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Machine-learning enabled wireless wearable sensors to study individuality of respiratory behaviors

Ang Chen [a,*], Jianwei Zhang [a], Liangkai Zhao [b], Rachel Diane Rhoades [a], Dong-Yun Kim [c,d], Ning Wu [b], Jianming Liang [e], Junseok Chae [a]

[a] School of Electrical, Computer, and Energy Engineering, Arizona State University, Tempe, AZ, 85281, USA
[b] College of Electrical and Information Engineering, Nanjing University of Aeronautics and Astronautics, Nanjing, 210016, China
[c] National Heart, Lung and Blood Institute, National Institutes of Health, Bethesda, MD, 20892, USA
[d] School of Nursing and Health Studies, Georgetown University, Washington, DC, 20007, USA
[e] College of Health Solutions, Arizona State University, Tempe, AZ, 85281, USA

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ABSTRACT

Respiratory behaviors provide useful measures of lung health. The current methods have limited capabilities of continuous characterization of respiratory behaviors, often required to assess respiratory disorders and diseases. This work presents a system equipped with a machine learning algorithm, capable of continuously monitoring respiratory behaviors. The system, consisting of two wireless wearable sensors, accurately extracts and classifies the features of respiratory behaviors of subjects within various postures, wirelessly transmitting the temporal respiratory behaviors to a laptop. The sensors were attached on the midway of the xiphoid process and the costal margin, and 1 cm above the umbilicus, respectively. The wireless wearable sensor, consisting of ultrasound emitter, ultrasound receiver, data acquisition and wireless transmitter, has a small footprint and light weight. The sensors correlate the mechanical strain at wearing sites to lung volume by measuring the local circumference changes of the chest and abdominal walls simultaneously. Eleven subjects were recruited to evaluate the wireless wearable sensors. Three different random forest classifiers, including generic, individual, and weighted-adaptive classifiers, were used to process the wireless data of the subjects at four different postures. The results demonstrate the respiratory behaviors are individual- and posture-dependent. The generic classifier merely reaches the accuracy of classifying postures of 21.9 ± 1.7% while individual and weighted-adaptive classifiers mark substantially high, up to 98.9 ± 0.6% and 98.8 ± 0.6%, respectively. The accurate monitoring of respiratory behaviors can track the progression of respiratory disorders and diseases, including chronic respiratory obstructive disease (COPD), asthma, apnea, and others for timely and objective approaches for control.

1. Introduction

Respiratory disorders and diseases, a significant worldwide health challenge, are responsible for more than 10% of all disability-adjusted life year (DALYs): a metric used in public health and health impact assessment that estimates the number of years of healthy life lost due to ill-health, disability or early death (Havelaar 2007; WorldHealthOrganization). Mortality, disability, and morbidity caused by respiratory diseases, which are second only to cardiovascular diseases (Kassebaum et al., 2016), imposed immense economic costs and health burden all over the world. Among respiratory diseases, chronic obstructive pulmonary disease (COPD) and asthma predominantly contribute to the burden. An estimated 65 million people have moderate to severe COPD, of which about 3 million die each year, making it the third leading cause of death worldwide, and the frequency of the disease remains increasing trajectory (Burney et al., 2015). About 334 million people have asthma (The Global Asthma Report, 2018), which is the most common chronic disease of childhood, affecting 14% of children globally. The prevalence of asthma in children keeps rising (Pearce et al., 2007). Alternatively, sleep-disordered breathing is a less well-quantified respiratory disorder, and more than 100 million people are suffering from it.

Characteristics of respiratory disorders and diseases suggest continuous monitoring of respiratory behaviors benefit patients. COPD and asthma, the two most common respiratory diseases, are characterized by

* Corresponding author.
E-mail address: achen29@asu.edu (A. Chen).

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airway inflammation, which causes breathlessness in terms of an extrinsic failure of the chest wall to obtain and maintain sufficient lung volume. However, symptoms of the changeability on COPD and asthma have been studied and described as time-dependent, even over one day (Kessler et al., 2011), thus it is challenging to generalize the characteristics of respiratory behaviors. The diagnosis of respiratory diseases is based on the history of patients, symptoms, and the outcome of attempted therapies. Therefore, the continuous monitoring of the respiratory behaviors offers valuable information to the pre-diagnosis by extracting the clinically relevant parameters to describe the progression of the respiratory condition of patients.

Respiration, as a physiological activity, is a systematic result of the nonlinear motion of the chest wall and the diaphragm, corresponding to the chest respiration and abdominal respiration, respectively. During inspiration, the expansion of the chest wall and the contraction of the diaphragm pull air into the lung. With further movement of the diaphragm, the content in the abdomen was pulled outward increasing the circumference of the abdominal wall; whereas in expiration, the chest wall and diaphragm relax and passively restore to their anatomic positions which pushes air out of the lung resulting in the circumferences of the chest and abdominal walls to decrease.

Several research groups have reported various respiration monitoring methods. For example, bands with sensors embedded or fiber-optic based strain gauges around the chest wall were used to detect chest wall perimeter change caused by respiration (Krehel et al., 2014). Inertial sensors or polyvinylidene-fluoride (PVDF) polymer-based piezoelectric transducers that were directly attached to the human chest to detect the pulsatile vibration due to the respiration (Cesareo et al., 2018; Mahbub et al., 2017). In other studies, strain sensors made of different materials, including graphene (Park et al., 2015), carbon nanotubes (Liang et al., 2018), and carbonized silk fabric (Wang et al., 2016), were attached to the human chest to measure local strain realizing the respiration monitoring. However, all those methods fail to monitor systematic breathing motion and are limited to produce respiratory rate, which has minimal clinical value (Folke et al., 2003). Optoelectronic plethysmography (OEP) offers readily available clinically valid information of respiratory monitoring, yet requires multiple external cameras to monitor the location of markers on the body to evaluate the respiration (Massaroni et al., 2017). Inertial measurement unit (IMU) and strain sensors were attached on abdomen and chest to monitor respiratory behaviors simultaneously when the subjects are in a standing posture (Chu et al., 2019; Elfaramawy et al., 2019); however, the non-optimal wear-ability or/and the potential monitoring failure caused by inductance plethysmography (RIP) belt slippage as well as the respiratory monitoring in a single posture may not be realistic or helpful for continuous monitoring. Unique skin-mounted soft electronics were recently reported to detect the human motions toward motion recognition (Jeong et al., 2017; Lee et al., 2020). Our wireless sensor is a stand-alone system, with no need for any specific external settings, thus allowing ubiquitous respiratory monitoring, e.g., home.

