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# Classification of Sleep Apnea Events Using Nasal Air Flow (NAF) Signals

# تصنيف أحداث توقف التنفس أثناء النوم باستخدام إشارات سريان الهواء خلال الأنف والفم

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**الملخص العربي :**

إن الكشف عن وتشخيص أنواع مختلفة من مرض توقف التنفس أثناء النوم (الانقطاع الانسدادي- الانقطاع المركزي وضعف التنفس) يعد واحد من المهام الرئيسية في طب النوم حيث أن تحليل إشارات سريان الهواء خلال الأنف والفم هو الأسلوب المباشر والأكثر فعالية للكشف التلقائي عن أحداث هذا المرض بالتحقق من خفض سعة المقدار. تم في هذا البحث استخدام تحليل متوسط المشتقة الثانية لهذه الإشارات لتصنيف أربعة أحداث من هذا المرض (طبيعي- الانقطاع الانسدادي- الانقطاع المركزي وضعف التنفس) ثم تم مقارنة أداء ثلاثة أنواع من المصنفات: شبكة كوهين للتعرف الذاتي ومصنف المنطق المبهم ونموذج ماركوف وأظهرت النتائج أن أعلى معدل للتصنيف هو ٩٥.٧% باستخدام نموذج ماركوف ذو الرتبة ١٣.

## *ABSTRACT*:

**Detecting and diagnosing different types of Sleep Apnea (Obstructive, Central and Hypopnea) is one of the major tasks in sleep medicine. Clinically, analyzing Nasal AirFlow (NAF) signal is the most sufficient and direct reliably effective method for the automatic detection of Sleep Apnea events by checking the airflow amplitude reduction. This paper investigates and compares the performance of three classifiers: a Kohonen self-organizing map (SOM), Adaptive Neuro Fuzzy Inference System (ANFIS) and Hidden Markov Model (HMM) for the classification of Sleep apnea events. The results have shown that the highest correct classification rate is 95.7% when using HMM with order 13.**

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# I.INTRODUCTION

Apnea is broadly classified as Central Sleep Apnea (CSA), which is caused by reduction of impulses from the central nervous system to the respiratory muscles causing blockage of airflow associated with lack of respiratory efforts and Obstructive Sleep Apnea (OSA), which is a disorder caused by obstruction of the upper airway and referred to cessation of AirFlow in the presence of continued respiratory efforts lasting more than 10 seconds.

A mild version of apnea is hypopnea [1] where the breath does not stop but decrease over 50% of its normal value followed by 4% desaturation of haemoglobin levels.

Essential sleep related parameters or indexes were derived directly from NAF signals to quantify the frequency of abnormal respiratory events per hour of sleep which helps in differentiating different types of Sleep Apnea and assessing the severity of Apnea.

These indexes are: Apnea-hypopnea index (AHI), Central sleep apnea index (CAI), and hypopnea index (HI) [2]. According to the American Academy of Sleep Medicine Task Force [2], definition of sleep apnea implies that: an Apnea-hypopnea index AHI less than 10 refers to normal subject, while an AHI greater than or equal 10 refers to Apneic patient with different degrees of severity. AHI of 10-15 episodes per hour refers to Mild Apnea, AHI of 15-30 refers to Moderate Apnea and AHI more than 30 refers to Severe Apnea.

Although, previous studies utilized several methods in apnea detection using various features of bio-signals; EEG, ECG, and heart rate variability [3-5], but it is still required to detect apneic events efficiently and robustly from a single Nasal Airflow (NAF) signal under varying situations [6-8]. Recently, Ayappa et al. [9] reported that the analysis of the NAF signals could provide a result similar to that obtained by full polysomngraphy (PSG) analysis and consider it as simple and efficient diagnostic tool for apnea detection.

NAF is commonly measured by a thermistor or thermocouple which is susceptible to offset and baseline drift [10]. Griffiths et al. [11] developed an algorithm that analyzes NAF signals using the average magnitude of the second derivatives which detect respiration strength robustly under offset or baseline drift.

The problem of classifying sleep apnea was previously addressed using signal processing and pattern recognition methodologies [12, 14]. Recently, Lini et al. [15] reported an approach for identifying sleep apnea syndrome using wavelet transform and neural networks.

