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Assessment and classification of normal and restrictive respiratory conditions through pulmonary function test and neural network

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In this work, an attempt to classify respiratory abnormality using a pulmonary function test and neural networks is reported. The flow – volume curves generated by spirometric pulmonary function tests were recorded from subjects under study. The pressure and resistance parameters were derived using theoretical approximation of the activation function representing the pressure – volume relationship of the lung. The pressure – time and resistance – expiration volume curves were obtained during maximum expiration. The derived values together with spirometric data were used for classification of normal and restrictive abnormality using feed forward network. Results demonstrate the ability of the proposed method in identifying and classifying pulmonary function data into normal and restrictive cases. The validity of the results was confirmed by measuring accuracy (92%), sensitivity (92.3%), specificity (91.6%) and adjusted accuracy (91.95%). As spirometric evaluation of human respiratory functions are essential components in primary care settings, the study carried out seems to be clinically relevant.

Keywords: Pulmonary function test; Spirometry; Restriction; Feed forward network

1. Introduction

Pulmonary function tests play a critical role in the diagnosis, differentiation and management of respiratory illnesses such as asthma, restrictive disorders and chronic obstructive pulmonary disease [1]. Restrictive lung conditions can be caused by chest wall disease, which prevents full expansion of lung and reduces vital capacity. The two main patterns of restrictive lung disease are chronic disease, characterized by inflammation of alveolar walls, and acute disease, characterized by diffuse alveolar damage. Conditions such as fibrosis or scarring of the lung are capable of restricting the expansion of the lungs and hence assessments of restrictive lung condition are clinically relevant [1 – 3].

The spirometric pulmonary function test is fundamental to the diagnosis and assessment of respiratory disorders. A spirometer measures the airflow and lung volumes during a forced expiratory manoeuvre after full inspiration [2,3] and is used to assess lung health in smokers and those exposed to occupational and environmental hazards [1]. It is used to evaluate the progression of lung disease and to monitor the effectiveness of therapy [2]. The tidal phase, inspiratory phase and expiratory phases are the three phases generated during the spirometric recording. The four different types of ventilation patterns identified are normal, obstructive, restrictive and a combined restrictive/obstructive pattern [1 – 3]. The parameters measured using spirometers are forced vital capacity (FVC), forced expiratory volumes at 0.5, 1 and 3 s ($FEV_{0.5}$, FEV_1, FEV_3), ratio of FVC to FEV_1 ($FEV_{1\%}$), peak expiratory flow (PEF) and forced expiratory flow 25 – 75% (FEF_{25-75}). Normal spirometry depends on the predicted values of the measured parameters and on the age, height and sex of the subjects.

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It has been proposed that artificial neural networks (ANN) can be used to support clinical decisions. They already have many applications in biomedical systems [4,5]. In order to carry out the classification procedure the neural network needs to be trained. During training, samples are presented to the input layer, and yield changes to the activation state of output processing elements. The calculated output value is compared to the required value or the target value given during the process. The network adjusts synaptic weights based on the difference between the required and calculated output values and this distribution constitutes the basis of the problem-solving algorithm [4,5]. ANN techniques have been employed with spirometric data by Botis and Halkiotis [6] and the prediction of the reference values has been carried. In this work an attempt has been made to classify normal and restrictive conditions using a neural network with spirometer data and the pressure and resistance values that are derived through a mathematical model.

2. Methodology

For the present study 100 (50 normal, 25 restrictive and 25 validation) adult volunteers were considered. The age, gender and race were recorded and the height and weight were measured before the test. The average age, height and weight of the subjects were 44 years, 166 cm and 67 kg, respectively. The portable MicroLab spirometer was used for the pulmonary function test and a gold standard digital volume transducer was used for data acquisition. These transducers have already been used for precise flow volume measurements with high accuracy and stability [7]. Acceptability and reproducibility criteria were adopted as per the recommendation given by American Thoracic Society (ATS) [3].

