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Recognizing the breathing resistances of wearing respirators from respiratory and sEMG signals with artificial neural networks[☆]

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Abstract

This study is devoted to recognizing the breathing resistances of wearing respirators from respiratory and surface electromyography (sEMG) signals. Ten subjects were required to sit for 5 min and walk for 5 min while wearing two different models of N95 filtering facepiece respirators (FFRs) and without a respirator. We recorded the sEMG signals from the respiratory muscles of the subjects, and the respiratory amplitude is also collected. Subsequently, fifteen features of the sEMG time domain and respiratory amplitude were extracted and used as input vectors to a recognition model based on artificial neural networks (ANNs). Finally, the experimental results show that these artificial neural networks are effective for recognizing different airway resistances of wearing respirators from sEMG and respiratory signals. The results also indicate that abdominal and scalene are the primary respiratory muscles affected by using N95 FFRs.

Relevance to industry: Respirator manufactures and administrations can readily employ this paper's findings for recognizing the breathing resistances of wearing respirators from respiratory and surface electromyography (sEMG) signals based on artificial neural networks automatically. Observations of the present study are in support of testing only the two primary muscles (abdominal and scalene) to simplify the evaluation of the effects of the breathing resistances of wearing respirators on respiratory muscles.

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Keywords: Breathing resistance, Surface electromyography, N95 filtering facepiece respirators, Respiratory amplitude, Artificial neural networks

1. Introduction

Concerns over air pollution have highlighted the importance of respiratory protection for workers and the general public. As a common form of personal protective equipment (PPE), N95 filtering facepiece respirators (N95 FFR) are widely used for medical staff and workers in atmospherically hostile environment [1, 2]. As is known to all, one of the primary reasons for workers disliking wearing respirators is discomfort [3]. In the last decades, greater attention has been paid to the physiological impact of the respirators on wearers [4, 5, 6, 7, 8]. Many researchers have been working on the following physiological indices: the cardiopulmonary effects of wearing the respirator [9, 7], resistance to breathing while wearing a respirator [5, 1], pressure [10], and heat stress [11] imposed by the use of a respirator. Breathing resistance with respirators has been identified as the cause of respiratory fatigue [12], which can be reflected by Surface electromyography (sEMG) signals of respiratory muscles and respiratory signals [13, 14]. However, there is little research concerning respiratory muscle responses to the use of a respirator.

We focus on the respiratory muscle and respiratory signal responses to the different airway resistances [7], which can be changed with different work intensities and filter resistances of respirators. According to former research [5], as work intensity increased, an increase in breathing resistance was found. Lee and Wang [1] also indicated that the use of N95 respirator increased the inspiratory and expiratory flow resistances. In our previous work [13], the results of the statistical analysis showed that the physiological responses to breathing resistance of wearing an N95 FFR for 5 min in sitting and walking are relatively small. However, the relationship between respiratory muscle and respiratory signal responses and breathing resistances are very difficult to describe quantitatively by traditional mathematics or mechanic due to the nonlinearity of the parameters and a large number of variables involved. This, however, seems to be an ideal situation for the application of artificial neural networks (ANNs), which are developed to tackle problems with large numbers of nonlinear variables [15].

An ANN imitates the behavior of biological neural networks to develop solutions to problems from the data provided to it. Neural networks take

previously solved examples and look for patterns, learn these patterns, and develop the ability to correctly classify new patterns (i.e. provide forecasts/predictions) [16]. The neural network learns by adjusting the inter-connection weights between layers. ANNs have shown accurate performance in different classification tasks. Attempts have recently been made to apply the ANN technique to clothing ergonomics and comfort. For example, Luo et al. [17] constructed a fuzzy neural network model for predicting clothing thermal comfort. Wong et al. [18] used ANN for Predictions of Human Psychological Perceptions of Clothing Sensory Comfort. At the same time, ANNs has been of considerable interest for classifying sEMG signals [19, 20, 21, 22]. The applications of ANNs in these areas show great promise because an ANN can deal with the nonlinearity of problems, detect patterns and relationships in the data, and interpret information from a lot of variables [15].