A Fuzzy Inference System (FIS) for the detection of Obstructive Sleep Apnea (OSA) has been proposed in [16].

In this paper, the performance of three classifiers for classifying sleep apnea events using Nasal AirFlow records was investigated.

These are: Kohenen self-organizing map [17, 18] (SOM), Adaptive Neuro-Fuzzy Inference System {ANFIS) [19, 20] and Hidden Markov Models (HMMs) [21, 22]. The three classification systems were implemented to process, analyze, abstract meaningful information and detect sleep apnea events. Our objective was to formulate the problem such that sleep apnea events can be detected at the highest recognition rate by the classification system.

## II. Training Data Set

One-hundred-twenty-eight subjects took part in this prospective study. The data were obtained during an initial portion of the patient's visit to Cairo Center For Sleep Disorder (Egypt) for diagnosis and treatment of OSA. The records were taken from normal and abnormal subjects (32 Normal, 32 OSA, 40 Hypopnea and 24 Central Apnea). The normal records were extracted from the Apneic records after treatment using Continuous Positive Airway Pressure (CPAP) giving more classification accuracy [2]. A sleep specialist determined the apnea and hypopnea events during the test time. A total of 512 NAF segments (128 normal, 128 OSA, 160 Hypopnea and 96 Central Apnea) were extracted from the patients dataset. Each record is of one hour duration to estimate the sleep related indexes. The sampling rate was 10 Hz.

## III. NAF signal Analysis and Feature Extraction

In consideration of the periodicity of the NAF signal, the measured signal was modeled as a summation of the respiration signal, baseline drift, and baseline offset [12].Generally, first derivate is used to eliminate the effect of the baseline offset, while second derivative eliminate the effect of baseline drift [12].

The average magnitude of the second derivatives (AMSD) of NAF signals is calculated as follows [12]:

1- Each record is divided into one epoch length of 30 seconds segments, which satisfies that Apnea event length should be at least 10 seconds.

2- Average Magnitude of Second Derivative (AMSD) of each NAF segment is calculated as follows [12]:

$$AMSD = \frac{\sum_{i=2}^{n-1} \left| (s(i+1) - s(i)) - (s(i) - s(i-1)) \right|}{n}$$

(1)

where n: is the size of the segment.

3- Each segment is compared with Apnea threshold, which is the AMSD of normal NAF record and classified into certain Apnea type as follows:

If AMSD of the segment is less than or equal 8% of Apnea threshold then it is classified as OSA event, if it is less than or equal 30% and greater than 10% of the threshold it is classified as hypopnea event, and if it is less than or equal 10% and greater than 8% of the Apnea threshold it is classified as CSA event.

4- For each one hour NAF records the following sleep-related features are calculated: total number of OSA events (TOE), total number of hypopnea events (THE), and total number of CSA events (TCE).

Apnea indexes: AHI, HI and CAI are then calculated as:

$$AHI = \frac{\text{Total number of Apnea and Hypopnea events}}{\text{Total Sleep time in minitues}} * 60, \quad (2)$$

$$CAI = \frac{\text{Total number CSA events}}{\text{Total Sleep time in minitues}} * 60, \quad (3)$$

And

$$HI = \frac{\text{Total number Hypopnea events}}{\text{Total Sleep time in minitues}} * 60 \ . \quad (4)$$

Table (1) shows the sleep-related features derived from NAF signals and Figure 1 shows the NAF signals and its first and second derivatives for Normal, OSA, Hypopneic and CSA events.

Table 1: Sleep-related features derived from NAF signals.

| Feature | Normal | OSA | Hypopnea | CSA |
|---|---|---|---|---|
| AMSD | 543.012±30.01 | 43.441 ± 10.443 | 160.221±16.85 | 54.313 ±9.79 |
| TOE | 13.219± 1.011 | 105.525±12.203 | 17.621 ±1.070 | 10.504±2.880 |
| THE | 12.987± 0.879 | 13.123 ± 1.962 | 108.556±14.01 | 6.098 ± 0.721 |
| TCE | 0.001± 0.031 | 7.234 ± 1.542 | 0.008 ± 0.002 | 50.911±4.053 |
| AHI | 5.324± 0.509 | 15.098± 1.132 | 14.876± 1.113 | 0.852± 0.056 |
| HI | 0.034± 0.043 | 3.008 ± 0.987 | 12.001± 1.122 | 0.338± 0.217 |
| CAI | 0.002± 0.033 | 0.010 ± 0.004 | 0.022 ± 0.023 | 8.095± 0.698 |

