt consisted of two major elements involving (i) the sensor-integrated smart textile belt and (ii) the wireless embedded system to collect data from the sensors. Both elements are discussed below.

1) *Integration of the pressure sensors*

We have created a chest belt housing a total of six pressure sensors covering almost the entire chest region. A set of three sensors was placed around the upper chest area and another set was placed around the lower chest area. The sensors were placed at the center and on both sides of the chest. To integrate the sensors into the chest belt, we stitched a piece of fabric connecting the sensors. A non-elastic fabric was chosen to provide the tightness of the belt and make it fit the body. For the back side of the belt, a Velcro strap was used to adjust the fitting. It was important to accommodate different chest sizes and ensure proper sensor positioning to collect reliable data. For this, the chest belt was created based on the largest size, then the fabric between the sensor pads was folded and clipped using fabric clips according to the smaller sizes such as medium, small, and extra small. These adjustments allowed the chest belt to be used on both females and males with different chest sizes.

2) *Wearable Data Acquisition System*

The RespWear was designed to be used in day-to-day life. Thus, it was important to collect data from the system which does not hinder one's movements. To achieve this a wearable data acquisition system (W-DAQ) was developed which could collect the data from the pressure sensors and send the data wirelessly to the computing device. The W-DAQ consisted of an ESP-32-based microcontroller, a 16-bit analog-to-digital converter (ADC), a battery monitor module, and a 3.7V Li-Po battery. The sensor data was sampled at 64 Hz using W-DAQ. All components were combined on a PCB and connected to the chest belt using wires. Fig. 1 shows the chest belt with the W-DAQ.

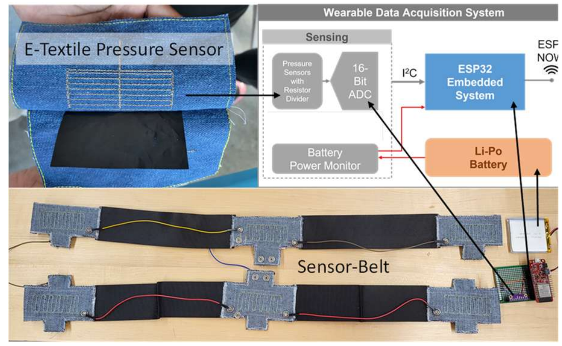

Figure 1: Overview of the RespWear System

Wireless data acquisition was performed over the ESP-Now, a 2.4GHz protocol. A laptop running Windows 10 was used to collect data wirelessly. The CoolTerm program was used to log the data to a CSV file.

III. EXPERIMENT AND METHODS

A. *Participants*

We recruited four participants (2 female and 2 male, average age = 27.2y) for this study. Females used the small size belt and males used the large size. Signed and informed consent was collected from participants. The study protocol was approved by the University of Rhode Island Institutional Review Board (protocol #1785106-6).

B. *Setup and Procedure*

The chest belt was placed on the participants' chest and adjusted according to different body sizes. In addition, OptiTrack marker-based motion capture was used as the ground truth for measuring the precise movement of different points on the chest associated with breathing. The OptiTrack motion tracking system used in this study acquires live video streams at 100 frames per second from multiple infrared cameras with IR LED light source. Reflective markers were placed on the belt, next to the sensors. Synchronization between the chest belt sensors and OptiTrack system is enabled through the use of the External Device Sync connector. The data from IR cameras and our system were captured in an interrupt-triggered time-synchronized manner.

The chest-belt sizes were determined according to the measurements taken from different people. Participants were asked to perform standing, sitting, and bending postures in between the camera setup as shown in Fig. 2. The experimental protocol is summarized in Table 1.

IV. RESULTS AND DISCUSSION

We aimed to validate the performance of the RespWear system. For this, we collected data from RespWear and the gold standard, OptiTrack, system in a time-synchronized manner. We present our comparative analysis of the data collected using these systems in this section.

Gozde Cay was supported by the Turkish Ministry of National Education during her PhD.

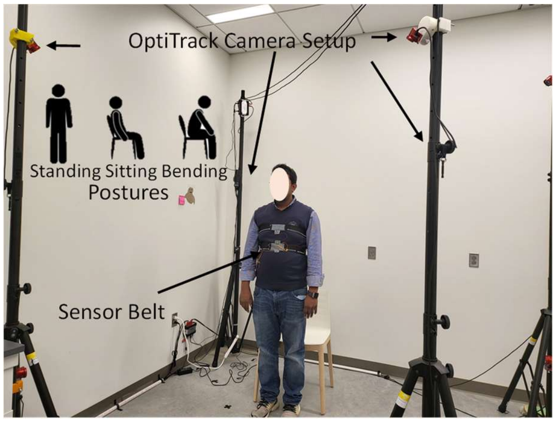

Figure 2: Experimental Setup

Table 1: Experimental Protocol

Section	Breathing Type	Number of Breaths	Duration (seconds)
Standing	Deep breath	10	~45
	Normal breath	10	~35
	Fast breathe	10	~15
Sitting	Deep breathe	10	~45
	Normal breath	10	~35
	Fast breathe	10	~15
Bending	Deep breathe	10	~45

