Original

Evaluation of the PSO Metaheuristic Algorithm in Different Types of Sleep Apnea Diagnosis Using RR Intervals

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ABSTRACT

Background: Sleep apnea is one of the most common sleep disorders that facilitating and accelerating its diagnosis will have positive results on its future trend.

Objective: This study aimed to diagnosis the sleep apnea types using the optimized neural network.

Material and Methods: This descriptive-analytical study was done on 50 cases of patients referred to the sleep clinic of Imam Khomeini Hospital in Tehran, including 11 normal, 13 mild, 17 moderate and 9 severe cases. At the first, the data were pre-processed in three stages, then The Electrocardiogram (ECG) signal was decomposed to 8 levels using wavelet transform convert and 6 nonlinear features for the coefficients of this level and 10 features were calculated for RR Intervals. For apnea categorizing classes, the multilayer perceptron neural network was used with the backpropagation algorithm. For optimizing Multi-layered Perceptron (MLP) weights, the Particle Swarm Optimization (PSO) evolutionary optimization algorithm was used.

Results: The simulation results show that the accuracy criterion in the MLP network is allied with the Backpropagation (BP) training algorithm for different types of apnea. By optimizing the weights in the MLP network structure, the accuracy criterion for modes normal, obstructive, central, mixed was obtained %96.86, %97.48, %96.23, and % 96.44, respectively. These values indicate the strength of the evolutionary algorithm in improving the evaluation criteria and network accuracy.

Conclusion: Due to the growth of knowledge and the complexity of medical decisions in the diagnosis of the disease, the use of artificial neural network algorithms can be useful to support this decision.

Keywords
Sleep Apnea; ECG; Polysomnography; RR Intervals; PSO; Wavelet Analysis; Algorithm

Introduction

Sleep apnea refers to the cessation of airflow for more than 10 seconds in an adult's airway, which may be due to upper airway obstruction, increased sympathetic activity due to repeated arousal, and hypoxia during sleep [1]. Any 25% to 50% decrease in airflow during respiration, accompanied by a sharp drop in saturated oxygen in the blood, is called a hypopnea [2]. Three types of apnea or respiratory arrest are seen during sleep. In central apnea, both breathing movements and airflow are lost during apnea. In the second type of apnea, called obstructive apnea, although the passage of air through the nose and mouth is not apparent during apnea, the vibrations and breathing movements are felt. Many people have both types of apnea, which is the third type of sleep apnea (mixed apnea). Disease during sleep at night may manifest all three types of apnea [3, 4]. Based on the statistics, 4% of men and 2% of women in the world have obstructive sleep apnea [5]. It is estimated that 93% of women and 82% of men with mild to severe form of the disease cannot be diagnosed clinically [6]. Evidence suggests that sleep apnea is partly genetic because apnea symptoms, in members of the affected family, are two to six times more common and it is more common in patients with the primary disease [7]. This disorder leads to severe snoring, hypoventilation, cessation of breathing, and patient's frequent waking, daily drowsiness, fatigue, dysfunction in daily activities, concentration disorder, irritability, cognitive impairment, and mood disorders [8-10]. Polysomnography is the gold standard method for diagnosing this disease. This method is fundamentally the most common type of sleep test, which is non-invasive, and also a test used to identify sleep patterns in people with sleep disorders. This is done via recording brain waves, blood oxygen levels, heart rate, and breathing during sleep. This test is typically done in a hospital or sleep center, where specialists can monitor patients to diagnose the type of disease at night [11]. Consequently, due to the problems of Polysomnography (PSG), numerous studies have been conducted to replace alternative and easier tests to diagnose this syndrome. Lili et al. separated the ECG signal into segments (not equal in length), then reduced the unexpected RR intervals with a local filter and lastly used the support vector machine (SVM) classifier to detect obstructive sleep apnea (OSA) [12].