Data are presented in mean ±S.D

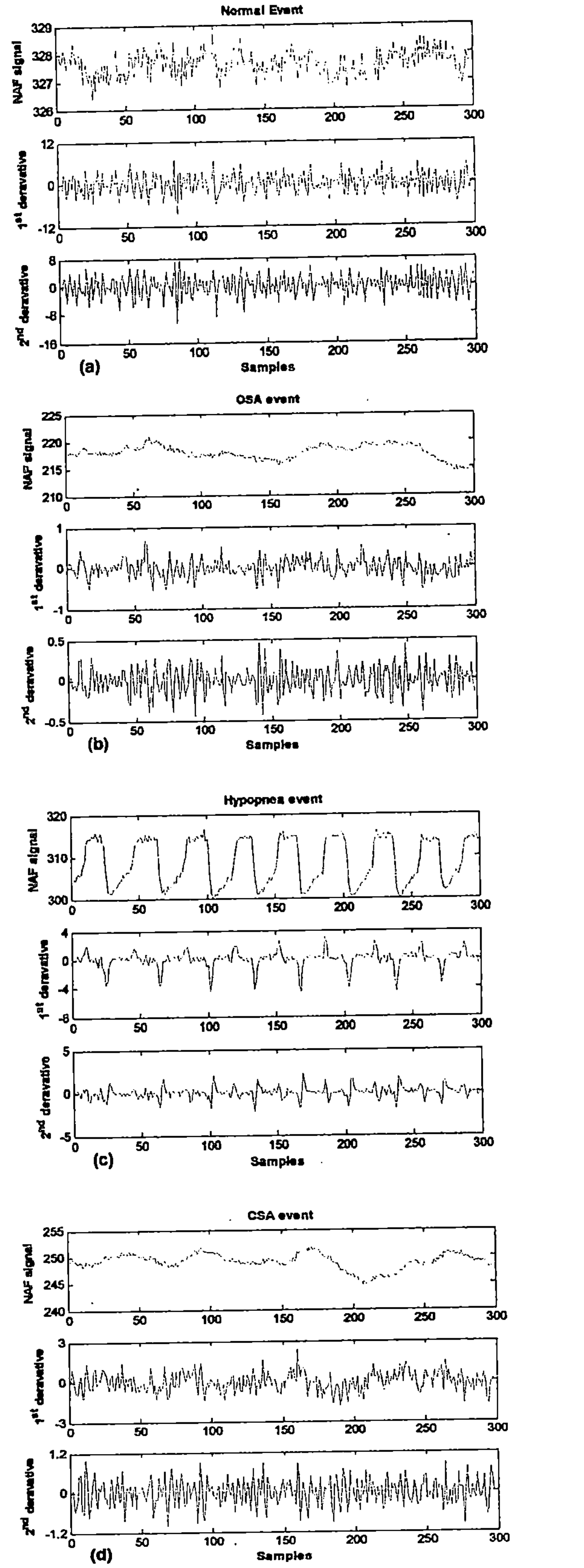


Figure 1: The NAF signal and the First and Second derivatives (a) Normal subject, (b) an OSA subject, (c) Hyponea subject, and (d) CSA subject.

# IV. Classifiers

Three classifier methodologies were chosen for the design of the classification systems for the apnea events:

## IV.I. Kohonen Self-Organizing Map (SOM)

Kohonen self-organizing map (SOM) is one of the basic types of artificial neural networks. Its architecture represents a two-dimensional grid of connected neurons, which are multi-dimensional vectors. The dimension of vectors is equal to the number of descriptors [18].

The learning of SOM is the projection from multi-dimensional space onto two-dimensional grid (array) of neurons, which involves two steps [18].

In the first step, a vector, which represents an object is presented to all neurons and the algorithm selects the neuron that is most similar to it (winning neuron). In the second step the weights of the winning neuron are modified to the vector values and in the same time the neighboring neurons are modified to become similar to it. Details and mathematical expressions are discussed in [17,18].

