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A different sleep apnea classification system with neural network based on the acceleration signals

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ABSTRACT

Background and objective: The apnea syndrome is characterized by an abnormal breath pause or reduction in the airflow during sleep. It is reported in the literature that it affects 2% of middle-aged women and 4% of middle-aged men, approximately. This study has vital importance, especially for the elderly, the disabled, and pediatric sleep apnea patients.
Methods: In this study, a new diagnostic method is developed to detect the apnea event by using a micro-electromechanical system (MEMS) based acceleration sensor. It records the value of acceleration by measuring the movements of the diaphragm in three axes during the respiratory. The measurements are carried out simultaneously, a medical spirometer (Fukuda Sangyo), to test the validity of measurement results. An artificial neural network model was designed to determine the apnea event. For the number of neurons in the hidden layer, 1-3-5-10-18-20-25 values were tried, and the network with three hidden neurons giving the most suitable result was selected. In the designed ANN, three layers were formed that three neurons in the hidden layer, the two neurons at the input, and two neurons at the output layer.
Results: A study group was formed of 5 patients (having different characteristics (age, height, and body weight)). The patients in the study group have sleep apnea (SA) in different grades. Several 12.723 acceleration data (ACC) in the XYZ-axis from 5 different patients are recorded for apnea event training and detection. The measured accelerometer (ACC) data from one of the patients (called H1) are used to train an ANN. During the training phase, MSE is used to calculate the fitness value of the apnea event. Then Apnea event is detected successfully for the other patients by using ANN trained only with H1's ACC data.
Conclusions: The sleep apnea event detection system is presented by using ANN from directly acceleration values. Measurements are performed by the MEMS-based accelerometer and Industrial Spirometer simultaneously. A total of 12723 acceleration data is measured from 5 different patients. The best result in 7000 iterations was reached (the number of iterations was tried up to 10.000 with 1000 steps). 605 data of only H1 measurements are used to train ANN, and then all data used to check the performance of the ANN as well as H2, H3, H4, and H5 measurement results. MSE performance benchmark shows us that trained ANN successfully detects apnea events. One of the contributions of this study to literature is that only ACC data are used in the ANN training step. After training for one patient, the ANN system can monitor the apnea event situation on-line for others.

1. Introduction

The breathing provided by contraction of the diaphragm muscle layer that separates the abdominal and chest cavity is an indispensable involuntary movement for living creatures. During the inspiration and expiration, the diaphragm size differs. Changes in the diaphragm size can give a clue to many diseases (the diaphragm eventration, chronic obstructive pulmonary disease (COPD), sleep apnea (SA), etc.) [1,2].

Stopping the airflow for at least 10 s during breathing is defined as Sleep Apnea. An apnea event is a reduction in the magnitude of respiration movement to less than 5% of normal value in breathing cases for a certain amount of time [3]. It can cause congestion of

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the throat's airway, which reduced the inhaled amount of oxygen during respiration [4]. Airflow congestion in each period of respiration is called apnea event [5]. Although the occurrence of apnea events might be physiological, if more than 5 events of apnea occur per sleeping hour, they would usually be regarded as being pathological [6]. The apnea syndrome is characterized by abnormal breath pause or reduction during sleep. It is reported in the literature that it affects 2% of middle-aged women and 4% of middle-aged men, approximately [7].

There are three types of SA, central sleep apnea (CSA), obstructive sleep apnea (OSA), and mixed sleep apnea (MSA). The diaphragm muscles are excited by the human brain to take a breath during sleep. CSA can be defined as a short-term respiratory stop resulting from the absence of a signal from the brain. Similarly, OSA can be defined as a short-term respiratory stop despite muscle effort to take a breath existence of the brain to send a signal. Respiration is failed because of airway congestion. MSA is a combination of the previous two types of apnea [8].

According to the American Academy of Sleep Medicine (AASM) apnea scoring guide, two criteria are adequately considered to assess SA [9].

1. At least 90% reduction in airflow amplitude
2. This reduction should last for at least 10 s

So, it is necessary to know the airflow for apnea detection. Fig. 1 shows breathing effort in the abdominal region, depending on the airflow.