Postures have a non-negligible influence on respiratory behaviors. The body postures affect the anatomical dimensions of the upper airway, which may become impaired in specific postures. Particularly during sleep with a lower consciousness, the collapsibility of upper airways has been identified as an important pathogenic factor in obstructive sleep apnea (OSA) (Penzel et al., 2001; Pevernagie et al., 1995; Safar et al., 1959). Further, respiratory behaviors are a function of the differences in the anatomy of the abdominal muscles and the influence of gravity caused by postures change (Kera and Maruyama 2005). Posture-related instability of the human airway and anatomy structures may have serious medical implications, yet few reports exist on a wearable respiratory monitoring system to analyze respiratory behaviors features of individuals at various postures, contributing meaningful, relevant clinical values.

This work presents a stand-alone wireless sensors system, equipped with a machine learning algorithm, that offers continuous measurement of respiratory behaviors. The system extracts and classifies key features of respiratory behaviors of individuals at different postures to study individual- and posture-dependent respiratory behaviors.

2. Material and method

2.1. •Wireless wearable sensor

The localized circumference changes of the chest and abdominal walls are the external appearance of the respiration and can effectively emulate the lung volume change during respiration (Cantineau et al., 1992; Collop et al., 2007; Farre et al., 2004; Konno and Mead 1967). We used two wireless wearable sensors: one (Sensor1) was placed 1 cm above the umbilicus for abdominal respiration (Cohen et al., 1997), and the other one (Sensor2) was placed on the midway between the xiphoid process and the costal margin for chest respiration, as shown in Fig. 1A, which has been validated by our previous work (Chen et al., 2019).

The wireless wearable sensor is composed of an emitter to radiate ultrasound and a receiver to receive the distance-elapsed attenuated ultrasound. The two parts of the wearable sensor move further apart during the inspiration due to the increase in the circumference of the chest and abdominal walls, which results in a more attenuated ultrasound signal. In contrast, during expiration, the two parts move closer, resulting in a stronger received ultrasound signal. To generate ultrasound, a non-polarized pulse stimulatory signal at 50 kHz is applied across the PVDF film. The respiratory signal modulates the emitted ultrasound carrier, which is received by another PVDF receiver that converts the mechanical signal to an electrical signal. After demodulation and amplification, the respiratory signal is extracted by an envelope detector, and the onboard Bluetooth module (MDBT40Q) wirelessly transmits the digitized respiratory signal to an external machine for data analysis, e.g., a laptop, that had custom-made data collecting program (Fig. S1, the interface of tailor-made data collecting program). Fig. 1A illustrates a simplified process, while more details of electronics and schematic used in the wearable sensor follow in the supplementary material (Fig. S2). The wearable sensor was fabricated on a flexible 0.1 mm-thick polyimide substrate (PCBWay), as shown in Fig. 1B. The wearable sensor occupied $55.6 \times 30.7 \times 3$ mm^3 and weighed 5.5 g, including two 1.6 g button cell batteries. Fig. 1C shows a simplified conceptual process.

2.2. •Study design

We recruited eleven subjects to attach the wireless wearable sensors on the midway between the xiphoid process and the costal margin, corresponding to the abdomen-apposed rib cage, and 1 cm above the umbilicus to collect respiratory behaviors within four postures. All participants provided informed consent, and this study was approved by the Arizona State University (ASU) Institutional Review Board (IRB).

Eligibility, inclusion, and exclusion criteria for subject recruitment: convenience sample from healthy adults (18 years or older) who responded to the recruitment flyer. Subjects who smoke or have a family history of respiratory diseases were excluded from the study. In total, eleven subjects were included in the study.

For each subject, the signals coming from the two wireless wearable sensors were organized into a series of segmented, Gaussian-filtered data with a moving window size of 100 data points, with the sliding scale of 20 data points. This data transformation was separately performed for the raw data stream received from two wearable sensors on the chest and abdomen and repeated for the four postures. From each data segment, summary features, i.e., mean and variance, filtered data themselves, the first and second differential of the data, and the wavelet coefficients were extracted.

Characterized by its ability to reduce overfitting problems and rank the importance of variables in classification naturally, the random forest classifier has been widely used in machine-learning applications. It is an