## IV.II. Adaptive Neuro Fuzzy Inference System (ANFIS)

The ANFIS is a fuzzy Sugeno model, put in the framework of adaptive systems to facilitate learning and adaptation [20]. Such framework makes the ANFIS modeling more systematic and less reliant on expert knowledge. ANFIS architecture consists of five layers of nodes.

Out of the five layers, the first and the fourth layers consist of adaptive nodes while the second, third and fifth layers consist of fixed nodes. To present the ANFIS architecture, two fuzzy if-then rules based on a first order Sugeno model are considered [20]:

$$\begin{array}{l} \text{If } x \text{ is } A_1 \text{ and } y \text{ is } B_1 \quad \text{THEN } f_1 = p_1 x + q_1 y + r_1 \\ \text{If } x \text{ is } A_2 \text{ and } y \text{ is } B_2 \quad \text{THEN } f_2 = p_2 x + q_2 y + r_2 \end{array} \quad (5)$$

where $x$ and $y$ are the inputs, $Ai$ and $Bi$ are the fuzzy sets, $fi$ are the outputs within the fuzzy region specified by the fuzzy rule, $pi$, $qi$ and $ri$ are the design parameters that are determined during the training process.

### IV.II.A. Learning ANFIS

A hybrid algorithm combining the least squares method and the gradient descent method is adopted to solve this problem [20]. The least squares method (forward pass) is used to optimize the consequent parameters in layer4 with the premise parameters fixed. Once the optimal consequent parameters are found, the backward pass starts immediately. The gradient descent method (backward pass) is used to adjust optimally the premise parameters in layer1 corresponding to the fuzzy sets in the input domain. The output of the ANFIS is calculated by employing the consequent parameters found in the forward pass. The output error is used to adapt the premise parameters by means of a standard backpropagation algorithm [20].

## IV.III. Hidden Markov Models

A hidden Markov model (HMM) is a tool to statistically model time-varient process with the following characteristics [21]:

1- Set of unobserved (hidden) states $Q=\{q_1,.....,q_N\}$, where $N$ is the number of hidden states in the model.

2- Set of observation symbols $O=\{o_1,.....,o_L\}$ where $L$ is the number of distinct emission symbol per state.

3- The transition matrix $A$ whose elements $a_{ij}$ represent the probability to go from state $q_i$ to state $q_j$

4- The emission matrix $B$ whose elements $b_{jk}$ represent the probability of emission of a symbol $o_k$ when the system state is $q_j$.

5- The set of initial state probability distributions $\Pi=\{\pi_1,.....,\pi_N\}$ whose elemnts $\pi_i$ represent the probability for $q_i$ to be the initial state. For convenience we denote HMM as compact notation notation $\lambda=\{A,B,\Pi\}$.

The learning task in HMMs is implemented using Baum–Welch algorithm which compute maximum likelihood estimates and posterior mode estimates for the parameters (transition and emission probabilities) of a HMM, when given only emissions as training data [21].

## IV.III. A. Training HMM

The Baum–Welch algorithm was used to train HMMs, one for each type of Sleep Apnea,

using the training data set [22]. It has been found that an order of 13 gives the highest

correct classification rate for each Sleep Apnea type.

A separate Model was defined for each class of patterns. Maximum likelihood classification of an unknown observation sequence can be achieved by calculating the probability of the observations given the model P(O/λ) for each model in turn.

The unknown Pattern is assigned to the class of the model that has the highest probability of generating the observed data; that is for $M$ classes $C=c_1, c_2,...c_M$, where $c_m$ is represented by model $\lambda_m$ then $O$ is assigned to the class $c_m$ if

$$P(O/\lambda) = \max_{d=1}^{M} P(O/\lambda_d) \qquad (6).$$

## V. Results

The Kohonen self-organizing map (SOM), Adaptive Neuro Fuzzy Inference System

(ANFIS) and three Hidden Markov Models (HMM) {5,7,13} were trained and tested using the seven elements feature vector derived from NAF signals analysis. The hold-out method was utilized for training [23] in which 50% of the

Data set were used for training and testing procedures. 256 NAF records (64 Normal, 64 OSA, 80 Hypopnea and 48 CSA) were used for training and the other 256 records were used for testing phase. The topology of the designed networks will be discussed as follows.