The spirometer does not measure the lung pressure and resistance, so they are derived using mathematical models. The model suggested by Suga and Sagawa [8], Barnea *et al.* [9] and Abboud *et al.* [10] was employed to derive these values. The elements based on which the model operates are the volume dependent pressure source and the viscous resistance to air flow. The pressure source includes an activation function E that represents the lung pressure–volume relationship developed by Suga and Sagawa [8]. The activation function varies with respect to time and is assumed to reach a constant level. $E(t)$ is expressed as an exponential function:

$$E(t) = E_{\max}(1 - e^{-t/\tau}), \tag{1}$$

where $E_{\max}$ is the maximum level of contraction expressed as a pressure-volume ratio in units of mmHg ml^{-1} and the time constant of contraction τ. The pressure $P(t)$ developed in the lung is a function of the activation function, the instantaneous lung volume $V(t)$, and residual volume (RV):

$$P(t) = E(t)(V(t) - RV). \tag{2}$$

The instantaneous lung volume can be expressed as the difference between total lung capacity and expired volume $V_e(t)$:

$$V(t) = TLC - V_e(t). \tag{3}$$

Substituting equation (3) in equation (2):

$$P(t) = E(t)(FVC - V_e(t)). \tag{4}$$

The airway resistance was represented by a volume-dependent piecewise-linear function [9, 10] having different coefficient for each volume range limited by V_e.

$$R(Ve) = a_0 + a_1 V_e, \tag{5}$$

where a_0 and a_1 are the coefficients. Using the above relations, the values of pressure and resistance were calculated for all the measurements. The pressure values were derived at four different time intervals, which include 0, 0.5, 1 and 3 s. The corresponding expiratory volume was also noted for finding the resistance. The statistical analyses on the obtained parameters such as mean value, standard deviation and standard error were also calculated.

Further, a supervised neural network was employed to analyse the data [4,5,11]. The ability of the neural network to solve classification problems based on mainly qualitative differences is exploited and a three-layer feed-forward network with one hidden layer was adopted. The parameters of the network were adjusted by training it on a set of reference data called the training set. Training of the network was performed under back-propagation of the error and the log sigmoid transfer function was used at hidden and output layers. Considering the maximum values of the parameter, the data were normalized to the range 0–1 and were then used for training the neural network. The weights and bias are initialized to zero. The output for the training network was taken as 0 (normal data) and 1 (restrictive data). The neural network studies were performed using Neural Network Tool Box 4.0 of MATLAB version 6.5.1.

The developed tests were evaluated by computing four evaluation indices [12,13]—accuracy, sensitivity, specificity and adjusted accuracy—which are commonly used for validating medical and clinical tests. The event that classifies normal data as restrictive is termed a false positive (FP), whereas the event that classifies restrictive data as normal is termed a false negative (FN). True positive (TP) and true negative (TN) events are those that classify normal data as normal and restrictive data as restrictive, respectively. Accuracy predicts the classifier performance in a global sense [12], sensitivity is the proportion of actual restrictive data that are classified as restrictive, specificity is the proportion of actual normal data that are correctly classified as normal and the adjusted accuracy is a measure that accounts for unbalanced sample data of normal and restrictive events. The values of these indices were calculated using the relation:

$$\text{Accuracy} = (\text{TP} + \text{TN})/(\text{TP} + \text{FP} + \text{TN} + \text{FN})$$
$$\text{Sensitivity} = \text{TP}/(\text{TP} + \text{FN})$$
$$\text{Specificity} = \text{TN}/(\text{TN} + \text{FP})$$
$$\text{Adjusted accuracy} = (\text{sensitivity} + \text{specificity})/2.$$

3. Results and discussion

The typical response of a spirometer is shown in figure 1, which depicts variation of airflow with lung volume for a normal subject. The normal flow volume curve has a distinct follow-through of the inspiratory and expiratory manoeuvres. In restrictive lung conditions fibrotic tissue increases the elastic recoil of the lung and this increases the airflow at a given lung volume, and hence the follow-through is altered. Due to this condition the peak expiratory flow is higher than the predicted value, as is evident from figure 2. The peak expiratory flow is also narrowed due to reduction in vital capacity. The variation of pressure with respect to time derived using the mathematical relation in equation (1) is plotted and is shown in figure 3. It is observed that there is a high magnitude difference in pressure with respect to time between normal and restrictive subjects. This is due to the fact that the restrictive subjects demonstrate low pressure during breathing phases. The values of resistance relating to expired volume, i.e. derived using the mathematical relation in equation (2), are shown in figure 4. Although there is a linear variation for both normal and restrictive subjects, the slope of the normal subjects is higher than those of restrictive subjects. These alterations in restrictive cases could be attributed to the reduction in lung vital capacity which could be due to various conditions that affect the lung tissue itself, or an inability to expand and hold a normal amount of air.