In this paper, we investigate the use of the ANN to recognize the breathing resistance of respirators from sEMG and respiratory signals. The purpose of this work is to verify the possibility of using non-linear techniques in this area and find out the main respiratory muscle affected during the use of N95 FFRs. The hypothesis is that ANN can be used to recognize the breathing resistance of respirators from sEMG and respiratory signals. A series of objective experiments were conducted to assess physiological changes, that is, sEMG signals and respiratory signals, with the use of N95 FFRs on actual human subjects in two conditions, which were sitting and walking.

2. Materials and methods

2.1. Participants

This study was approved by the Ethics Committee of Donghua University. Ten healthy men volunteered to participate in the experiment (M=26, SD=1.8, range from 25 to 32 years), the majority of whom (8/10) were experienced N95 FFR users. All participants had a medical examination to eliminate any subject with respiratory muscle diseases and respiratory infection. After introducing the nature, purpose, methods and the risk of the study to the participants, they were required to complete a background questionnaire about personal information such as height (M=173.5, SD=2.8, range from 168 to 178 cm) and weight (M=69.5, SD=2.7, range from 65 to 72 kg).

2.2. N95 FFRs selection

In this study, we selected two models of N95 FFRs. FFRA (3M 8210, N95 FFR) and FFRB (3M 8210v, N95 FFR/EV) were used, and the EV opens to release exhaled air and closes during inhalation. They are designed to fit all users [23]. The presence of an EV is intended to affect breathing resistance by reducing exhalation pressure. Adding a valve typically lowers the exhalation pressure drop by 50%. Thus, two models of N95 FFR are all cup-shaped respirators and have different filter resistances. The selected respirators are shown in Figure 1.

Figure 1: Tested respirators

2.3. Tested respiratory muscles

In the experiment, there is the issue of the proper choice of muscles and the corresponding location of the electrodes [24]. According to previous researches, the respiratory muscles include the diaphragm, the intercostal, the abdominal, the sternomastoid and scalene [13, 25, 26, 27].

2.4. Experimental protocol

The experiment contains six trials, and each trial differs in breathing resistance via changing work intensities and types of respirators [5, 1]. The trials are shown in Table 1. The subject performed a walking on a treadmill with a speed of 1.6 m/s [28], which is comfortable for an adult. All participants were required to sign a consent form with a detailed description of the experiment.

One week before this experiment, a fit test was performed to ensure that each subject had his personal respirator with an adequate size and was well

Table 1: Types of trials

Types of trials	Respirator conditions	Motion conditions
Trial 1	No respirator	Sitting
Trial 2	FFRA (3M 8210, N95 FFR)	Sitting
Trial 3	FFRB (3M 8210v, N95 FFR/EV)	Sitting
Trial 4	No respirator	Walking
Trial 5	FFRA (3M 8210, N95 FFR)	Walking
Trial 6	FFRB (3M 8210v, N95 FFR/EV)	Walking

fitted without leaking air. For the NIOSH bivariate panel, small headforms were defined as those falling in cells 1-3, medium headforms were those falling in cells 4-7, and large headforms were those falling in cells 8-10 [29]. The experimental results of Lei et al. [30] also showed that the combinations of 4-6 cells (medium headforms) and 3M 8210 respirator were matching. Thus, the subjects with medium headforms were selected in this experiment.

The duration of each trial is 5 minutes. During experimental phase, a subject entered the climate chamber controlled at an air temperature of 25 and a relative humidity of 70%. After cleaning the skin with alcohol and applying electrolyte gel, the subject was fitted with respiratory and sEMG sensors. The placement of sensors can be seen in the Figure 2. Before wearing a respirator, the subject took a rest for 30 min on a chair. After being acclimatized to the respirator for a minimum of a 5-min period, he was required to breathe for 5-min during each trial. Between two trials, the respirator was removed and the subject was required to take a rest for 20 min. The six 5-min trials were performed randomly. After completing the six trials, the respirator was removed.