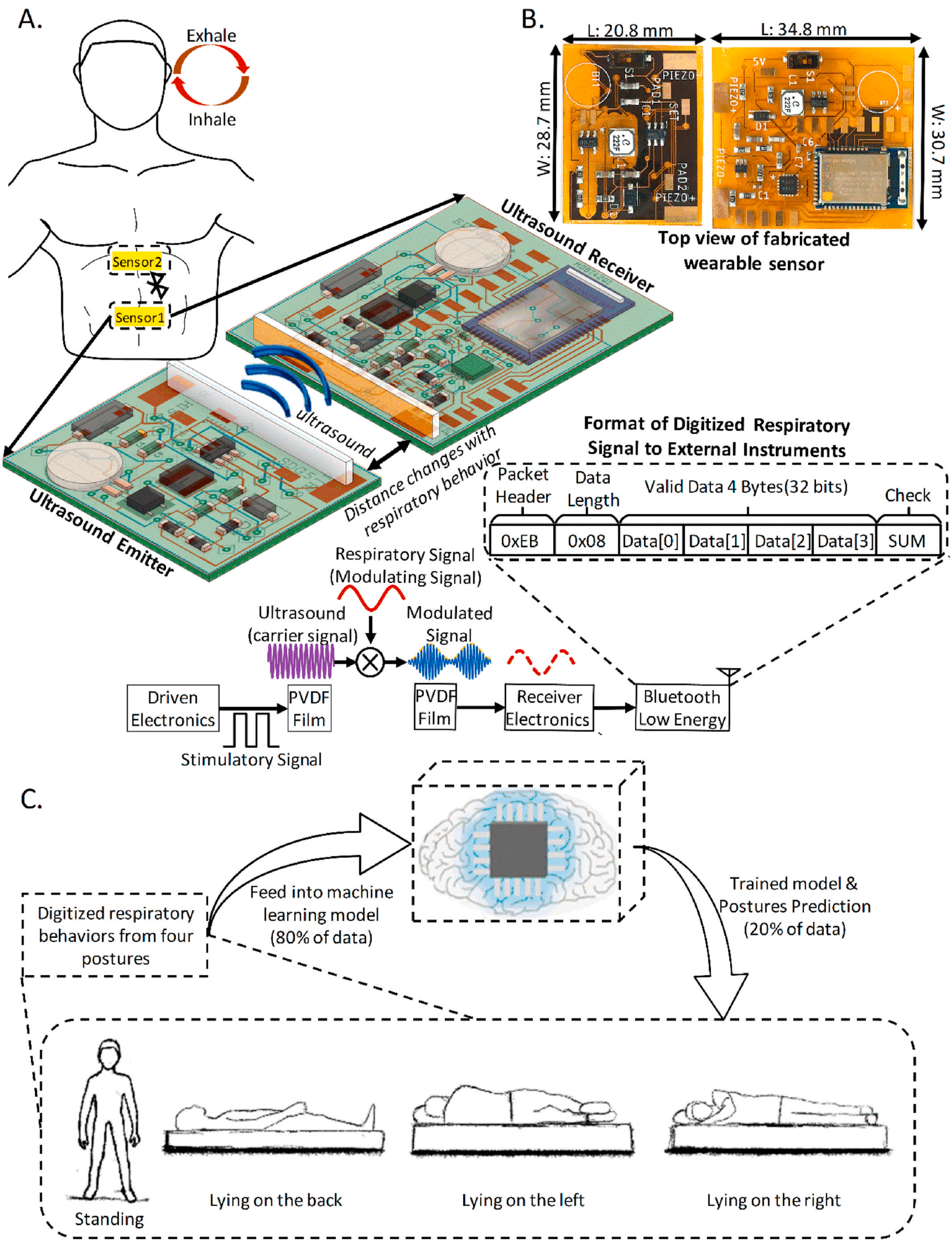

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Fig. 1. (A) Wireless wearable sensors attached on the midway of the xiphoid process and the costal margin, one on each location, corresponding to the abdomen-apposed rib cage, and 1 cm above the umbilicus, respectively. The wearable sensors convert the local strain, by measuring the attenuation in ultrasound as a function of the distance between the emitter and the receiver, to lung volume. The respiratory behaviors signal was amplified and extracted by onboard electronics and wirelessly transmitted to an external machine. (B) Photo of the top view of the fabricated wireless wearable sensor on a flexible polyimide substrate with a footprint of 30.7 × 55.6 × 3 mm^3. (C) Respiratory behaviors data collected from four postures of subjects were fed into a machine learning algorithm. Among the data, 80% were used to train the random forest classifier, and the remaining 20% was used to be the test dataset to predict the respiratory postures based on the extracted features.

algorithm for classification based on the bagging algorithm and uses an ensemble learning technique. We used the random forest classifier in the sci-kit-learn package (Python 3.6) and determined 200 decision trees in the finalized random forest classifier. To build a prediction classifier for the subject posture, the feature sets, subject posture information, and other relevant information were entered into a random forest classifier. In general, the training/test set was split into an 80/20 ratio, using 80% of data for training and 20% for testing. The classifier produced multinomial probability models for the four postures. The posture assigned with the highest probability was selected as the predicted value and compared against the actual posture. The proportion of the correct classification was calculated for each run to assess the performance of the random forest classifier.

We constructed three separate prediction classifiers: the generic, individual, and the weighted-adaptive classifiers. For the generic classifier, the entirety of the feature sets from a small number of subjects at a time was used to construct the classifier and used to predict the outcome of the subject not included in the classifier building step. The predicted