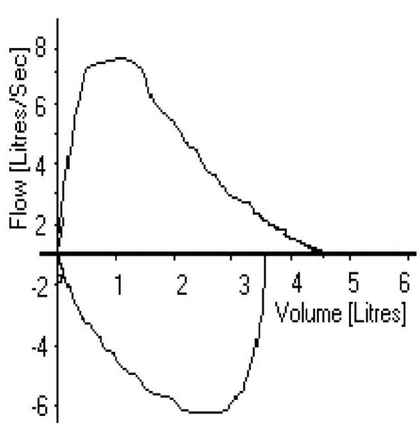

Figure 1. Variation in flow volume of normal subject.

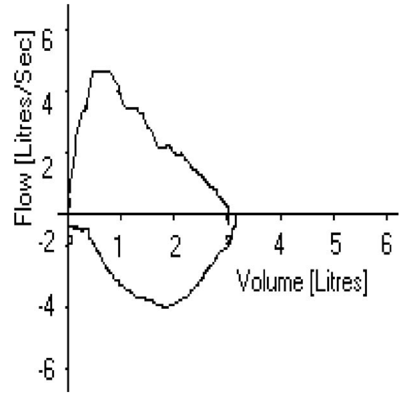

Figure 2. Variation in flow volume of restrictive subject.

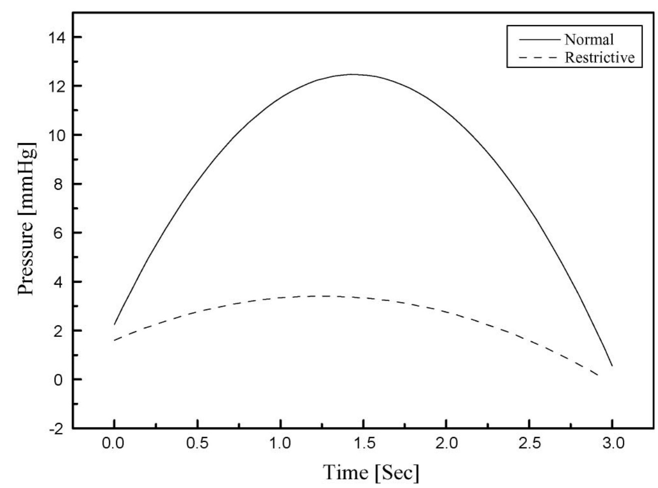

Figure 3. Pressure – time relation for normal and restrictive subjects.

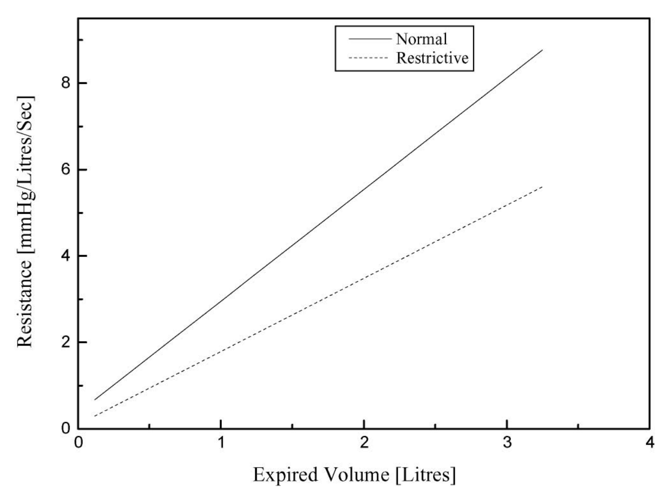

Figure 4. Resistance – expired volume for normal and restrictive subjects.

Table 1. Statistical analyses of the significant parameters.