While the abdominal movements continue in the OSA and MSA at the time of apnea event, in CSA, abdominal movements are significantly reduced at the time of apnea. So, CSA information can be obtained through the breathing effort on the diaphragm. CSA is detected in this study.

In recent years, very different techniques have been developed that relate to the diagnostic work of the apnea event. Especially Artificial intelligence (AI) methods have been studied in many numbers of papers. Artificial Neural Networks (ANNs) method is one of the AI methods and is widely used in the apnea classification [11,12]. Besides, at the related works in the literature [13,14], Particle Swarm Optimization (PSO) and Machine Learning (ML) techniques are used to find a solution to diagnose apnea. Similarly, the detection of sleep apnea events from photoplethysmography (PPG) waves variation patterns during sleep was one of the most recent methods in recent times [15]. Apnea event detection using the heart rate variability and the electrocardiogram-derived respiration signals [16], signal classification technique [17] and using a 3D camera are also different methods in literature [18]. The apnea events detection with the help of airflow signals [19] and respiratory signals [20] are also quite conventional methods.

The data about apnea events can also be measured by a spirometer with a suitable nozzle [21], although the spirometer is used to scan people who are at risk of pulmonary disease [22].

The accelerometer sensors measure the acceleration along the three axes (X, Y, and Z). It is possible to use the three axes measurement to determine the movement of the diaphragm during respiration [23]. The accelerometer sensors might be used as a reliable diagnostic technique for certain pulmonary diseases such as COPD, pulmonary hypertension, etc.

Since apnea is known to be a respiratory disease, so, many works have been done on the detection of apnea by using breathing signals. Many of these have occurred in the form of breath signal analysis through diaphragm movements [24–26]. Relation of accelerometer signals (ACC) and respiratory information have also been published in many studies [27,28].

This work aimed at the detection of apnea events using an accelerometer-based ANN model. For this purpose, diaphragm movements are monitored continuously with MEMS (microelectromechanical systems) based accelerometer, which placed on the patient's diaphragm. During sleep time, the apnea events are screened continuously by a closed-loop control system in real-time. If there is no movement on the diaphragm for at least 10 s, that means there is no acceleration on the sensor, this is detected by the accelerometer. The measurements are carried out simultaneously a medical spirometer (device (Fukuda Sangyo brand spiroanalyz ST-75 model, Prg ver: 2.36B 16-Bit)) to test the validity of measurement. Continuous positive airway pressure mask used in patients for spirometer measurements.

2. Materials and methods

2.1. ACC measurement setup

Types of MEMS-based accelerometers using from military to health industry have been summarized in [29]. ADXL345, one of the MEMS-based 3-axis accelerometer with digital output, is used in the measurement setup. Details about the structure and properties of ADXL345 are given in [30] to detect the lying position. ACCs can use to diagnose a respiratory-related disease like apnea. In this