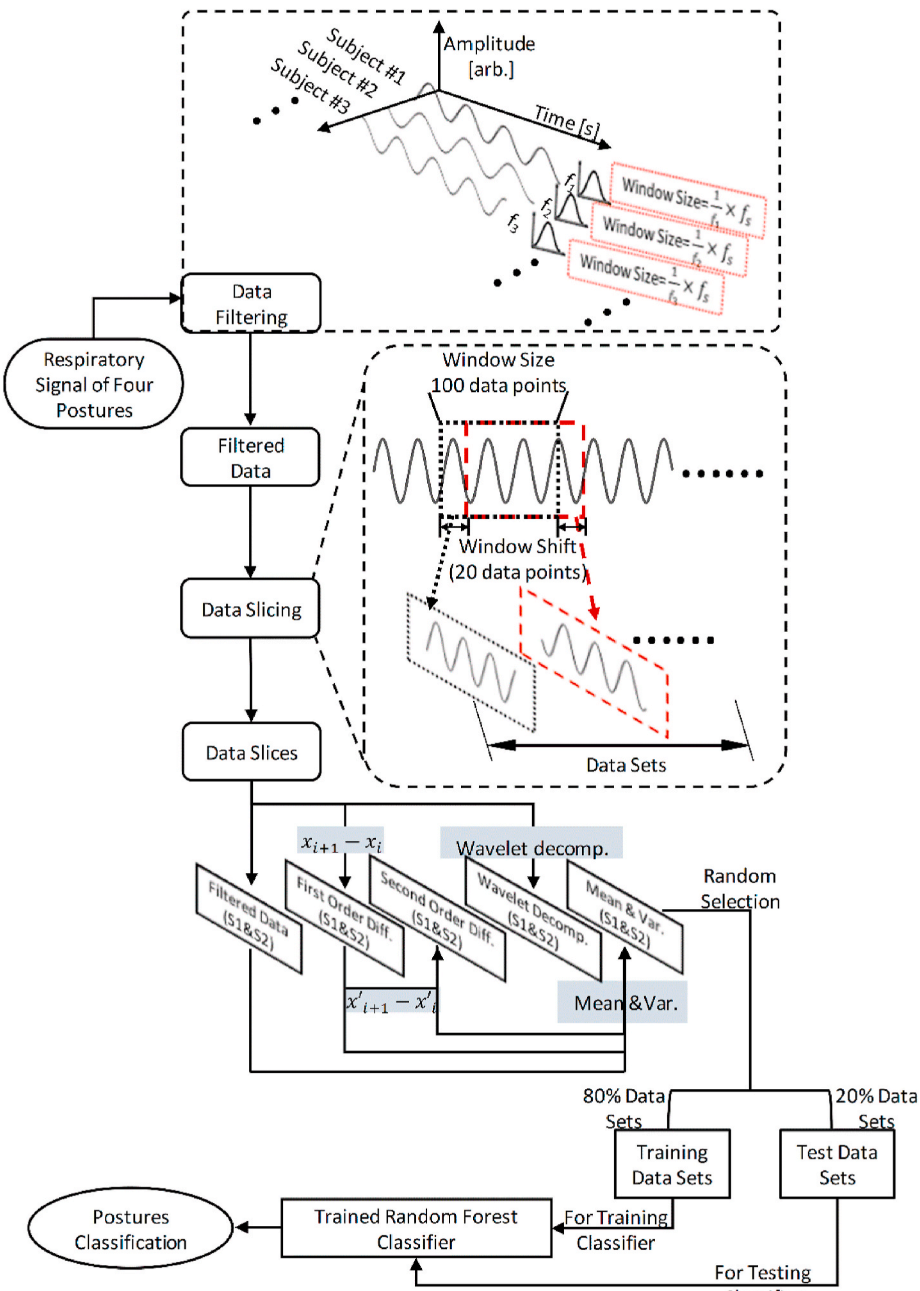

Fig. 2. Machine learning algorithm process flow. Respiratory signals collected from subjects using two wireless wearable sensors were fed into the Gaussian filters with respiratory rate-dependent windows size. After filtering, respiration signals were sliced by a 100 data points wide window. The slicing window shifts with a step of 20 data points resulting in 300 slices for a given posture and 1200 slices in total for four postures per individual. Upon the preparation of the data sets, 80% of them were used to train the random forest classifier, and 20% were used to test the classifier. Features extraction were performed in the following order: filtered respiration signal (Sensor1 or/and Sensor2), fist order differential (Sensor1 or/and Sensor2), second-order differential (Sensor1 or/and Sensor2), mean values with variances (Sensor1 or/and Sensor2). Resulting features of training data sets (80% of data) were used to train the random forest classifiers, followed by accuracy testing using the well-built random forest classifier on the remaining test data sets (20% of data), resulting in the final prediction of respiratory behaviors posture.

values were compared against the actual subject postures. The performance of the generic classifier was assessed across all 120 possible combinations that arise from choosing three subjects out of ten (excluding one subject for test purpose). For the individual classifier, it was applied separately for each subject, using only the feature sets and/or sensors relevant to the particular subject. This created multiple prediction classifiers for each subject. The overall classification performance was assessed by computing the average performance across the individual prediction outcomes. We also considered a weighted-adaptive classifier that is a weighted probability of the multinomial probabilities from the generic and individual classifiers to explore how to keep accuracy and improve applicability. We used the randomly resampled data from the same individual to construct the equal number of predictive multinomial distributions from random forest classifier to compute weighted probabilities of finding the final predicted accuracy.

2.3. •*Respiratory behaviors collecting protocol*

Eleven subjects were included in this study. To better illustrate the respiratory behaviors, subjects were tested in quiet breathing (Stedman 2006). Each subject wearing two wireless wearable sensors attached to selected locations performed quiet breathing on the following four postures: standing, lying on the back, lying on the left, and lying on the right.

2.4. •*Three cases to monitor respiratory behaviors*

For a given posture, we collected 10 min of respiratory behaviors wirelessly using two wearable sensors with a sampling frequency of 10 Hz. A healthy adult has a respiratory rate within the range of 12–18 respiratory cycles per minute (Ganong 1995), corresponding to 30 to 50 data points per respiratory cycle at a sampling frequency of 10 Hz. This repetitive nature becomes very attractive to train machine learning algorithms. We evaluated the efficacy of the use of one or/and two wearable sensors in postures classification by using machine learning algorithms. Three cases: the abdominal respiration only (Sensor1), the chest respiration only (Sensor2), and both the abdominal and chest respiration (Sensor1 & Sensor2). Fig. 2 shows the process flow of the collected data. It started with the Gaussian window filtering data with respiratory rate-dependent window size (more details of the Gaussian filter window size are in supplementary material, S-Page 5). This was followed by the data slicing using a window size of 100 data points, approximately covering two respiratory periods. With a sliding scale of 20 data points, we obtained 300 slices at one given posture and 1200 slices in total for four postures per subject. The processed data were used to extract multiple features, including mean and variance, filtered data themselves, the first and second differential of the data, and the wavelet decompositions. 80% of features were chronologically selected for training the random forest classifier, and the remaining 20% were used as test data for evaluating the trained classifier.