2.5. Data acquisition

We used a 14-channel digital system (ZJE-II, ZJE Studio Ltd., China) for collecting, amplifying and transmitting respiratory and sEMG signals. The respiration sensor (ZJE Studio Ltd., China), which includes an easy fitting high durability latex rubber band fixed with a self-adhering belt, monitors the respiratory amplitude. The sEMG sensors (ZJE Studio Ltd., China) can detect sEMG signals from 0 to 2000 μV . The raw signals were sampled at 1000 samples/s and band-pass filtered at 10-500 Hz with a notch filter implemented to remove the 50 Hz line interference.

Figure 2: The placement of sensors. E1, sternomastoid electrodes; E2, scalene electrodes; E3, intercostal electrodes; E4, diaphragm electrodes; E5, abdominal electrodes; RB, respiration band, around the abdomen. Here, yellow represents negative electrode, blue represents positive electrode, black represents common electrode.

The disposable electrodes (Jun Kang Medical Supplies Ltd., China) made of silver/silver chloride electrodes (10 mm in diameter), conductive paste and backing (non-woven fabric, foam) composition (50 mm in diameter) were used to measure sEMG activity. Before electrode attachment, alcohol was used to clean the skin, and the conductive gel was used to improve the contact of the electrode with the skin [31]. A photograph of data acquisition session can be illustrated in Figure 3.

2.6. Feature extraction

From respiratory signals, respiratory amplitude (RA, μV) was recorded as an input parameter. The RA is measured by calculating the difference between the highest and lowest points in one breath [32]. We can collect one parameter per participant per breath from respiratory signals.

From sEMG signals, time domain features such as average EMG amplitude (aEMG), variance (VAR) and Root Mean Square (RMS) [33, 34, 35] were recorded as input parameters. The formulas are as follows:

$$aEMG = \frac{\sum_{i=1}^N (X_i)}{N} \quad (1)$$

Figure 3: A photograph of data acquisition session

$$VAR = \frac{\sum_{i=1}^N (X_i - aEMG)^2}{N} \quad (2)$$

$$RMS = \sqrt{\frac{\sum_{i=1}^N (X_i)^2}{N}} \quad (3)$$

where X_i is the i th sampling value of EMG signals in one sampling period.

These features of sEMG signals were extracted during each epoch. The beginning of the inspiration in one breath was set as the epoch onset, and the ending of the expiration of the breath was set as the epoch endpoint. We can collect a number of time domain characteristics $(3) \times \text{Number of tested muscles } (5)$, amounting to 15 parameters per participant per breath from sEMG signals. Thus, we can collect totally 16 parameters per breath per participant from respiratory and sEMG signals.

2.7. Artificial neural network construction

We used the feed-forward multilayer perceptron (MLP) neural networks for this work. MLP neural networks are the most commonly used feed-forward neural networks due to their fast operation, ease of implementation, and smaller training set requirements [36, 37]. MLPs are normally trained with the back-propagation algorithm. The back-propagation rule propagates the errors through the network and allows adaptation of the hidden parameters. The number of input and output vectors depends on how many parameters or variables are provided to and expected from the ANN. The weights in the neural networks are used to transmit activity between inputs and outputs by means of transfer functions within the network. They are modified

during the learning cycles, and the significance of each input is reinforced or weakened by adjusting the weight according to its activity [15].

As one of the most common artificial neural networks (ANNs), MLP has been widely used in pattern recognition models for sEMG signals [38]. A three-layer network consisting of one input layer, one hidden layer with a sigmoid function, and one output layer with a hyperbolic tangent (TanH) function was used to set up the MLP classifier.