The SOM classifier using model with output grids size 8*3 was developed with hexagonal neighborhood functions. The number of neurons in the SOM map is decided according to the number of sleep apnea types wanted to be classified, which is four types. The initial learning rate was selected to be 0.9. Training for self-organizing feature map was carried out for 1000 epochs and the desired error to be reached was about 0.0001.

The ANFIS network have used, three fuzzy sets with generalized bell curve membership function (gbellmf) ,a total of 2187 fuzzy rules and one output. The initial and final membership function for AMSD input are shown in Figure 2.

Three HMM models with different number of hidden states N= {5, 7, 13} were used for each type of Sleep Apnea (Normal, OSA, hypopnea and CSA).

Table 2 illustrates the results of classifications obtained using the three classifiers. The results revealed that the best average classification rate reached about **95.7%** using HMM model of order 13.

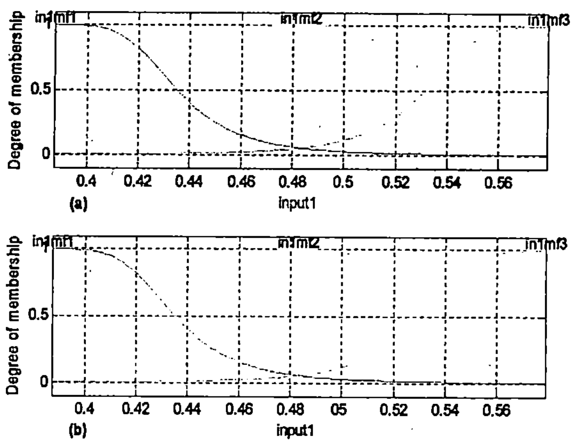


Figure 2: (a) Initial membership function for AMSD, (b) Final membership function for AMSD.

Table 2: Classification Results Using Different Classifiers

| Classifier | Classes | | | | %Average Classification |
|---|---|---|---|---|---|
| | Normal | OSA | Hypopnea | CSA | |
| SOM | 63/64 | 58/64 | 75/80 | 40/48 | 92.18% |
| ANFIS | 62/64 | 60/64 | 77/80 | 45/48 | 95.31% |
| HMM | 62/64 | 62/64 | 75/80 | 46/48 | 95.70% |

## VI. CONCLUSIONS

This study compares the performance of three different classifiers: a Kohonen self-organizing map (SOM), Adaptive Neuro Fuzzy Inference System (ANFIS) using hybrid learning algorithm and a Hidden Markov Model (HMM) in order to provide a classification for detecting sleep apnea events using Nasal AirFlow signals. Such a system would detect apnea and hypopnea events automatically. The hold-out method was applied for training and testing stages for each classifier. Classification results are satisfactory, where a correct classification rate of **95.7%** was achieved using HMM of orders 13.

Further work is required to apply the suggested methodologies to a larger data set with a wide spectrum of sleep-related breathing disorders and to develop a complete intelligent system that can be used as an assistant tool in sleep laboratories.

## REFERENCES


1. Iber, "The AASM Manual for the Scoring of Sleep and Associated Events. Rules, Terminology and Technical Specifications," AASM Manual for Scoring Sleep, pp. 1-59, 2007.
2. K. Banno , M. H. Kryger, Sleep apnea: Clinical investigations in humans, Elsevier science, Sleep Medicine, vol. 8, pp.400–426, May 2007.
3. F. Morisson, G. Lavigne, D. Petit, T. Nielsen, J. Malo, J. Montplaisir , "Spectral analysis of wakefulness and REM sleep EEG in patients with sleep apnoea syndrome, " Jour. Eur. Respir., vol. 11: 1135–1140, 1998.
4. A. Lewicke, E. Sazonov, M. J. Corwin, M. Neuman, and S. Schuckers, "Sleep versus wake classification from heart rate variability using computational intelligence: Consideration of rejection in classification models, " IEEE Trans.on Biom.Eng., vol. 55, No. 1, pp.108-118. Jan. 2008.
5. C. Zywietz, B Widiger, T. Penzel, "Polysomnographic Sleep Recording with Simultaneously Acquired 12 Lead ECGs: A Study for Detection and Validation of Apnea Related ECG Changes," Computers in Cardiolog., vol.29, pp. 573–576, 2002.
6. J. Bock, and D. A. Gough, " Toward Prediction of Physiological State Signals in Sleep Apnea, " IEEE Trans. Biomed. Eng. , vol. 45, No. 11, Nov. 1998.
7. H. Nakano, T. Tanigawa, T. Furukawa and S. Nishima," Automatic detection of sleep-disordered breathing from a single-channel airflow record," Jour. of Eur. Respir, vol.29, pp.728-736, 2007.