3. Results and discussion

3.1. • *Wireless acquisition of respiratory signals using the wireless sensor system*

Subject A, abdominal breather, wearing the wireless sensor in standing posture, performed the quiet breathing. Sensor1 (abdominal respiration) produces lager amplitude change than Sensor2 (chest respiration) does for subject A (Fig. 3A): the abdominal respiration contributes more than the chest respiration. Subject B, chest breather, showed the opposite (Fig. 3B): a smaller amplitude change from Sensor1 than that from Sensor2, translating subject B has a primarily chest respiration. On the other hand, respiratory behaviors may change as a function of postures. During quiet breathing, Fig. 3C shows subject B is an abdominal breather when supine and a chest breather when upright (Sharp et al., 1975).

3.2. •*Verification of the wireless wearable sensor in a practical setting*

In our previous work (Chen et al., 2019), the wireless wearable sensor was tested on the surface of different curvatures, at different rotation angles, under different temperatures, and characterized by dynamic tests including walking and running with a speed of 1.2 and 2 m/s for 20 s. Besides, the wireless wearable sensor was tested as a function of relative humidity levels, in the range of 10%–50%, covering the human comfort zone of relative humidity levels in daily life, which is lower than 60% and higher than 25% (Fig. 3D) (Fincher and Boduch 2009). The amplitude of the sensor decreases as the humidity increases, as expected, as the attenuation of the ultrasound increases in the air (Raišutis et al., 2020). The amplitude of sensors changes as a function of humidity, yet the inhale/exhale cycle, e.g., average 15 times a minute, occurs significantly faster than humidity change of daily life. Thus, the wirelessly collected data may be treated insensitive to humidity change at the time of acquisition. The temporal outputs of Sensor1 and Sensor2 were collected simultaneously along with a spirometer (Pneumotrac Spirometer, Model 6800, Vitalograph Inc.), as shown in Fig. 3E, suggesting that the temporal data of the wireless sensor may be a great source in recognizing the features of respiratory behaviors.

3.3. •*Optimization of training time and window size*

The posture prediction accuracies of Sensor1, Sensor2, and two combined were evaluated as a function of training time (Fig. 4A), demonstrating a stable and accurate trained random forest classifier after 6 min, approximately 4800 data points. Fig. 4B illustrates the accuracies as a function of window sizes. The accuracies are rather independent of window sizes within 60–100 data points per window. We chose 100 data points per window to meet the tradeoff between the accuracies and a large number of data slices for training. The random forest classifier trained by the two sensors combined offer higher accuracy than that of Sensor1 or Sensor2 alone, regardless of the training time and window size, highly suggesting the data from two sensors monitor the respiratory behaviors more entirely and more accurately.

3.4. •*Wavelet decomposition analysis*

Fig. 4C shows the importance ranking of extracted respiratory features Sensor1 and Sensor2. The wavelet decomposition predominantly contributes to the final prediction in a random forest classifier. Feature importance rankings of abdominal respiration only (Sensor1), and chest respiration only (Sensor2) are in Supplementary Material Fig. S3. Featured by the strengths of the capability of analyzing transient, non-stationary signals, like respiratory signals (Wang and Veluvolu 2017) as well as time-frequency analysis (Keissar et al., 2009), the wavelet decomposition shows strong relevance in both time and frequency domains for extracting more details of respiratory features for classifier training.

3.5. •*Three random forest classifiers*

We developed and evaluated three random forest classifiers, including generic, individual, and weighted-adaptive classifiers, to study the individuality of the respiratory behaviors of eleven subjects.

The generic classifier offers a one-fits-all classifier to extract the common characteristics of subjects. We built the generic classifier of three, five, seven, and nine subjects, and the prediction accuracies decrease as the number of subjects included in the classifier increases. Thus, the generic classifier of three subjects is chosen for the comparison throughout this work. More details are shown in supplementary material (Fig. S4). The generic classifier executed all possible 120 combinations,