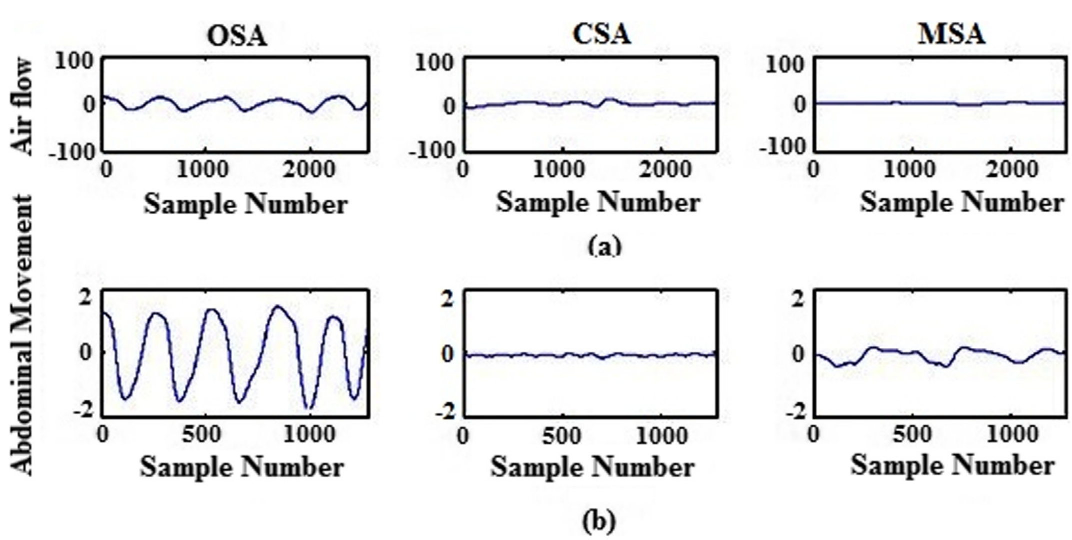

Fig. 1. Classification of apnea according to breathing signals, (a) airflow, (b) abdominal movement [10].

study, ACC data were measured with the developed measuring device (contains ADXL345 MEMS-based 3-axis accelerometer), defined in [31].

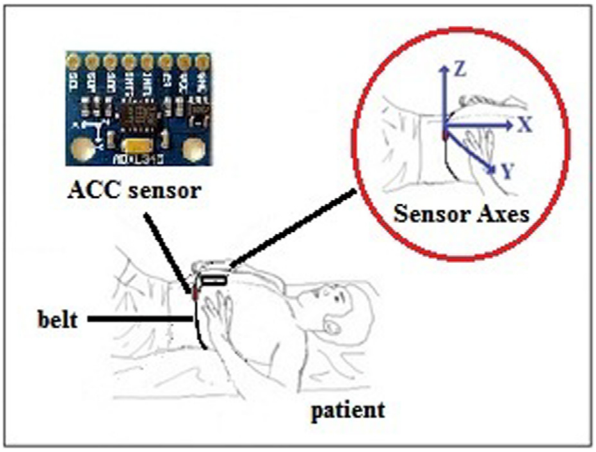

Fig. 2. The working principle of the system.

It was understood from the literature [32–35] that the ideal location for the accelerometer is the space between the 7th ribs, the region above the diaphragm (the solar plexus). Thus, in the designed system, the acceleration sensor was placed on a patient's diaphragm, to XY-plane become parallel to the floor and the z-axis perpendicular to the diaphragm. Placing the sensor on the patient's diaphragm and working principle of the system can be seen in Fig. 2. The sensor was connected to the body (the abdomen region) with the help of a belt.

Especially for patients with sleep apnea, the patient's position of residence is of great importance. The risk of sleep apnea increases with the position of the bed. Apnea/Hypopnea Index (AHI) is usually increased in the lying position on the back, while this rate decreases in the right or left side. When there is a half-decline in the AHI rate during sleep in other positions, positional Apnea is mentioned. Patients with positional sleep apnea were found to be lying in the supine position, in general [36]. This is a great risk for patients, and these patients need special therapy. Thus, in this study, apnea events in the supine position were detected.

Movements of the diaphragm may be in an arbitrary direction, so a three-axis acceleration sensor is used in the measurement setup — power axis of the gravitational acceleration (g) measured in real-time with an accelerometer [37]. During inspiration, the

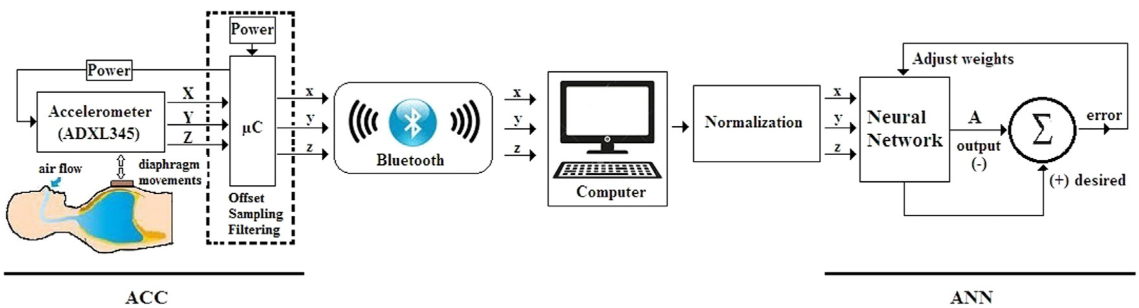

Fig. 3. ANN structure with ACC input.