Two critical characteristics of the MLP are: the nonlinear processing elements (PEs) which have a nonlinearity that must be smooth (the sigmoid function and the TanH function are the most widely used); and their massive interconnectivity (i.e. any element of a given layer feeds all the elements of the next layer) [39]. In our study, the activation function which is the sigmoid function for the hidden layer is given by:

$$f(x) = \frac{1}{1 + e^{-ax+b}} \quad (4)$$

The activation function which is the TanH function for the output layer is given by:

$$g(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}} \quad (5)$$

The MLP is trained with error correction learning, which works in the following way: From the model response at PE j at iteration k , $y_j(k)$, and the desired response $d_j(k)$ for a given input pattern an instantaneous error $e_j(k)$ is defined by

$$e_j(k) = d_j(k) - y_j(k) \quad (6)$$

Using the gradient descent learning, each weight in the ANN can be adapted by correcting the present value of the weight with a term that is proportional to the present input and error at the weight, i.e.

$$w_{jl}(k+1) = w_{jl}(k) + \eta \delta_j(k) x_l(k) \quad (7)$$

where the local error $\delta_j(k)$ can be directly computed from $e_j(k)$ at the output PE or can be computed as a weighted sum of errors at the internal PEs. The constant η is the step size. The procedure represents backpropagation (BP) algorithm. Momentum learning is used to speed up and stabilize convergence, and the equation to update the weights becomes

$$w_{jl}(k+1) = w_{jl}(k) + \eta \delta_j(k) x_l(k) + \alpha(w_{jl}(k) - w_{jl}(k-1)) \quad (8)$$

where α is the momentum.

To start the BP, a small random value is set as an initial value for each weight, and the BP proceeds until the termination criterion is met. In our study, two termination criteria were set for the training phase: the maximum number of iterations was 2000, and the minimum mean square error (MSE) was less than 0.01. If either criterion were satisfied, the training would stop.

To investigate the effects of the different respiratory muscles on the recognition performance of ANN, we constructed the MLP recognition models for each respiratory muscle. Seven sets of parameters were used as input vectors to construct seven MLP-based recognition models respectively, as shown in Table 2. Taking the input set of all 16 parameters as the example, the basic structure of the proposed MLP-based recognition model is shown in Figure 4. The training and testing of the MLP model were constructed in the simulation software NeuroSolutions 6 on Windows 7.

Table 2: The Parameters of the seven MLP-based recognition models

Recognition models	Input sets	Input vectors
1	Respiratory parameter	RA
2	Abdominal parameters	RMS, VAR and aEMG of abdominal
3	Scalene parameters	RMS, VAR and aEMG of scalene
4	Diaphragm parameters	RMS, VAR and aEMG of diaphragm
5	Intercostal parameters	RMS, VAR and aEMG of intercostal
6	Sternomastoid parameters	RMS, VAR and aEMG of sternomastoid
7	All 16 parameters	RMS, VAR and aEMG of 5 muscles, RA

In this paper, accuracy rate (AR) is adopted to evaluate the recognition effect of the model. The algorithm can be written as follows:

$$AR = \frac{m}{M} \times 100\% \quad (9)$$

where m is the number of samples recognized correctly, and M is the total number of samples.

3. Results and discussions

3.1. Results of feature extraction

Because of different respiratory rates of each trial per participant, there were different epochs/breaths for six trials and ten participants. The epochs

Figure 4: MLP-based breathing resistance recognition model

during 5 minutes for each subject are shown in Table 3. 100 epochs were randomly selected from each subject and each trial, amounting to 1000 epochs for each trial. 16 parameters were successfully extracted during each epoch. The dataset was randomly divided into two subsets, a training set and test set. We randomly selected 70% of the data as the training set and 30% as the test set.

Randomly selected respiratory signals and electromyograms for the six trials with different breathing resistances of wearing respirators are shown in Figure 5.