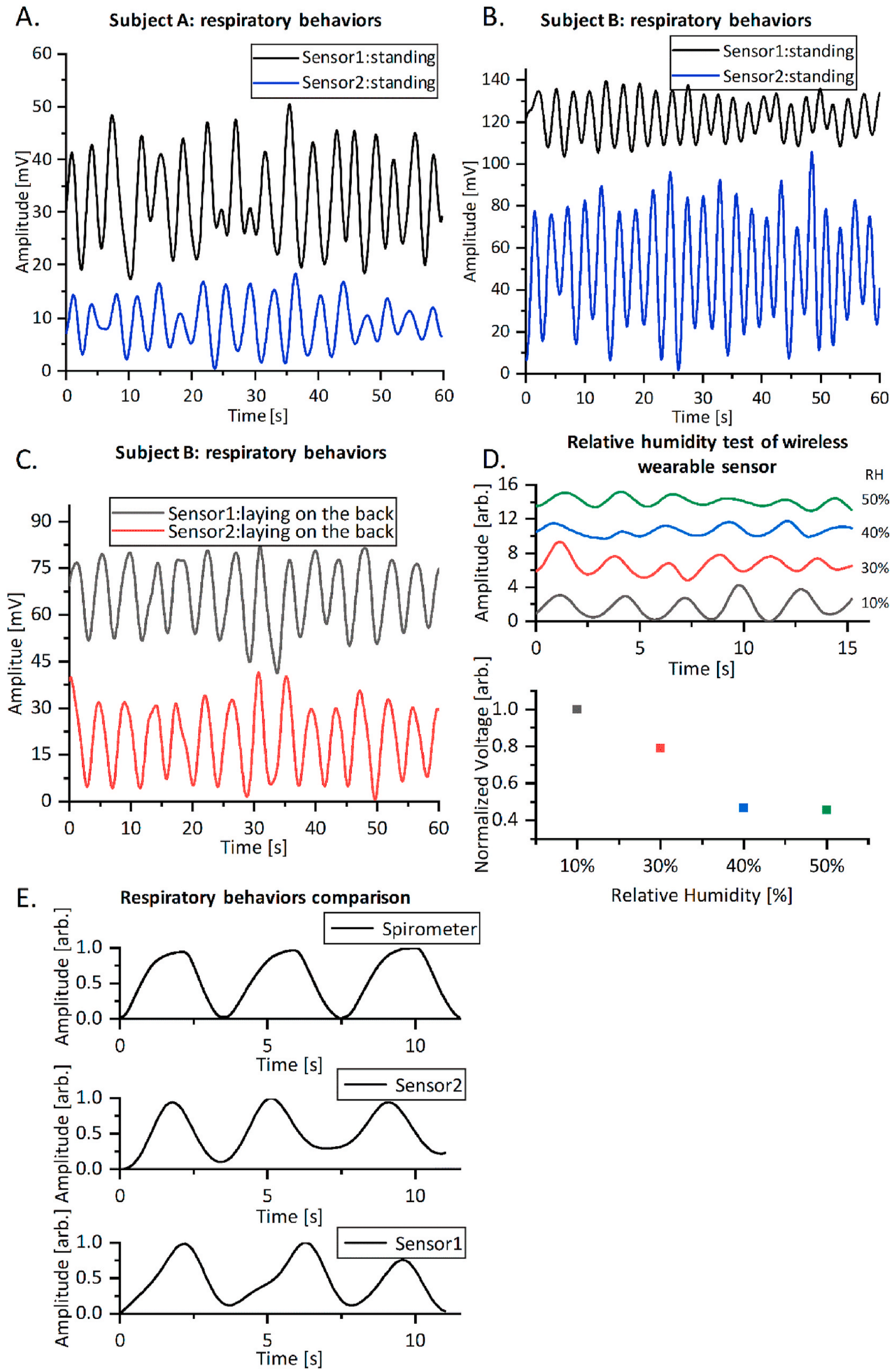

Fig. 3. (A) Temporal data collected from the abdominal (Sensor1) and the chest (Sensor2) walls of subject A in standing posture, who is a primarily abdominal breather, and (B) those from subject B who is a primary chest breather. (C) data from subject B (chest breather) at a different posture (lying on the back). The amplitude change of Sensor1 is more significant than that of Sensor 2, suggesting subject B shows primarily abdominal respiration when lying on the back. (D) The relative humidity levels test of the wireless wearable sensor. With the relative, peak to peak amplitudes of the respiratory behaviors decrease when humidity increases from 10% to 50%, as expected due to the attenuation of ultrasound in the air as a function of humidity. (E) The comparison of the normalized respiratory behaviors collected by Sensor1, Sensor2, and Spirometer.

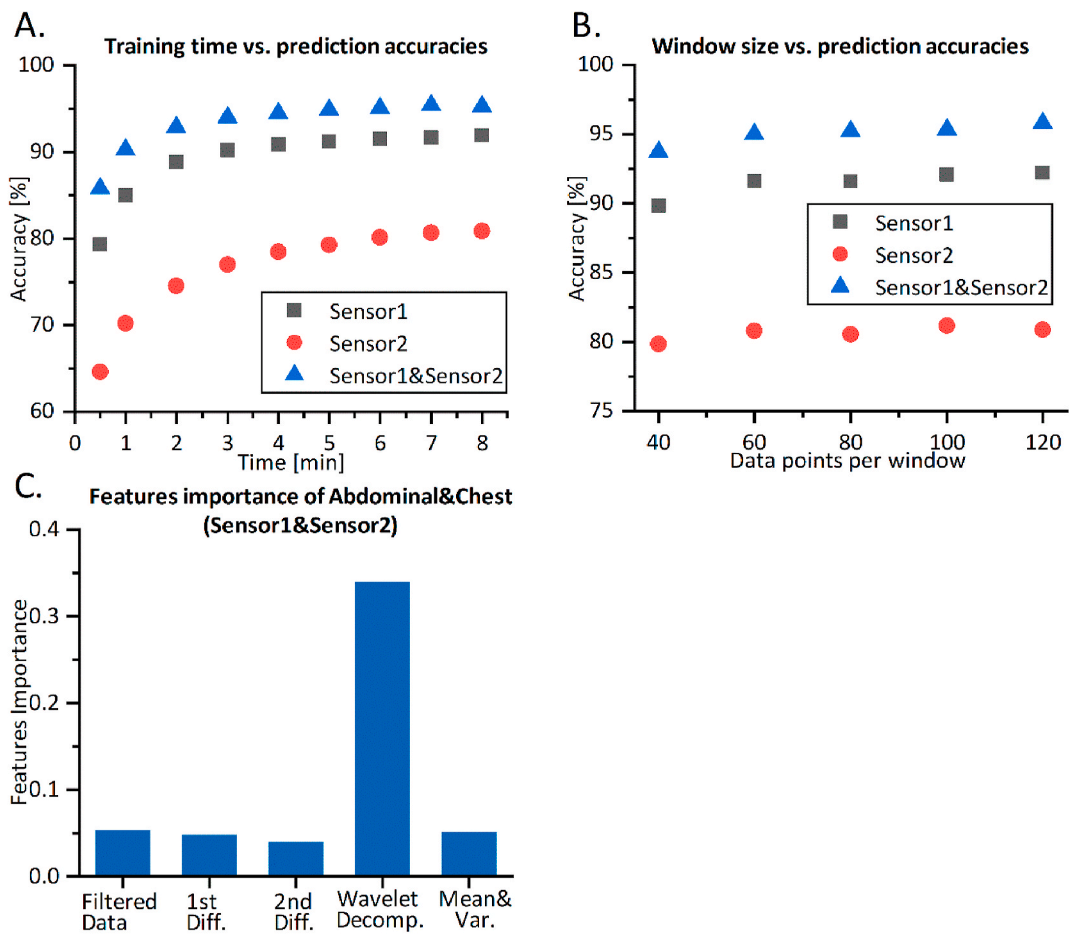

Fig. 4. (A) Training time optimization. The accuracy of two sensors combined mark higher than those of Sensor1 or Sensor2 alone. The accuracies saturate at 5–6 min of training, showing the efficacy of repetitive breathing data. (B) Selection of the width of the slicing window. The accuracies mark high at >60 data points per window. (C) The importance order of the extracted features used in the random forest classifiers. The wavelet decomposition dominates over other features, which has a good agreement with the non-stationary, transient, and non-linear characteristics of the respiratory behaviors.