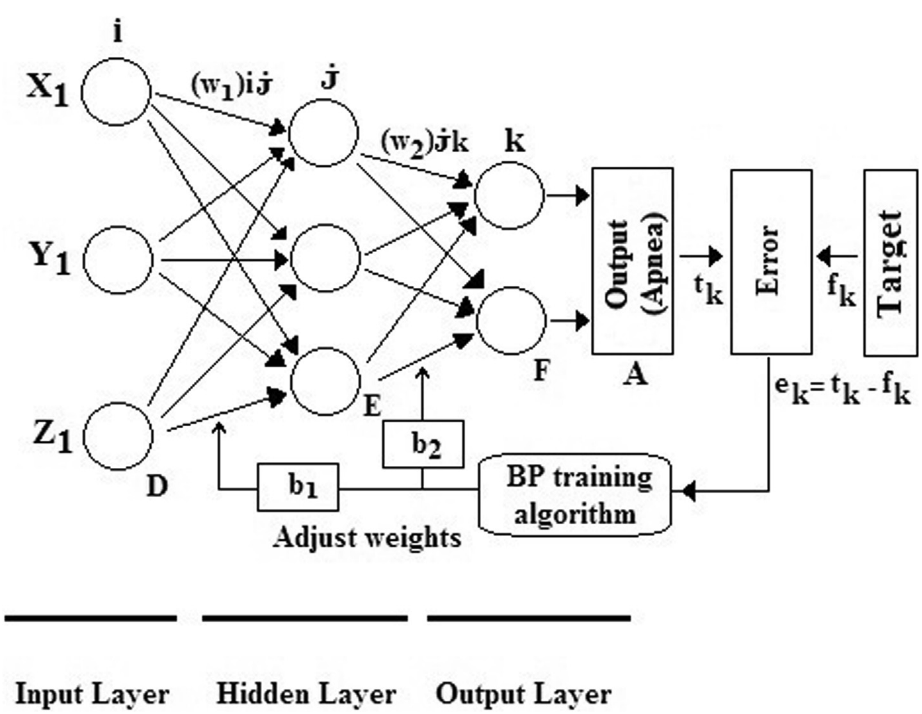

Fig. 4. ANN architecture.

diaphragm contracts and the lungs are filled with air. During this process, the thorax moves in both the ventral and cranial direction. Acceleration sensor values can be taken from either diaphragm or thorax.

The average lower and upper threshold values were determined for the measured acceleration values. (LTV: Lower threshold value; 0.32 g; UTV: upper threshold value: 0.42 g). Thus, the areas above and below the threshold values were regarded as normal breathing, while the areas in between above and below the threshold values were regarded as apnea. In the case of tiny movements, a threshold was taken, that means, the patient cannot get breathing and apnea starts.

All data were recorded on the SD card. The data were digitized at 20 Hz sampling frequency using 32-bit resolution. Each 32-bits of received float type data contained x, y, and z data. The transferred data size, 20 × 3 × 32 = 1920 bits/sec, was suitable for a wireless transmission. 10 point averaging low pass filter was created to reduce the noise at the MATLAB program (version 7.12.0.635 (R2011a) 32-bit win32). DC components were thrown from the raw signal. In order to get rid of the high-frequency noise component of the obtained signals, a digital filter was designed in MATLAB. The filter used is 10 point moving average low-pass filtering, and smoothing algorithm (Smooth Algorithm) as shown in (1):

$$y[i] = \frac{1}{P}\sum_{i=0}^{p-1} x[i+j] \tag{1}$$

where x is a raw signal, y is averaged signal, P is the average number of points.

In this work, a total of 12.723 XYZ data measured with the help of the measurement system in the reference [30] was used in the designed ANN for apnea event detection.