Considering time dependence and the use of 70 ECG records, a method based on the Hidden Markov model (HMM) was presented for OSA diagnosis [13]. Da Woon et al. used ECG records from the PhysioNet database and predicted the apnea-hypopnea intensity index using the regression model [14]. In [15], a method is proposed for identifying obstructive apnea from 389 frequency range and network-based ECG recordings. RR distances were separated into sections, and the Lomb-Scargle technique was used to calculate spectral density and a dynamic time interval was used to evaluate the similarity. Heenam et al. used a slow-wave sleep method on ECG signals of 21 healthy individuals and 24 patients with obstructive apnea extracting RR interval and Heart Rate Variability (HRV) traits for normal diagnosis of obstructive apnea [16]. For easy access and low cost, most studies have used the ECG signal to diagnose obstructive apnea or normal apnea. If the type of apnea is determined, accordingly, the type of treatment can be provided, leading to saving in time and costs. Consequently, this study aimed to optimize the neural network structure using PSO metaheuristic algorithm for increasing the accuracy of diagnosing different types of sleep apnea.

Material and Methods

This study is descriptive-analytical that in this part, a suitable algorithm and its implementation on the data are studied.

Database

The data recorded in the sleep clinic of Imam Khomeini Hospital in Tehran have been used. Fifty ECG recorded signals, including 34 males and 16 females were randomly selected and analyzed with the age range of ($32 \leq$ age ≤ 64) and ($24 \leq$ BMI ≤ 35), sleep duration between 7 and 9 h, 100 Hz signal recording frequency and 16-bit resolution, the results of which was already clear that they were randomly selected and checked. Of the 50 cases, 10, 13, 17 and 9 were normal, mild, moderate and severe, respectively.

Preprocessing

The first step in analyzing the electrocardiogram signal is removing the obtained noise from the existing signals. In the current study, finite impulse response (FIR) digital filters have been used in order to remove noise. This filter means limited impulse response. In digital signal processing, filters are one of the most important and basic processing blocks. In general, each system and processing block can be displayed with a type of filter that has a range response and phase response. Each filter can be represented by a differential equation. Filters are separated into two parts, infinite impulse response (IIR) and finite impulse response. Equation (1) is the Finite Impulse Response (FIR) equation in which the delayed input coefficients are multiplied by the filter coefficients and summed up at the end.

$$Y = \sum_{k=0}^{m} a_k x[n-k] \qquad (1)$$

In Figure 1, the Signal-flow Graph of a system is shown [17, 18].

To detect peak R, Shannon's energy is first obtained from the ECG signal, and after applying the following processes, the location of the signal peak is determined. Shannon's energy method is derived from the Shannon Energy and Hilbert Transform (SEHT) method. The proposed algorithm consists of 4 steps: 1) digital filters 2) Shannon energy calculation 3) identification of signal peaks and 4) identification of the exact location of the R peaks. The block diagram of this method is shown in Figure 2 [19].

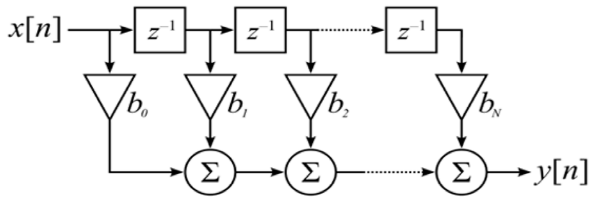

Figure 1: The signal flow graph of a Finite Impulse Response (FIR) system.

The distance between the R peaks (RR intervals) was calculated from the following formula:

$$RR(i) = R(i+1) - R(i) \quad i = 1, 2, ..., n \qquad (2)$$

According to the Apnea definition, the 10-second windows were selected so that the end of each window was the beginning of the Apnea. Then a one-second shift was placed on the window to increase the accuracy and analysis of the whole signal, and this shift continues until the beginning of the window overlaps with the end of the apnea. Because apnea has different lengths, on average, the researchers consider a 30-second window for each apnea with a frequency of 100, and to calculate

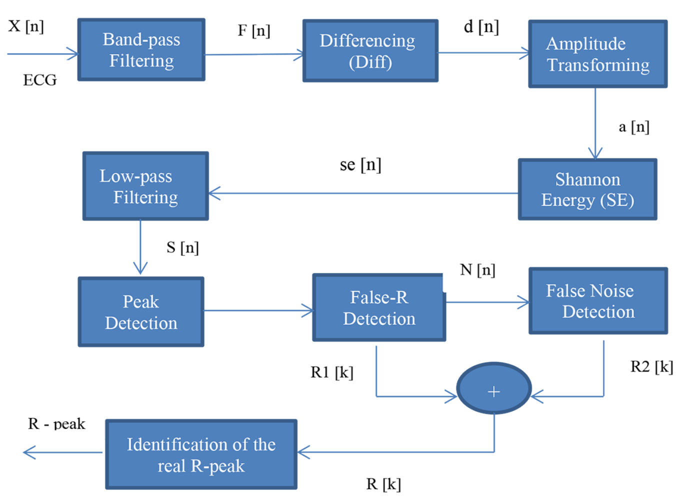

Figure 2: Block diagram of R peak detection.

the number of normal windows, the number of apneas was multiplied by 1000. In this way, all the windows were determined that should be given to the appropriate classification.