3.2. Statistic analysis of the sEMG indices

The averages of aEMG, VAR and RMS for the diaphragm, the intercostal, the abdominal, the sternomastoid and scalene muscles for the different trials are shown in Figure 6. These averages are the means of these indices for the ten participants. The error bars represent the standard error (SE). According to Figure 6, the error is small, meaning that the consistency of the data collected across participants is high. Thus, the recognition algorithms can be performed on the data across subjects.

Table 3: Number of epochs during 5 minutes for 10 subjects

Subjects	Number of epochs during 5 minutes					
	Trial 1	Trial 2	Trial 3	Trial 4	Trial 5	Trial 6
1	120	110	115	235	220	230
2	119	111	116	236	221	234
3	121	112	117	237	221	231
4	120	108	115	235	222	232
5	122	107	114	230	223	233
6	118	109	118	234	219	229
7	119	110	113	233	218	227
8	120	112	116	238	220	228
9	122	113	117	235	221	231
10	121	108	115	234	217	230

Figure 5: Respiratory signals and electromyograms of six trials across participants, each panel illustrating a single breath taken from a single participant

3.3. Classification results

The confusion matrixes of the classifications using different sets of input vectors based on the MLP classifier are shown in Figure 7.

Figure 6: Histogram bars and error bars of 16 parameters (Error bar denote SE of the means). (a) Histogram bars and error bars of RA, (b) histogram bars and error bars of aEMG, (c) histogram bars and error bars of VAR, and (d) histogram bars and error bars of RMS

3.4. Statistic analysis of accuracy rates (ARs)

To check for statistical significance, one-way ANOVA was performed on classification accuracy rates (ARs) of seven MLP-based recognition models. The significance level represented by α is selected as 0.05. The result of this test shows statistically significant differences among these recognition models ($p=0.000$). The results of post-hoc Tukey-Kramer tests were shown in Figure 8.

Table 4: The Parameters of the six MLP-based recognition models

Recognition models	aAR for the training set (%)	aAR for the test set (%)
Respiratory amplitude	71.75	70.82
abdominal	62.92	62.28
Scalene	61.57	60.83
Diaphragm	58.3	57.55
Intercostal	54.32	53.12
Sternomastoid	50.18	48.87
All 16 parameters	81.52	80.55

aAR, average accuracy rate.

The average recognition accuracy for seven MLP-based recognition models is shown in Table 4. As shown in Figure 8 and Table 4, recognition model with all 16 parameters significantly has the highest recognition accuracy, followed by recognition model with respiratory amplitude, recognition model with abdominal parameters, recognition model with scalene parameters, recognition model with diaphragm parameters, recognition model with intercostal parameters, and recognition model with sternomastoid parameters. Further, for the five respiratory muscles, abdominal was not significantly better than scalene, scalene was not significantly better than the diaphragm, the diaphragm was not significantly better than intercostal, and intercostal was not significantly better than sternomastoid.

3.5. Discussion

Surface EMG-based approaches have been successfully used for assessing muscle activity [27] and fatigue [40] with linear [41] and non-linear [42] techniques. These researchers developed clinically viable activity and fatigue assessment strategies. However, to our knowledge, there are limited studies

published to assess respiratory muscle activity and fatigue caused by wearing respirators. In our previous work [13], we firstly used statistics to assess the physiological responses (respiratory signals and sEMG signals) to different breathing resistances of wearing respirators. As a continuation of our previous work, this paper is the first reported study that presents a systematic comparison of different input parameters for recognition of six trials with different breathing resistances of wearing respirators from respiratory and sEMG signals using artificial neural networks.

The results suggest that our MLP-based model can be used for recognizing six trials of different breathing resistances from physiological signals. The results supported the hypothesis that ANN can be used to recognize the breathing resistance of respirators from sEMG and respiratory signals. The basis of this achievement is revealed by the graphs of respiratory signals and electromyograms Figure 5 which show that the respiratory signals and respiratory muscles have different amplitudes when participants bearing different breathing resistances.