Input	Parameter	Normal (50)		Restriction (25)	
		Mean $\pm$ S.D	Standard error	Mean $\pm$ SD	Standard error
1	Pressure (0)	0	0	0	0
2	Pressure (0.5)	13.5 ± 1.9	0.268	6.62 ± 1.6	0.32
3	Pressure (1)	8.1 ± 2.04	0.288	1.85 ± 0.95	0.19
4	Pressure (3)	0.78 ± 0.23	0.032	0.11 ± 0.3	0.06
5	Resistance (FEV0)	0	0	0	0
6	Resistance (FEV0.5)	5.3 ± 0.83	0.117	3.52 ± 0.52	0.104
7	Resistance (FEV1)	7.05 ± 0.97	0.137	4.86 ± 0.74	0.148
8	Resistance (FEV3)	8.48 ± 1.08	0.152	0.74 ± 0.98	0.196

The statistical analysis of the input to the neural network is performed and shown in table 1. The mean values of the pressure and the resistance parameters in normal subjects are distinctly higher than those in the restrictive cases, and the difference is always greater than 20%. The standard deviation and the standard error also show significant changes. These pressure and resistance values are input into the neural network for training purposes and also for validation. It is observed that the sum square error was minimum for the considered training sets with four hidden neurons. The incomplete data were fed to the trained neural network and are subjected to validation. Further, the outputs were also analysed by clinical observation. The results are shown in table 2. The accuracy, sensitivity, specificity and adjusted accuracy were found to be 92%, 92.3%, 91.6% and 91.95% respectively. The performances of the trained network were further assessed by comparing the mean and the standard deviation of normal and restrictive subjects in training and validation sets. It can be concluded that the network is efficient for the purpose for which it was trained, as the mean and standard deviation are the same for both. The corresponding data are presented in table 3.

Table 2. Sensitivity and specificity.

	ANN based classification	Clinical observation
Total true positive	12	13
Total true negative	11	12
False positive	01	–
False negative	01	–

Table 3. Comparison between training and validation sets. Figures are means $\pm$ SD.

Parameter	Training set (75)		Validation set (25)	
	Normal	Restriction	Normal	Restriction
Pressure (0)	0	0	0	0
Pressure (0.5)	13.6 ± 3.27	6.22 ± 2.48	13.09 ± 1.18	8.3 ± 5.4
Pressure (1)	8.1 ± 2.02	1.95 ± 1.95	8.3 ± 2.6	5.4 ± 7.8
Pressure (3)	1.003 ± 0.314	0.11 ± 0.3	0.8 ± 0.2	2.7 ± 5.7
Resistance (FEV_0)	0	0	0	0
Resistance ($FEV_{0.5}$)	6 ± 0.43	3.52 ± 0.71	4.8 ± 1.2	3.2 ± 0.6
Resistance (FEV_1)	7.66 ± 0.57	4.56 ± 0.74	6.5 ± 1.5	3.8 ± 2.1
Resistance (FEV_3)	8.88 ± 0.66	0.74 ± 1.95	7.8 ± 1.3	4.6 ± 2.7

4. Conclusion

Lung function analysis plays an important role in the diagnosis, prognosis and mass screening of respiratory disorders, and spirometric investigations remain central in clinical practice [14,15]. In a restrictive disease, such as fibrosis, forced vital capacity is compromised [1–3] due to the low compliance of the lung, and in such conditions the spirometric FEV_1/FVC ratio may be normal or even greater than normal. It has been shown that 50% of spirometric results were unacceptable due to failure to complete the test [14], as these investigations depend on the ability of the investigated subject to complete the test and on the skills and approach of the investigator. However, high accuracy is required in medical diagnosis because medical decisions are often critical, and a good and credible clinical decision support system is therefore always helpful.

In this work, restrictive disorders have been analysed using an artificial neural network, which have been shown to be a valuable alternative to standard statistical methods [16]. Further, the pressure and resistance values derived from mathematical relations [8–10] were also used as inputs to the network in addition to the spirometric pulmonary function data. The pressure values are a significant determinant of the disease, as the ability to generate pressure during forced expiration depends on the lung volume. The classification and analyses were carried out through the feed-forward neural network algorithm and the conclusions are made after testing the architecture, the number of hidden neurons required and the goal. A solution for the classification of the spirometer data using neural network has been generated for unknown cases. It appears that the classification of the recorded spirometer data into normal and restrictive cases is acceptable after incorporating the pressure and resistance data that are derived from mathematical equations, and this is supported by the high values of sensitivity and specificity. The proposed method could thus be used for automated analysis and seems to be clinically relevant. An efficient algorithm-based automated analysis using a network trained with more input parameters could be useful for assisting physicians for accurate diagnosis.

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