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A System for the Analysis of Snore Signals

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Abstract

Sleep apnoea syndrome (SAS) is a disease consisting in the nocturnal cessation of oronasal airflow at least 10 seconds in duration. The standard method for SAS diagnosis is the polysomnographic exam (PSG). However it does not permit a mass screening because it has high cost and requires long term monitoring.

This paper presents a preliminary software system prototype for snoring signal analysis, whose main goal is to support the doctor in SAS diagnosis and patient follow-up. The design of the system is modular to allow a future hardware implementation in a portable device for personal snore collection and monitoring.

Keywords: snoring signal analysis, sleep apnoea syndrome

1. Introduction

Sleep apnoea syndrome (SAS) is a common disorder that affects both children and adults. Apnoea is defined as a cessation of oro-nasal airflow of at least 10 seconds in duration [1]. It is possible to distinguish three types of apnoea:

- Obstructive sleep apnoea syndrome (OSAS) is a type of sleep apnoea due to upper airway obstruction despite persistent ventilatory movements. It is the most common type of SAS.
- Central sleep apnoea caused by a decreased respiratory centre output is characterized by the absence of both ribcage and abdominal movements. It is the least common form of sleep apnoea syndrome (SAS).
- Mixed sleep apnoea is a type of sleep apnoea characterized by central apnoea followed by obstructive apnoea.

Many serious complications arise from SAS, such as diminished quality of life brought on by chronic sleep deprivation and cardiovascular problems. The common measure used to describe respiratory disturbances during sleep is the Apnoea Hypopnoea Index (AHI), which is the total number of apnoea and hypopnoea episodes occurring during sleep divided by the hours of sleep time: mild (5-15 events per hour), moderate (15-30 events per hour) and severe (> 30 events per hour) [2].

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Currently, the gold standard method for diagnosing SAS is polysomnography (PSG) [3]. Numerous physiological sensors are attached to the patient to record night-time breathing, brain activity, heart rate, pulse oxymetry and thoracic and abdominal movements. Clinical guidelines suggest four types of diagnostic methodologies: Level I or standard PSG, Level II or not supervised portable PSG (the exam could be performed not only in clinical laboratory but also at the patients home), Level III or portable systems of sleep apnoea (devices register four or more cardiopulmonary bio-parameters) and, finally, Level IV or continuous recording of one or two bio-parameters. Although the PSG is the standard approach for SAS diagnosis, it shows several disadvantages [4]. The limits of current approaches are described in the following. PSG requires the collection and analysis of a lot of data coming from several types of sensors. The analysis of acquired signals usually requires that the doctor analyzes the entire signal registration in a manual way. So, it is a labour-intensive and time-consuming diagnostic methodology. Generally, the patients spend a full-night in hospital during standard PSG exam. Thus, it is highly costly and not suitable for mass screening, because usually it is possible to monitor few patients for night for instrument. Current portable PSG devices present also the same disadvantages of standard PSG, in fact patients do not sleep comfortably because they are in contact with many sensors. Level III and IV systems are not advisable for first diagnosis or screening use in sleep laboratories or in non supervised environments because they do not rely on accurate measurement methodologies [5].

Efforts are being directed to the identification of alternative single-channel contact-less reliable methods for SAS diagnosis to permit clinicians to detect automatically and objectively SAS events saving time and work. Current methods alternative to PSG are: overnight oximetry, which measures a patient's oxygen saturations throughout the night [6], ECG [7] or snore monitoring [8]. Overnight oximetry is not considered completely adequate as a screening test, since the oxygen levels in the blood of many patients with SAS do not provide the information needed to understand their condition. Thus, there is a growing interest in developing portable snore-based devices for SAS monitoring. Snoring is the most common symptoms of SAS [9, 10]. The low-cost snore acquisition instrumentation does not need expert humans to operate, and will be suitable for population screening and paediatric use. Furthermore, the large amount of time a sleep expert has to devote to the manual scoring of overnight data can be saved, due to the availability of reliable automated acoustic signal processing techniques.

The goal of the paper is to present a system for the semi-automatic analysis of the snoring signal allowing the doctor to concentrate only on the events relevant to SAS, i.e. apnoeic and post-apnoeic snores. The proposed system starts from a whole registration, detects snores events, detects post-apnoeic snore events, measures apnoea intervals and finally provides punctual and aggregated data useful to support the doctor in SAS detection and classification. The rest of the paper is organized as follows: Section 2 outlines the main methodologies used in such analysis and presents a survey of related system; Section 3 and Section 4 presents, respectively, the architecture and a first prototype of the proposed system for the analysis of snore signals. Finally Section 5 concludes the paper and outlines future work.