Using all 16 parameters as input vectors, the MLP model was able to have the highest recognition accuracy. The finding is in accordance with Linderman et al. [43], who pointed out that the recognition accuracy was improved by increasing the muscle numbers. Interestingly, recognition model using respiratory amplitude has a relatively higher recognition accuracy than remaining 5 recognition models with different sEMG parameters of respiratory muscles (Figure 7 and Figure 8, Table 4). This finding is also in alignment to our previous research [13], which claimed that the respiratory amplitude has the highest Pearson's correlation coefficient with subjective assessment of overall breathing resistance. Moreover, among the five muscles, the recognition models of abdominal and scalene parameters had the highest recognition accuracy (Figure 7 and Figure 8, Table 4). The finding is also in accordance with our previous study [13], which also indicated that they are the primary muscle affected during the use of N95 FFRs. However, the findings that we got from statistical analysis of previous research [13] is more ambiguous than those we get from this study that used artificial neural networks. Thus, it can be concluded that ANN is more effective for measuring the relationship between physiological signals and breathing resistance changes of wearing respirators than statistics (MANOVA) [13].

Nevertheless, our findings and the general approach have several limitations and challenges:

- (1) In this study, we used the most common ANN, that is, MLP, for

Figure 7: Confusion matrixes of the classifications using seven sets of parameters as input vectors (1, Trial 1; 2, trial 2; 3, trial 3; 4, trial 4; 5, trial 5; 6, trial 6). (a) Respiratory amplitude for the training set, (b) respiratory amplitude for the test set, (c) abdominal parameters for the training set, (d) abdominal parameters for the test set, (e) scalene parameters for the training set, (f) scalene parameters for the test set, (g) diaphragm parameters for the training set, (h) diaphragm parameters for the test set, (i) intercostal parameters for the training set, (j) intercostal parameters for the test set, (k) sternomastoid parameters for the training set, (l) sternomastoid parameters for the test set, (m) all 16 parameters for the training set, and (n) all 16 parameters for the test set.

Figure 8: Means Comparison Plot of post-hoc Tukey-Kramer tests. 1, recognition model with respiratory amplitude; 2, recognition model with abdominal parameters; 3, recognition model with scalene parameters; 4, recognition model with diaphragm parameters; 5, recognition model with intercostal parameters; 6, recognition model with sternomastoid parameters; 7, recognition model with all 16 parameters.

recognition model construction. There are many other kinds of ANN can be used for further research, such as Elman neural networks [44, 45], Radial Basis Function networks [38] and Learning Vector Quantization networks [46]. In future studies, we plan to use other advanced classifiers to see whether the performance of our recognition method can be further improved.

(2) We only used two models of N95 respirators (3M 8210 and 3M 8210v), so more other models having obviously different mmHg pressure drops can be used for future research. As an approximate values, 3M 8210 is around 8-9 mmH_2O at 85 L/min of constant airflow, and 3M 8510 is around 5-6 mmH_2O at 85 L/min of constant airflow.

(3) We only tested two kinds of work intensity (sitting still and walking). In future work, we should test on more kinds of work intensity.

(4) Only a few subjects were tested in our experiment. In future research, we plan to collect sEMG signals from participants covering a range of ages, countries, races, body types and of both genders, to increase the

generalizability of the findings.

(5) We only used sEMG amplitude-based parameters as input vectors. To further improve the recognition accuracy, sEMG parameters based on spectral analysis, sEMG parameters based on timefrequency distributions and non-linear parameters could be additionally used.

4. Conclusions

Our work has demonstrated that it is possible to recognize breathing resistances of wearing respirators by using artificial neural networks. This study also indicated that respiratory amplitude, abdominal and scalene muscles are more sensitive to the changes of breathing resistances of wearing respirators. While the results are encouraging, additional research is needed to further develop the method. Our future work will concentrate on the evaluation of longer periods of FFR wear. In addition, subjective ratings by the test subjects will also be obtained and compared with the resistance and sEMG data.

Conflict of Interest Statement

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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