A. Characterization of the Pressure Sensors

To analyze the breathing, the raw data coming from the pressure sensors were filtered using a bandpass filter (0.1-0.35 Hz). Subsequently, we applied a peak detection algorithm over the filtered data. We computed the time interval (T) between each peak (created by the breathing event) and computed the respiration rate (RR). Fig. 3 shows the raw and filtered signals collected from the belt. It is seen that the breathing amplitude and the time difference between the peaks decreased when the breathing rate increased. Since fast breathing happens promptly, the magnitude of expansion and contraction of the chest becomes condensed and causes a decrement in the breathing amplitude. The breathing amplitude change shows that our sensors can capture those small changes.

B. Validation of the Sensor Belt with the Benchmark System

To validate our sensor belt system, we compared the data acquired using the sensor belt with the OptiTrack IR cameras. We computed the correlation coefficient between the movement-related data captured by the sensor belt and the OptiTrack system. We observed an excellent agreement (r-value=>0.9) between the data collected by these two systems.

We further investigated the data to understand the agreement between the breathing rate extracted using the sensor belt data and the breathing rate extracted using the OptiTrack data. Here, we found that there was an excellent agreement (r-value = 0.836) between the respiration rate recorded using our system and the respiration rate recorded using the OptiTrack camera system at almost zero lag position which shows that there was a good time synchronization between systems.

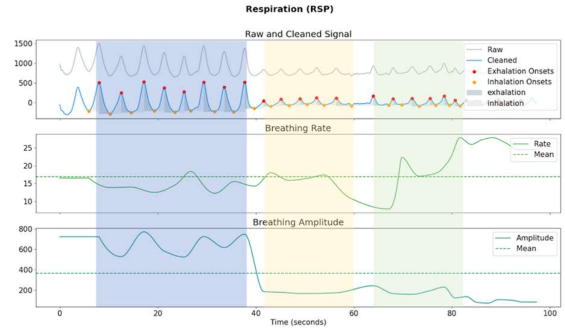

Figure 3: Raw data, filtered data, breathing rate, and breathing amplitude of the data collected using the sensor belt during standing
Note: Blue Highlights Deep Breathing; Yellow Highlights Normal Breathing; Green Highlights Fast Breathing

Table 2: Mean Absolute Error between breathing recorded using RespWear and OptiTrack System
Note: DB: Deep Breathing; NB: Normal Breathing; FB: Fast Breathing; AVG: Average; STD: Standard Deviation

Posture	**Standing**			**Sitting**			**Bending**
Breathing	**DB**	**NB**	**FB**	**DB**	**NB**	**FB**	**DB**
P1	0.05	0.61	0.18	1.66	0.84	0.95	0.21
P2	0.46	0.65	0.86	0.05	5.29	0.94	9.25
P3	0.05	2.65	0.67	0.06	0.76	0.79	1.21
P4	0.30	0.96	0.66	0.69	0.91	1.85	2.87
AVG	0.21	1.22	0.50	0.59	1.95	0.20	3.38
STD	0.20	0.97	0.46	0.79	2.23	1.37	4.06

C. Different Postures and Accuracy of the System

We also wanted to understand the effects of different pastures on the breathing rate measured by our system. We computed the mean absolute error (MAE) in the measurement of respiration rate done using our system and the OptiTrack data. Table 2 shows the MAE for each participant in different positions. It was seen that there were missing data points for the sitting and bending postures in the OptiTrack data particularly when the line of sight of the cameras was obstructed by the posture. This situation caused an increase in the MAE for the respiration rate for sitting and bending postures.

V. CONCLUSION

In this paper, we presented a wireless, smart textile-based respiration monitoring system called RespWear. We developed textile-based sensors, a sensor belt and a wearable data acquisition system. We used the OptiTrack camera system as a benchmark to validate our system. To evaluate the performance of RespWear, we recruited 4 participants. Our findings showed that RespWear can sense the different respiration rates (even in different postures) accurately. This shows the potential of RespWear to be a reliable candidate for monitoring respiration and related applications such as pulmonary rehabilitation, COVID rehabilitation, or apnea monitoring in real-life settings. In the future, we would like to conduct experiments with more participants and do a detailed analysis to evaluate the performance of RespWear. Also, we would like to explore different benchmarking methods to avoid line-of-sight issues posed by cameras.