The magnitude of the data set (total 12.723 measured data) was normalized in the range from 0 to 1 using Eq. (2):

$$S_i^{norm} = \frac{S_i - S_{\min}}{S_{\max} - S_{\min}} \tag{2}$$

where Si is the value of the ith (i = 1, 2, ……12723) segment to be normalized and Smax and Smin are the biggest and the smallest values of the data set.

2.2. ANN structure with ACC input

In modeling with ANN, V7.12.0.635 (R2011a) Matlab software version which has Neural Network Toolbox is used. Acceleration values of the XYZ axes measuring by the developed device (ACC) were applied to the ANN as input after normalization. ANN structure with ACC input showed in Fig. 3.

2.3. ANN learned by backpropagation

ANN is a machine learning method that has become popular in recent times and is preferred in many areas [38,39]. The backpropagation (BP) algorithm is usually used to train multilayer ANNs [40,41]. Multilayer backpropagation networks are composed of three layers; input, hidden, and output layers. BP algorithms are supervised learning procedure to get optimum weights and biases between the input layer and the output layer.

In this study, the ANN system that has 3 inputs (XYZ) and one output (A- Apnea event) constructed shown in Fig. 4.

where,

i, j, and k are the input, hidden and output layers, respectively.

b1, bk; biases,

w1, w2; weights,

A; apnea event,

The input layer has D neurons and input vector I = [I1, I2,. . ., ID], and the output layer has F neurons and has output vector O = [O1, O2,. . .,OF] while the hidden layer has E neurons. The output signals of the network (A) were compared with the desired output value (the target), which was found in the training data set. Weights and bias are the parameters that define the behavior. Input vector was constructed from ACC data (X, Y, and Z), and the output vector was constructed from A.

As the ANN algorithm, feed-forward neural networks named standard backpropagation training algorithm was preferred. In the designed ANN, three layers were formed that 3 neurons in the hidden layer, the 2 neurons at the input and 2 neurons at the output layer. In the hidden layer, 1-5-10-18-20-25 numbers of neurons were tried, and the network with 3 hidden neurons giving the most suitable result was selected. The best result in 7000 iterations was reached (the number of iterations was tried from 1 to

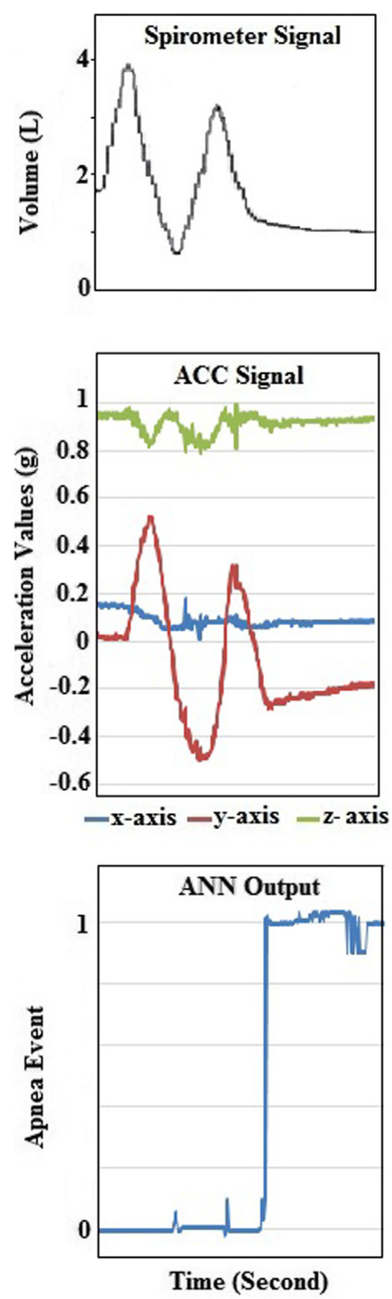

Fig. 5. Performance of ANN for H1.

10.000 with 1000 steps). The sigmoid (log-sig) function limiting the output in the range from 0 to 1 is one of the most commonly used activation function. Therefore, the log-sig function was selected as the activation function. The mathematical expression of this function was given in (3) and (4), [42].

$$netj = \sum_i w_i I_i + b_i \quad (3)$$

Table 1
Calculated MSE value of ANN for the patient H2, H3, H4 and H5 (ANN is trained by using only H1 data).