$C_{10}^{3} = 120$ (three out of ten subjects (excluding one subject for testing purpose)). The accuracies of the generic classifier are poor, <40% (Fig. 5A), as expected, because of highly significant individuality in respiratory behaviors. Furthermore, the chest and the abdominal respiration are systematic, yet are different on extracted respiratory features due to the nonlinear motion of the chest and abdominal walls. These suggest the generic classifier may not be suitable to capture the various respiratory behaviors within four postures of subjects.

The individual classifier uses 80% data for training and 20% data for testing from each individual. The individual classifier marks significantly higher accuracies than those of the generic classifier 83.56 ± 2.15%, 63.35 ± 2.46%, and 99.53 ± 0.04%, respectively, on abdominal respiration only (Sensor1), chest respiration only (Sensor2) and from both abdominal and chest respiration (Sensor1&Sensor2) shown in Fig. 5A. In particular, Sensor1 & Sensor2, the individual classifier using both chest and abdominal respiratory data, yields higher accuracy than Sensor1 or Sensor2 alone by 19.1% and 57.1%, respectively, supporting using both sensors can trace and translate the systematic respiratory behaviors more accurately.

The individual classifier of Sensor1 and Sensor2 marks very high accuracy to predict posture-dependent individual-dependent respiratory behaviors. A limitation exists, however, on the individual model: narrow applicability. To address the limit of single classifier, multiple classifiers are lumped together to aggregate the predictions of individual classifiers (Dietterich 2000; Kotu and Deshpande 2015; Peng et al., 2016; Zheng and Lu 2016). We introduce a weighted-adaptive classifier, which is a weighted probability of 20% probability from generic classifier and 80% probability from the individual classifier at a given posture (Details of weight selection follows in Fig. S5). The maximum probability among four weighted probabilities, corresponding to four postures, determines the final classification decision (Fig. 5B). The evaluation of the weighted-adaptive classifier was performed by a two-tailed *t*-test with a null hypothesis of the prediction accuracies of the weighted-adaptive classifier equal to those of individual classifier. $P = 0.908$ in Fig. 5D indicates strong evidence to accept the null hypothesis.

The weighted-adaptive and individual classifiers show significantly high prediction accuracies over that of the generic classifier, verified by $P < 0.0001$ in Fig. 5D. For an individual, the individual classifier performs optimally to describe the individuality of respiratory behaviors. Alternatively, the weighted-adaptive classifier may be attractive, as being featured by the competitive prediction accuracy and better applicability. A summary of prediction accuracies of eleven subjects using the respiratory features from both the chest and abdominal respiration of three origins are shown in Fig. 5C. Despite the small number of subjects, the prediction accuracies show consistency across all eleven subjects and demonstrate the accurate tracing capabilities of the two wireless wearable sensors monitoring the systematic respiratory behaviors in order to contribute to respiratory disease management.

4. Conclusion

We report a wireless wearable sensors system enhanced by a machine-learning algorithm, capable of monitoring the individuality of the respiratory behaviors via postures classification method. Eleven