ACKNOWLEDGMENT

The authors would like to thank all the participants and National Science Foundation (Award #2139724).

REFERENCES

[1] Milenković, A., Otto, C., & Jovanov, E. (2006). Wireless sensor networks for personal health monitoring: Issues and an implementation. Computer Communications, 29(13), 2521–2533. https://doi.org/https://doi.org/10.1016/j.comcom.2006.02.011

[2] Subbe, C. P., & Kinsella, S. (2018). Continuous monitoring of respiratory rate in emergency admissions: evaluation of the RespiraSenseTM sensor in acute care compared to the industry standard and gold standard. Sensors, 18(8), 2700.

[3] Yang, X., Chen, Z., Elvin, C. S. M., Janice, L. H. Y., Ng, S. H., Teo, J. T., & Wu, R. (2014). Textile fiber optic microbend sensor used for heartbeat and respiration monitoring. IEEE Sensors Journal, 15(2), 757–761.

[4] Cay, G., Ravichandran, V., Saikia, M. J., Hoffman, L., Laptook, A., Padbury, J., Salisbury, A. L., Gitelson-Kahn, A., Venkatasubramanian, K., & Shahriari, Y. (2021). An E-Textile Respiration Sensing System for NICU Monitoring: Design and Validation. Journal of Signal Processing Systems, 1–15.

[5] Granato, M. (2019). Emotions Recognition in Video Game Players Using Physiological Information.

[6] Homma, I., & Masaoka, Y. (2008). Breathing rhythms and emotions. Experimental Physiology, 93(9), 1011–1021.

[7] Kowalczuk, Z., Czubenko, M., & Merta, T. (2019). Emotion monitoring system for drivers. IFAC-PapersOnLine, 52(8), 200–205.

[8] Liu, X., Wang, Q., Liu, D., Wang, Y., Zhang, Y., Bai, O., & Sun, J. (2018). Human emotion classification based on multiple physiological signals by wearable system. Technology and Health Care, 26(S1), 459–469.

[9] Zamoscik, V. E. (2018). Back to the roots: the role of sensory sensitivity and respiration pattern variability in mental health.

[10] Ćosić, D. (2016). Neuromarketing in market research. Interdisciplinary Description of Complex Systems: INDECS, 14(2), 139–147.

[11] Czub, M., & Kowal, M. (2019). Respiration entrainment in virtual reality by using a breathing avatar. Cyberpsychology, Behavior, and Social Networking, 22(7), 494–499.

[12] Moorthy, K., Smith, S., Brown, T., Bann, S., & Darzi, A. (2003). Evaluation of virtual reality bronchoscopy as a learning and assessment tool. Respiration, 70(2), 195–199.

[13] Rajeswaran, P., Hung, N.-T., Kesavadas, T., Vozenilek, J., & Kumar, P. (2018). AirwayVR: learning endotracheal intubation in virtual reality. 2018 IEEE Conference on Virtual Reality and 3D User Interfaces (VR), 669–670.

[14] Tinga, A. M., de Back, T. T., & Louwerse, M. M. (2020). Neurophysiological changes in visuomotor sequence learning provide insight in general learning processes: Measures of brain activity, skin conductance, heart rate and respiration. International Journal of Psychophysiology, 151, 40–48.

[15] Sperlich, B., Aminian, K., Düking, P., & Holmberg, H.-C. (2020). Wearable Sensor Technology for Monitoring Training Load and Health in the Athletic Population. Frontiers in Physiology, 10, 1520.

[16] Corbishley, P., & Rodriguez-Villegas, E. (2007). Breathing detection: towards a miniaturized, wearable, battery-operated monitoring system. IEEE Transactions on Biomedical Engineering, 55(1), 196–204.

[17] Shneerson, J. M. (2009). Sleep medicine: a guide to sleep and its disorders. John Wiley & Sons.

[18] Werthammer, J., Krasner, J., DiBenedetto, J., & Stark, A. R. (1983). Apnea monitoring by acoustic detection of airflow. Pediatrics, 71(1), 53–55.

[19] Folke, M., Granstedt, F., Hök, B., & Scheer, H. (2002). Comparative provocation test of respiratory monitoring methods. Journal of Clinical Monitoring and Computing, 17(2), 97–103.

[20] Lee-Chiong, T. L. (2005). Sleep: a comprehensive handbook. John Wiley & Sons.

[21] Storck, K., Karlsson, M., Ask, P., & Loyd, D. (1996). Heat transfer evaluation of the nasal thermistor technique. IEEE Transactions on Bio-Medical Engineering, 43(12), 1187–1191. https://doi.org/10.1109/10.544342

[22] Tobin, M. J. (1988). Respiratory monitoring in the intensive care unit12. Amer. Rev. Respiratory Disease, 138(6), 1625–1642.