Wavelet transform was used to extract the feature. Wavelet transform is a method of returning a function or signal to a specific form of signal that is accountable for further study or it allows the main data set to be described differently. To make a wavelet transform, a wavelet is required and is in the form of a damped wave. The discrete version of the wave is a series of waves sampled from a continuous transformation. Therefore, the information in it is redundant and leads to an increase in computational load. The processing process is that the signal first passes through a low-pass filter and then through a high-pass. The output coefficients of the low-pass filter have a process similar to the original signal, and due to this fact, it is called approximation coefficients, and the output coefficients of the high-pass filter correspond to the signal details. The main signal is calculated in terms of wave coefficients using Equation 3 [20]:

$$\mathrm{x}(\mathrm{t}) = \sum_{m=-\infty}^{\infty}\sum_{n=-\infty}^{\infty} T_{m,n}\psi_{m,n}(\mathrm{t}) \quad (3)$$

Where,

$$T_{m,n} = \int_{-\infty}^{\infty} x(t)\psi_{m,n}\,dt \quad (4)$$

And also,

$$X(t) = \sum_{m=-\infty}^{\infty}\sum_{n=-\infty}^{\infty} \langle x, \psi_{m,n}\rangle \psi_{m,n}(t) \quad (5)$$

An approximation of the m-the scale signal is as follows:

$$X(t) = \sum_{n} s_{m,n}\phi_{m,n}(t) \quad (6)$$

Where the approximate coefficients of $s_{m,n}$ are as follows:

$$S_{m,n} = \int_{-\infty}^{\infty} x(t)\phi_{m,n}\,dt \quad (7)$$

Using the above formulas, 4 detail coefficients and an approximation coefficient were obtained for ECG. Then 6 nonlinear features were calculated for these coefficients:

1. Mean; $\bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i$ (8)

2. Standard deviation; $Sd = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(x_i - \bar{x})^2}$ (9)

3. Geometric mean; $Gm = \left(\prod_{i=1}^{n} x_i\right)^{\frac{1}{n}}$ (10)

4. Skewness; $S = \frac{E(x-\bar{x})^3}{\sigma^3}$ (11)

5. Kurtosis; $K = \frac{E(x-\bar{x})^4}{\sigma^4}$ (12)

6. Mean absolute deviation;

$$MAD = mean\left(\left|x - mean(x)\right|\right) \quad (13)$$

Table 1 also shows 10 features extracted from RR intervals [21].

A total of 16 features were used. After extracting the features, the t-test statistical test with a significance level of α=0.05 was used to determine the difference between the extracted characteristics. The results showed a significant difference.

Classifier

Neural network design has two main aspects: architecture and learning algorithm.

Architecture: The desired neural network seems to have a multi-layered perceptron structure that performs better than other methods [22].

MLP is a set of nonlinear neural cells organized and connected in a progressive structure. The multilayer perceptron neural network algorithm is used for prediction and classification problems. An MLP consists of an input layer, several intermediate layers as a hidden layer, and an output layer. Each layer consists of a certain number of neurons. Each layer has outputs as many as its neurons, and these outputs go as input to the next layer. The input vector to the first layer is the same as the input vector of the problem and the output vector of the last layer is the network response vector for that input vector [23, 24].

Table 1: Features extracted from RR intervals.