Patient No.	MSE
H1	0,0025316
H2	0,0025366
H3	0,0025364
H4	0,0025367
H5	0,0025368

$$fj = \frac{1}{1+e^{-netj}} \quad (4)$$

where,

netj is the sum of the total weighted input and the bias,

wij is the weight which is related to the connection between the node in the ith input layer and the node in the jth hidden layer,

Ii is the input at the node in the ith input layer,

bi is the bias associated at each connection link between the input layer i and hidden layer j,

fj is the output of activation function at hidden layer j.

As an error function Mean Square Error (MSE) was used (Eq.5) in order to check the error at each iteration. The training process was stopped when the calculated MSE error is smaller than the predefined acceptable error [42].

$$MSE = \frac{1}{2}\sum_k (t_k - f_k)^2 \quad (5)$$

where,

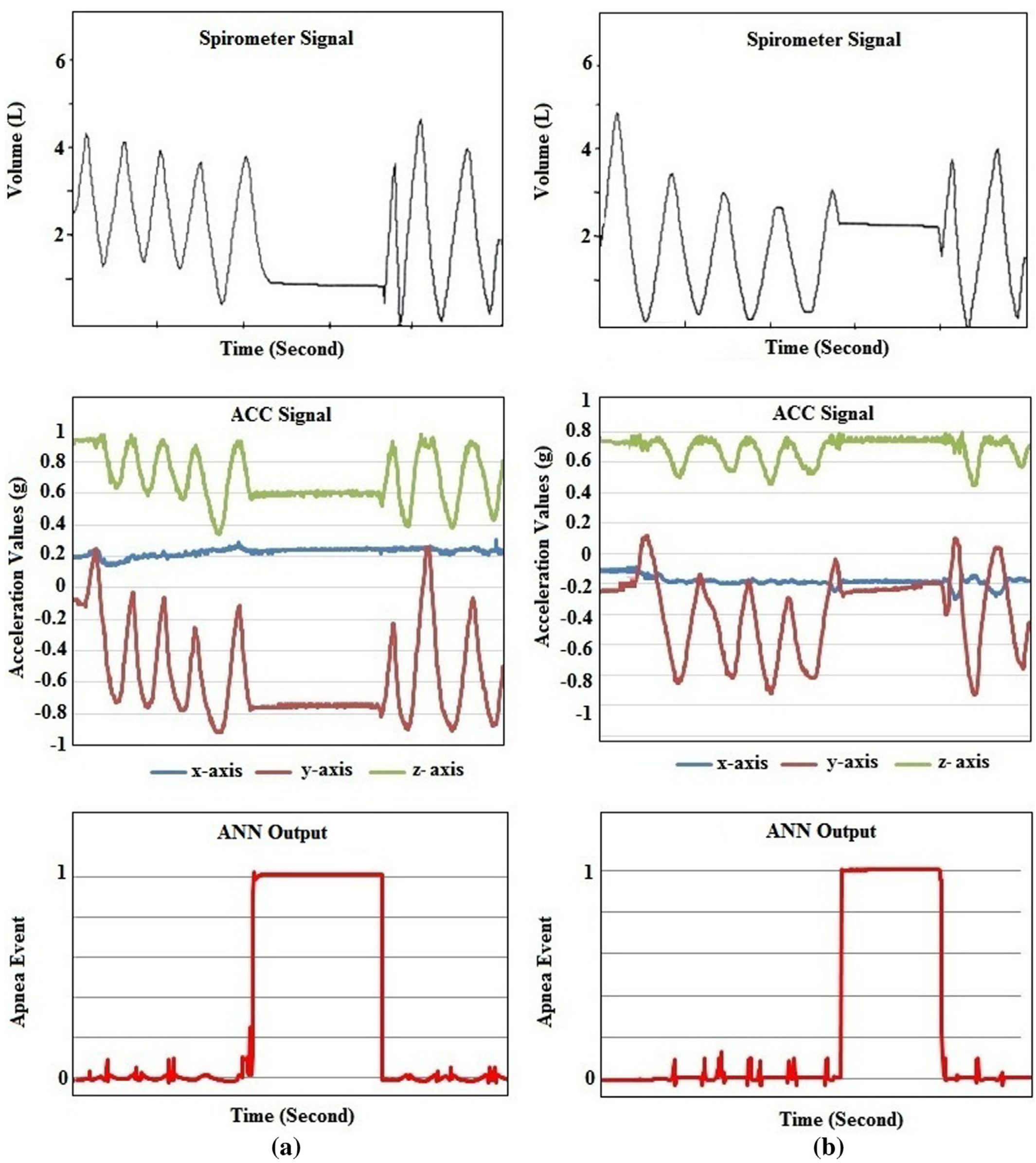

Fig. 6. Apnea event detection performance of ANN with Spirometer measurement and accelerometer g values for the patient (a) H2, (b) H3, (c) H4, (d) H5.