[23] Mayer, O. H., Clayton Sr, R. G., Jawad, A. F., McDonough, J. M., & Allen, J. L. (2003). Respiratory inductance plethysmography in healthy 3-to 5-year-old children. Chest, 124(5), 1812–1819.

[24] Nepal, K., Biegeleisen, E., & Ning, T. (2002). Apnea detection and respiration rate estimation through parametric modelling. Proceedings of the IEEE 28th Annual Northeast Bioengineering Conference (IEEE Cat. No.02CH37342), 277–278.

[25] Prisk, G. K., Hammer, J., & Newth, C. J. L. (2002). Techniques for measurement of thoracoabdominal asynchrony. Pediatric Pulmonology, 34(6), 462–472.

[26] Strömberg, N. O. T., & Nelson, N. (1998). Thoracoabdominal asynchrony in small children with lung disease–methodological aspects and the relationship to lung mechanics. Clinical Physiology, 18(5), 447–456.

[27] Leonard, P., Beattie, T. F., Addison, P. S., & Watson, J. N. (2003). Standard pulse oximeters can be used to monitor respiratory rate. Emergency Medicine Journal, 20(6), 524–525.

[28] Wertheim, D., Olden, C., Savage, E., & Seddon, P. (2009). Extracting respiratory data from pulse oximeter plethysmogram traces in newborn infants. Archives of Disease in Childhood. Fetal and Neonatal Edition, 94(4), F301-3. https://doi.org/10.1136/adc.2008.145342

[29] Dingab, S., Zhua, X., Chena, W., & Weia, D. (2004). Derivation of respiratory signal from single channel ECGs based on source statistics. Intl Journal of Bioelectromagnetism, 6(2), 43–49.

[30] Mazzanti, B., Lamberti, C., & De Bie, J. (2003). Validation of an ECG-derived respiration monitoring method. Computers in Cardiology, 2003, 613–616.

[31] Moody, G. B., Mark, R. G., Bump, M. A., Weinstein, J. S., Berman, A. D., Mietus, J. E., & Goldberger, A. L. (1986). Clinical validation of the ECG-derived respiration (EDR) technique. Computers in Cardiology, 13(1), 507–510.

[32] O'Brien, C., & Heneghan, C. (2007). A comparison of algorithms for estimation of a respiratory signal from the surface electrocardiogram. Computers in Biology and Medicine, 37(3), 305–314.

[33] Tarassenko, L., Mason, L., & Townsend, N. (2002). Multi-sensor fusion for robust computation of breathing rate. Electronics Letters, 38(22), 1314–1316.

[34] Nakajima, K., Matsumoto, Y., & Tamura, T. (2001). Development of real-time image sequence analysis for evaluating posture change and respiratory rate of a subject in bed. Physiological Measurement, 22(3), N21.

[35] Tan, K. S., Saatchi, R., Elphick, H., & Burke, D. (2010). Real-time vision based respiration monitoring system. 2010 7th International Symposium on Communication Systems, Networks & Digital Signal Processing (CSNDSP 2010), 770–774.

[36] Zakrzewski, M., Raittinen, H., & Vanhala, J. (2011). Comparison of center estimation algorithms for heart and respiration monitoring with microwave Doppler radar. IEEE Sensors Journal, 12(3), 627–634.

[37] Al-Khalidi, F. Q., Saatchi, R., Burke, D., & Elphick, H. (2010a). Facial tracking method for noncontact respiration rate monitoring. 2010 7th International Symposium on Communication Systems, Networks & Digital Signal Processing (CSNDSP 2010), 751–754.

[38] Chekmenev, S. Y., Rara, H., & Farag, A. A. (2005). Non-contact, wavelet-based measurement of vital signs using thermal imaging. The First International Conference on Graphics, Vision, and Image Processing (GVIP), Cairo, Egypt, 107–112.

[39] Hsu, C.-H., & Chow, J. C. (2005). Design and clinic monitoring of a newly developed non-attached infant apnea monitor. Biomedical Engineering: Applications, Basis and Communications, 17(03), 126–134.

[40] Zhu, Z., Fei, J., & Pavlidis, I. (2005). Tracking human breath in infrared imaging. Fifth IEEE Symposium on Bioinformatics and Bioengineering (BIBE'05), 227–231.

[41] Al-Khalidi, F., Saatchi, R., Elphick, H., & Burke, D. (2011). An evaluation of thermal imaging based respiration rate monitoring in children. American Journal of Engineering and Applied Sciences, 4(4),586–597.