RR (m)	RR (m) = $\{rr_i\}_{i=1}^{m}$	Feature Count
Mean: The sum of all data values divided by the number of data values	$\mu_{rr} = E[rr_i] = \frac{1}{m}\sum_{i=1}^{m} rr_i$	1
Standard deviation RR-interval.	$SD = \sqrt{E\left[(rr_i - \mu_{rr})^2\right]}$	1
Number of pairs of adjacent RR intervals where the first RR interval exceeds the second RR interval by more than 50ms.	$NN50\ (Variant\ 1) = \sum_{i=2}^{m} unit\left[\lvert rr_i - rr_{i+1}\rvert - 50ms\right]$	1
Number of pairs of adjacent RR intervals where the second RR interval exceeds the first RR interval by more than 50ms.	$NN50\ (Variant\ 2) = \sum_{i=2}^{m} unit\left[\lvert rr_{i+1} - rr_i\rvert - 50ms\right]$	1
Ratio of NN50v1 to segment length.	$PNN50v1 = \frac{\mathrm{NN50v1}}{m}$	1
Ratio of NN50v2 to segment length.	$PNN50v2 = \frac{\mathrm{NN50v2}}{m}$	1
Standard deviation of the differences between adjacent RR intervals.	$SDSD = \sqrt{E\left[(rd_i - \mu_{rd})^2\right]} rd_i = rr_{i+1} - rr_i$ and $\mu_{rd} = Erd_i$	1
Square root of the mean of the sum of the squares of differences between adjacent RR intervals.	$RMSSD = Erd_i^{\,2}$	1
Mean absolute deviation values: subtraction of the mean RR interval values from all the RR interval values in an epoch.	$MAD = \frac{\sum_{i=1}^{m} \lvert rr_i - \mu_{rr}\rvert}{m}$	1
Inter-quartile range: difference between $75^{th}(Q_4)$ and $25^{th}(Q_1)$ percentiles of the RR interval value distribution	$IQR = Q_4 - Q_1$	1

Learning algorithm: One of the most important goals of the neural network is to find weights proportionate to the neurons in different layers. This network is trained based on the error backpropagation (BP) algorithm. The BP algorithm uses two forward and backward paths to calculate network weights so that the actual outputs are compared to the desired outputs, and the weights are adjusted under the BP algorithm in the supervised state to create a suitable model [25].

Despite the BP algorithm pervasiveness, this method, similar to other gradient-based minimization algorithms, is a local search engine and is sensitive to the starting point. Consequently, the trained local network using an algorithm will not have the expected performance, thus, there is a propensity to use evolutionary algorithms to conduct a public search. Optimizing communication weights is a public search issue for a pre-determined and fixed neural network architecture [26, 27].

Particle Swarm Optimization Meta-heuristic Algorithm

This algorithm is an optimization technique based on probability rules [28]. One of the main characteristics of the PSO algorithm is the stress on the collective state of thinking and intelligence. PSO algorithm starts with a group of random answers. It then searches to find the optimal answer in the problem space by updating the current answers. Each particle in the problem space is defined by two n-dimensional vectors (v_i, x_i) that represent the spatial position and velocity of the ith particle, respectively. At each stage of mass motion, each particle is updated by three components of particle speed, best personal position, and best neighborhood position. Particle velocity is the direction of the particle's current motion in the problem space. The best personal position is the position in which the particle has the best response in terms of merit up to now; consequently, the value of the best merit and the corresponding position must be stored for each particle. The best neighborhood position for each particle is the best position ever obtained by all its neighboring particles. If in the definition of neighborhood, all particles are considered neighbors, the best location of the neighborhood is the best global; otherwise, we call it the best local position. After finding the two best personal and local locations, the velocity of each particle is updated according to Equation (14) and the new location of the particle is updated according to Equation (15).

$$v^{(t+1)} = wv^t + c_1 r_1 \left(P^{best} - x\right) + c_2 r_2 (L^{best} - x) \quad (14)$$

$$x^{(t+1)} = x^{(t)} + v^{(t+1)} \quad (15)$$

Where, in the above relationships, w is the inertial weight c_1, c_2 learning factors or acceleration coefficients r_1, r_2 random numbers with uniform distribution in the range (0, 1). P^{best} is the best personal position of the particle and L^{best} is the best local position of the particles. $x^{(t)}$, $v^{(t)}$ are the vectors of velocity and position of the particle in step t, respectively. To prevent algorithm divergence, the velocity vector of the particle is limited to the range [V^{Min}, V^{Max}] [29, 30].