8. FR .de Almeida, NT .Ayas, R .Otsuka ," Nasal pressure recordings to detect obstructive sleep apnea," Sleep Breath, vol.10, pp.62–69, 2006.

9. Ayappa, RG .Norman, M .Suryadevara, DM. Rapoport. ," Comparison of limited monitoring using a nasal-cannula flow signal to full polysomnography in sleep-disordered breathing," Sleep, vol.27, pp.1171–1179, 2004.

10. L. M. Rofail, K. K. H. Wong, G. Unger, G. B. Marks, and R. R. Grunstein, " The Role of Single-Channel Nasal Airflow Pressure Transducer in the Diagnosis of OSA in the Sleep Laboratory," Jour. Clin. Sleep Med.,vol. 15; 6(4), pp. 349–356, August 2010.

11. A. Griffiths , J. Maul, A Wilson and Stick, "Improved detection of obstructive events in childhood sleep apnoea with the use of the nasal cannula and the differentiated sum signal," Jour. Sleep Res.,vol. 14, pp.431–436, 2005.

12. P.Várady, T.Micsik, Sándor Benedek, and Z. Benyó, "A Novel Method for the Detection of Apnea and Hypopnea Events in Respiration Signals," IEEE Trans.on Biom.Eng., vol. 49, No. 9, pp.936-942, Sep. 2002.

13. A.B.Sankar, "Energy Based Feature Extraction for Classification of Respiratory Signals Using Modified Threshold Based Algorithm," Inter. Jour. of Eng. Science and Technology ,vol. 2, pp.5488-5496,2010.

14. A.A El-solh, M. Jeffery et.al., " Validity Of Neural Networks In Sleep Apne," Jour. Sleep, vol.22, pp. 105-111, 1999.

15. R. Lini, R.Lee, C. Tseng, H. Zhou, C. Chao and J. J.Ang, "A New Approach For Identifying Sleep Apnea Syndrome Using Wavelet Transform And Neural Networks," Biom. Eng.Appl., Basis & Communications, pp.38-44, 2006.

16. H. Nazeran, A. Almas, K Behbehan, J. Burk, and E. Lucas, "A Fuzzy Inference System for Detection of Obstructive Sleep Apnea, " Proc. 23rd Annual Conference – IEEE/EMBS Oct.25-28, Istanbul, TURKEY, 2001.

17. T.Kohonen, O. Erkki, S. Olli, V. Ari and K. Jari ,"Engineering Applications of the Self-Organizing

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Map," IEEE Proc., vol.84, no. 10, pp. 1358-1384, Oct. 1996.

18. H. Yin," Learning Nonlinear Principal Manifolds by Self-Organising Maps," LNCSE 58, Springer, 2007.

19. M. AL-Fadi, L.Fraiwan, M.A.Jaradat, N.Khasaweneh, "Adaptive Neuro Fuzzy Interface System For Automatic Sleep Multisatging Level Scoring Employing EEG, EOG, AND EMG Extracted Features," Appl. Artif. Intell., vol.25, pp. 163-179,2011.

20. K. Pplat, S. Yosunkaya, and S. Güneş, "Pairwise ANFIS Approach to Determining the Disorder Degree of Obstructive Sleep Apnea Syndrome," Jour. of Med. Sys., vol.32 ,No.5, Oct.2008.

21. T.Al-ani , Y.Hamam , R.Fodil , F.Lofaso , and D.Isaby : "Using Hidden Markov Models For Sleep Disorderd Breathing Identification," Simulation Practice and Theory, Special Issue, vol.12, 2004.

22. P. Dymarski, Hidden Markov Models: Theory and Applications, http://www.intechopen.com.

23. Duda & Hart. Pattern Classification and Scene Analysis. J. Wiley, 1973.