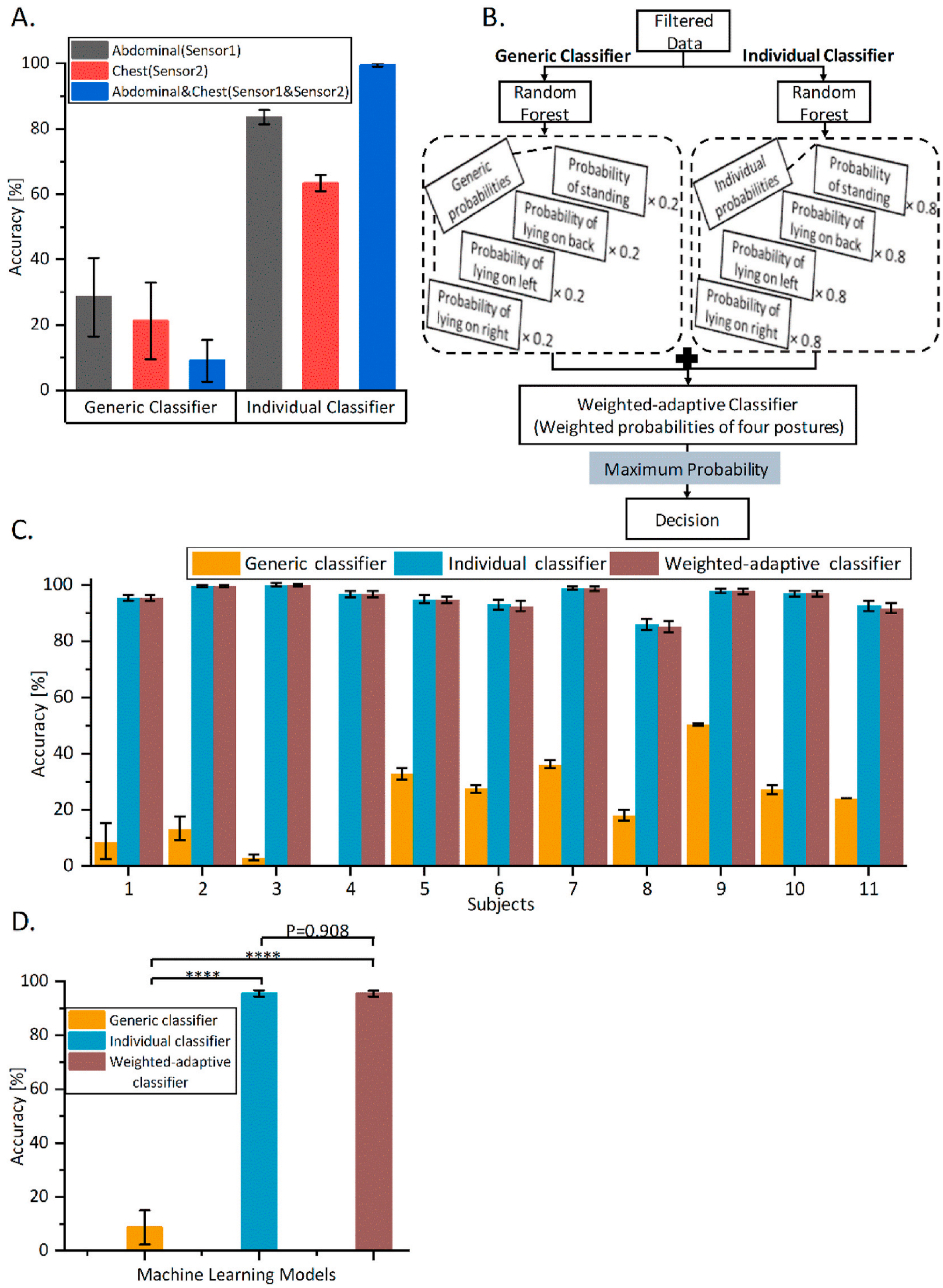

Fig. 5. (A) Comparison between the generic classifier and the individual classifier. Generic classifier, a classifier combing all the features of respiratory behaviors of all the subjects together, marks poor capability to distinguish the differences of the respiratory behaviors within different postures for all three cases: Sensor1, Sensor2, and Sensor1 & Sensor2; whereas the individual classifier, a classifier custom-tailored for an individual, shows significantly higher prediction accuracy in recognizing the respiratory features within different postures. (B) The simplified illustration of the weighted-adaptive classifier. The weighted-adaptive classifier is comprised of 80% of the individual classifier and 20% generic classifier, taking advantage of both broad applicability and high accuracy. (C) The accuracies of generic, individual, and weighted-adaptive classifiers on all eleven subjects. All eleven subjects show the lowest accuracy on the generic classifier and considerably high accuracies on individual and weight-adaptive classifiers. (D) The significance analysis of the generic, individual, and weight-adapted classifiers: the accuracies of predicting the postures of subjects based on collected respiratory data. The individual and weighted-adaptive classifiers show significantly higher accuracies over the generic classifier (****P < 0.0001) and mark almost equivalent accuracies (P = 0.908) between the two classifiers.

subjects were included in this study; the number of subjects is relatively small, but similar to the sample size of other studies, for examples, respiration mechanism and respiration-related disease explorations, which have drawn significant clinically-meaningful results (Agostoni et al., 1965; Ayappa et al., 2000; Bergofsky 1964; DeGroote et al., 1997; Kera and Maruyama 2005; Padasdao et al., 2018; Penzel et al., 2001), exploring respiration monitoring by wearable sensors recruited only one subject and tested with a single posture (Liu et al., 2017; Pang et al., 2018; Park et al., 2015; Wang et al., 2016; Xue et al., 2017).

Several future works may improve our current study. Due to the small number of and rather homogeneous nature of the subjects in the study, the applicability and generalizability of the study findings to a broader population are unknown at this point. Diversifying the subjects pool, i.e., by including the elderly and the youth, and healthy and unhealthy subjects, will enhance the applicability and performance of the wireless wearable sensor enabled with a machine learning algorithm.

Secondly, the generic classifier we explored showed low accuracy for predicting the posture of the subjects. We surmise that it may be due to the individuality of highly individual-dependent respiratory behaviors that were not included in the feature set that was used to train the classifier, such as demographics. Hence incorporation of the inherent individuality helps us to develop a more accurate generic model.

For an individual, the individual classifier is the ideal option due to its most substantial ability to detect different respiratory behaviors. The apparent weakness of the individual classifier is the generalizability. The prediction classifier constructed from the data of one subject does not produce useable guidance for the next subject.

The alternative weighted-adaptive classifier, taking advantage of broad applicability and higher accuracy, addresses the weak applicability of the individual classifier, opening the potential of the applicability to a large group of people to study respiratory behaviors accurately, thereby contributing to the diagnosis and control of respiratory diseases. The weighted-adaptive classifier is still dependent on the individual classifier (80% weight); thus, it inherits a similar weakness regarding generalizability.

However, the loss of the generalizability may not be a significant limiting factor in some applications. The broad applicability of a predictive model is crucial only when one requires a one-size-fits-all classifier that can be used for all people without any modifications. Such an application may have greater appeal in field devices that require quick but fairly good accuracy as a first-line diagnostic tool where the person's past medical history is completely unknown, e.g., in emergencies. On the other hand, in the ubiquitous mobile health era, a subject's respiratory data, recorded by our wearable sensors, could be utilized to construct the custom-tailored individual model. This approach may be more in line with precision medicine.

Some challenges remain for future work. The wireless wearable system has two sensors monitoring and translating the chest and abdominal respiration within quiet breathing, respectively. Within daily dynamic breath (respiratory behaviors during activities), additional electronics are necessary on the sensors to be references removing artifacts induced by human activities. Correspondingly, we need a more robust and sophisticated machine-learning algorithm to monitor respiratory behaviors and accurately extract unique features of respiratory behaviors within various human activities in daily life.

CRediT authorship contribution statement

Ang Chen: Conceptualization, Methodology, Writing - review & editing, Project administration. **Jianwei Zhang:** Methodology, Formal analysis. **Liangkai Zhao:** Software. **Rachel Diane Rhoades:** Methodology, Writing - review & editing. **Dong-Yun Kim:** Formal analysis. **Ning Wu:** Software, Supervision. **Jianming Liang:** Methodology. **Junseok Chae:** Conceptualization, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.bios.2020.112799.

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