In the current study, by trial and error method, different patterns of neural network with learning rates of 1% to 5%, momentum 85% to 95% and the number of nodes between 5 to 15 neurons in the middle layers and various activating functions to the data was fitted. The PSO algorithm was also used to optimize network weights.

Results

According to the method of windowing, the research findings revealed that out of 50 cases, including 10 normal, 13 mild, 17 moderate and 9 severe cases, a total of 51300 apnea windows (including: normal, obstructive, central, mixed) were examined with 16 features. Out of the 134 network structures considered with different architecture and parameters, the best structure with 16 input neurons, 6 neurons in the first hidden layer and 9 neurons in the second middle layer and 1 output neuron with a learning rate of 2%, momentum size 9%, the activation function of the middle layer is of the sigmoid type and the activator function in the neurons is in the only linear output layer. To determine the best training algorithm, 70% of the data for training and 30% of the data for testing based on all features were analyzed and compared to MLP classifier with BP training algorithms and PSO optimization algorithm for the best network structure. The rates selected for the parameters v, w, c_1, c_2 are 1.3, 1, 1.5, 2, respectively.

To examine the success and efficiency of these networks, three indicators of accuracy, sensitivity, and specificity of the confusion matrix were used using the following relationships. Averagely, 10 experiments were repeated in each design to achieve greater accuracy in evaluating the obtained results.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{16}$$

$$\text{Specificity} = \frac{TN}{TN + FP} \tag{17}$$

$$\text{Sensitivity} = \frac{TP}{TP + FN} \tag{18}$$

Where, the correct diagnoses of true negative (TN) and true positive (TP), false negative (FN) and false positive (FP) are the wrong diagnoses for each class.

The results of MLP implementation with the BP training algorithm in the best-selected network structure and for the case where all the features are entered in the model are shown in Table 2.

The results of MLP implementation with the PSO algorithm in the best-selected network structure and for the case where all the features are entered in the model are shown in Table 3.

A comparison of MLP implementation results with the BP training algorithm and PSO optimization algorithm for the best network structure is shown in Figure 3.

A comparison of the results illustrates that the optimized neural network has higher evaluation criteria in diagnosing different types of apnea.

Discussion

Lately, because these processes can find optimal network architecture without external interference interest in evolutionary procedures for adapting communication weights within the network, network architecture and learning rules according to the problem space have greatly augmented. Via these procedures, the repetitive and tedious steps of trial and error to achieve the desired work error are eliminated. The advantage of automated design over manual neural network design becomes more obvious with the increasing complexity of the network. The evolutionary artificial neural network (EANN) provides a general framework for examining different areas of evolution and education [31, 32].

In this study, the researchers proposed a method for identifying the types of apnea based on optimized MLP using the PSO evolutionary algorithm with an emphasis on native data. First, the data were pre-processed in

Table 2: Multi-layered Perceptron (MLP) evaluation criteria with Backpropagation (BP) algorithm.

Scale evaluation	Normal (%)	Obstructive (%)	Central (%)	Mixed (%)
Accuracy	92.05	93.93	89.33	89.53
Specificity	95.67	97.30	90.47	93.29
Sensitivity	82.44	81.48	81.55	81.03

Table 3: Multi-layered Perceptron (MLP) evaluation criteria by applying Particle Swarm Optimization (PSO) algorithm.

Scale evaluation	Normal (%)	Obstructive (%)	Central (%)	Mixed (%)
Accuracy	96.86	97.48	96.23	96.44
Specificity	98.27	98.91	96.90	97.23
Sensitivity	93.12	92.59	94.30	93.96