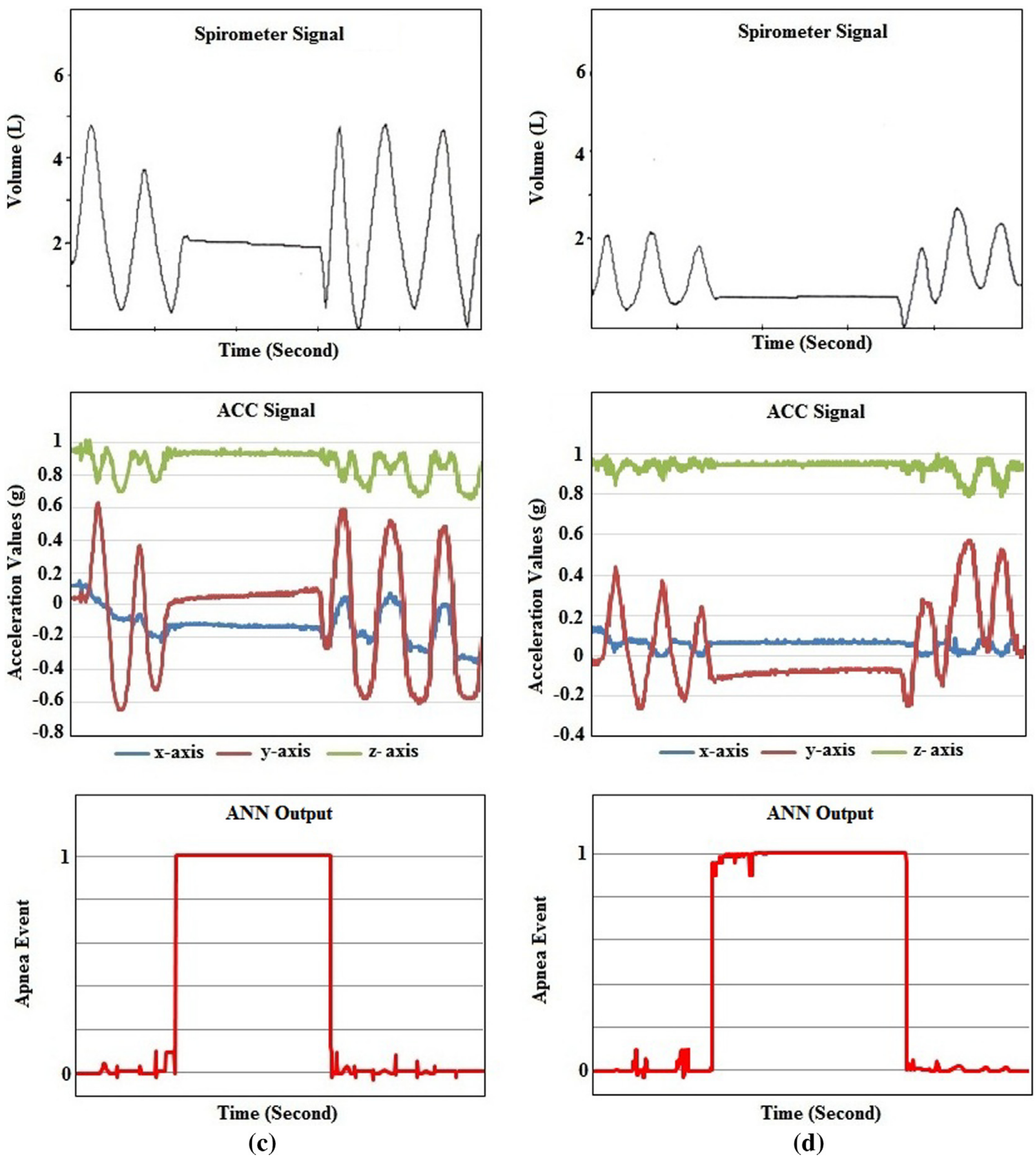

Fig. 6 (*continued*)

k is the output layer,
tk is the desired output at the kth output layer,
fk is the final output at the kth output layer.

3. Experimental studies and results

Measurements were taken on 5 patients (H1: 2763, H2: 2748, H3: 2439, H4: 2436, H5: 2337) that were known to have apnea syndrome in the study. In other words, a total of 12723 acceleration data was measured for 5 different patients. ANN was trained using the data which are measured from H1 by both developed accelerometer (as XYZ input) and spirometer (as target/desired output).

All of the data measured from H1 were divided into two: Training Data: 605 $\times$ 3 and Test Data: 316 $\times$ 3. Then training data applied to ANN. After the network was trained, 316 test data were applied to the network. The resultant graphs showing ANN performance is given in Fig. 5. In this Fig. 5, it shows that apnea has occurred. ANN system, trained with H1 ACC data, can detect apnea events successfully for H1.

Then, the other 4 patients' data were applied to this network (trained by using only H1 data, and apnea events were detected. The calculated MSE of each one is tabulated in Table 1.

Performance of ANN for the patients H2, H3, H4, and H5 are given in Fig. 6 with Spirometer measurement result and accelerometer readout values. ANN system, trained with only H1 ACC data, can detect apnea events successfully for H2, H3, H4, and H5 as well as H1. This means that, after the successful learning step, the ANN system can monitor the apnea situation for any patients simultaneously.

The confusion matrix of the ANN for all the patients has been given in the Table 2.

Table 2
The confusion matrix of the ANN for all the patients.

A	P	
	Predicted (NO)	Predicted (YES)
Actual (NO)	21444	38
Actual (YES)	30	1424

4. Conclusions and discussion

In this paper, a sleep apnea event detection system is presented by using ANN from directly acceleration values. Measurements are performed by MEMS-based accelerometer and Industrial Spirometer (Fukuda Sangyo brand spiroanalyz ST-75 model, Prg ver: 2.36B 16-Bit) simultaneously. Total of 12723 acceleration data is measured from 5 different patients.