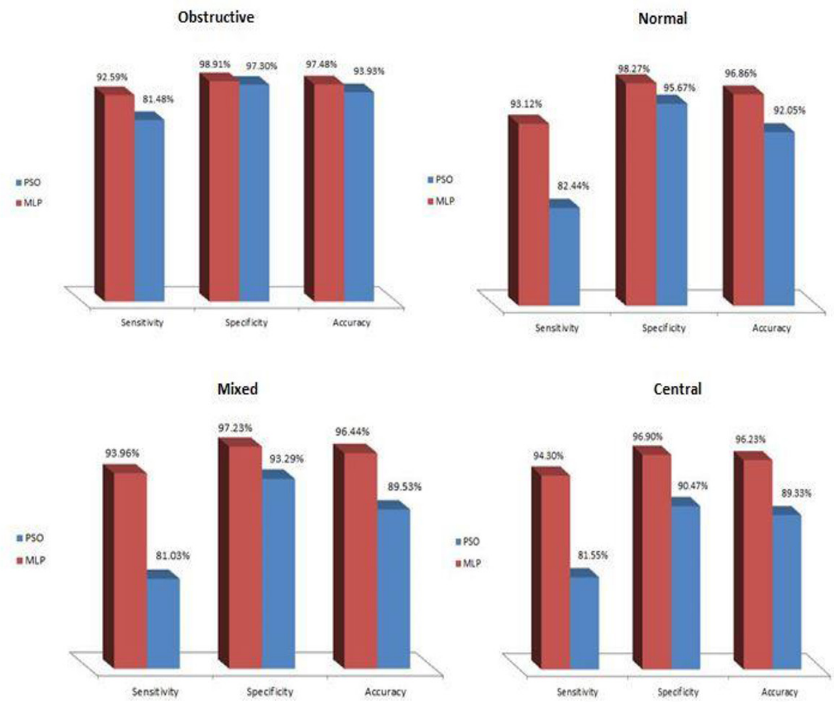

Figure 3: Comparison of algorithms results.

three steps of noise elimination, R peak detection and windowing, respectively, then 16 features were extracted using wavelet transform, and in the next step, the data were classified into 4 categories by optimized MLP method. In MLP, first the BP algorithm, then the PSO evolutionary algorithm was used. Accuracy assessment criteria were obtained %96.86, %97.48, %96.23, and % 96.44 for normal, obstructive, central, mixed apnea, respectively.

In previous studies, discriminative hidden Markov model via estimating the relevant parameters based on the ECG signal and considering the time dependence of the signal was used for OSA detection [13]. To validate this approach, 70 records (35 records for training and 35 records for testing) of the PhysioNet database were used. The classification accuracy was 97.1% for each record and for every part that OSA was diagnosed, it was 86.2%. Hassan et al. used hidden information in the ECG signal to classify healthy and unhealthy windows. They investigated the problem of automatic sleep apnea detection using single-lead ECG signals. Firstly, parts of the ECG signals were decomposed using a data-compatible signal decomposition scheme, i.e. Tunable Q-Factor Wavelet Transform (TQWT). Three statistical features were extracted from the TQWT sub-bands. In this work, a new machine learning algorithm, i.e. Random Under-Sampling Boosting (RUSBoost), has been implemented classify. The overall algorithmic performance of this method was investigated for different values of TQWT parameters. The optimal values of these parameters were examined and determined. Then using statistical characteristics extracted from each sub-bands, healthy and unhealthy windows were categorized with 88.88% accuracy [33]. Li Wang et al. used the remaining network method to show information in RR to automatically detect apnea. This method has been experimented using a set of general data available to PhysioNet to diagnose apnea in each section. Thirty nightly records were used for training and 5 records for testing. The accuracy, sensitivity and specificity obtained were 94.4%, 93.0% and 94.9%, respectively. This model also showed good compatibility while using the respiratory signal derived from ECG (EDR) in experiments and using fewer input samples, a better result is obtained [34].

The obtained results show that the optimized neural network in this study and diagnosing different types of apnea has been more successful than other studies in diagnosing this disease. In addition to the diagnosis of different types of Sleep Apnea, the results of this study show that the optimized neural networks perform better compared to other studies. The collection of indigenous data by the researchers and the use of an optimized MLP method on this data in one of the strengths of this study which leads to more accuracy in diagnosis of Sleep apnea. Accuracy increase in identifying people with sleep apnea depends on the increase in the size of the database, thus in future research can use a larger database to increase the number of records as well as the accuracy of the algorithm. This method can also be used to diagnose other diseases because it will be very economical due to the low cost and high speed of the process.

Conclusion

Due to the ability of the optimized MLP classifier in analysis of the relationship between data, this method is faster than other methods as well as its better generalizability and it is recommended as a physician's assistant in medical centers for early detection of sleep apnea. If the software is designed using the proposed algorithm in medical centers, an effective step would be taken in sleep apnea diagnosis which leads to the medical care cost reduction.

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Conflict of Interest

None

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