In the designed ANN, three layers were formed that 3 neurons in the hidden layer, 2 neurons at the input and 2 neurons at the output layer. For the number of neurons in the hidden layer, 1-3-5-10-18-20-25 values were tried, and the network with 3 hidden neurons giving the most suitable result was selected. The best result in 7000 iterations was reached (the number of iterations was tried up to 10.000 with 1000 steps). 605 data of only H1 measurements are used to train ANN, and then all data used to check the performance of the ANN as well as H2, H3, H4, and H5 measurement result. MSE performance benchmark shows us that trained ANN successfully detects apnea event.

One of the contributions of this study to literature is that only ACC data are used in the ANN training step. After training for one patient, the ANN system can monitor the apnea event situation on-line for others.

Depend on lying position ACC measurement can be changed. As a next step, it is planned to find the relation between axis acceleration values and diaphragm movement related to lying position to detect apnea event. Besides that, in order to increase ANN performance as well as the accelerometer misaligning, one or more extra sensors can be added to the system.

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Ethical approval

The method of work and the developed measuring instrument were approved by the faculty member of Ondokuz Mayıs University, medical faculty, clinical research unit ethics committee with number 2015/123.

Author contributions

All the authors actively participated in the literature analysis, the interpretation of results and the preparation of the manuscript. All authors read and approved the final manuscript.

Conflicts of interest

The author declares that there is no conflict of interest regarding the publication of this paper.

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