2. Related Work

2.1. Software Systems

Snore signals carry vital information on the state of the upper airways. The snoring sound is a result of air passing through the oesophagus and nasal cavity causing structures including the base of the tongue, the tonsils and the oesophagus to vibrate. For the detection of SAS events, the analysis of snoring signals has been performed in time or in frequency domain [11]. In the time domain the evaluated parameters include duration of snores, mean value/standard deviation of pitch and max/average intensity sound [12].

In the frequency domain the parameters of interest are fundamental frequency, formants, median frequency, central frequency and max frequency [13]. The spectral parameters are extracted from the power spectrum evaluated by parametric (Auto-Regressive Model) or non parametric methods (FFT, Welch periodogram). By convention, a distinction is made between steady snoring, which shows little variation and little or no interruptions, and the irregular snoring that characterizes the resumption of breathing between obstructive apnoea events. The first hint for acoustic differences between these two phenomena was provided by Perez Padilla et al. [14]. They analyzed snoring noise from 10 non-apnoeic heavy snorers and 9 OSAS patients. Most of the power of snoring noise was below 2000 Hz and the peak power was usually below 500 Hz. Patients with apnoea showed a sequence of snores with spectral characteristics that varied markedly through an apnoea-respiration cycle. The first post-apnoeic snore consisted mainly of broad-band white noise with relatively more power at higher frequencies. Patients with OSA had residual energy at

1000 Hz, whereas the non-apnoeic snorers did not. It was found that the ratio of power above 800 Hz to power below 800 Hz could be used to separate snorers from patients with OSA.

Fiz et al. studied [15] 10 OSAS patients and 7 simple snorers. They observed the presence of a fundamental frequency and several harmonics in the simple snorers. Another frequency pattern was characterized by a low-frequency peak with the sound energy scattered on a narrower band of frequencies, but without clearly identified harmonics. This pattern was present in the majority of OSAS patients, and was associated with a significantly lower peak frequency of snoring. All but one OSAS patient and only one non-apnoeic snorer showed a peak frequency below 150 Hz. In contrast with previous studies, no residual power in the higher frequency bands was observed in the OSAS group. Methodological issues could have accounted for this discrepancy.

In a study by Sola-Soler et al. [16], analyzing snores from 9 simple snorers and 15 OSAS patients, significant differences were found in formant frequencies variability between simple snorers and OSAS patients, even when non post-apnoeic snores were considered. Ng et al. [17] investigated snoring sounds of 30 apnoeic snorers and 10 benign snorers. The snoring events were modelled using a Linear Predictive Coding technique. Quantitative differences were demonstrated between apnoeic and benign snores in the extracted formant frequencies $F1$, $F2$ and $F3$. Apnoeic snores exhibited higher values than benign snores, especially with respect to $F1$.

2.2. Portable Devices

Few portable devices have been developed to collect and analyze snore signals from potential apnoeic patients. In [18], the design of a portable device for home-based snore monitoring is described. It performs detection and selection of the snores, while discarding any other events that are present in the sound recording, as cough, voice, and other artefacts. The device performs temporal analysis of signals. It detects snore events by evaluating signal amplitude and detects possible apnoea events by measuring the delay between snores.

Another portable device for snore detection is described in [19]. The device itself also serves as a Web server. Doctors and caregivers can access real-time and historical data via a Microsoft Internet Explorer browser or a remote application program for tele-monitoring of snoring and OSAS symptoms. Both systems are able to detect only snore events through time analysis and they do not reach high success rate and sensitivity. They do not exploit frequency-based and time-frequency-based analysis. In [20] is described a prototype that acquire tracheal respiratory sounds and SaO_2. The system performs automatic sound segmentation, based on the evaluation of the median of the logarithm of signal variance, and Apnoea-Hypopnoea detection, based on the evaluation of sound segments energy duration and the relationship between the energy values of the adjacent segments.

There are also commercial bio-feedback snoring device. These portable devices can record snoring signals through non-contact microphone and give, for example, an acoustic feedback to snorers to alert them about snoring activity. These systems do not extract clinical useful parameters.

Few automatic systems for the clinician decision support for SAS diagnosis have been developed. In [21] a software system developed for analyzing the whole night respiratory sound recordings is described. It computes related statistics and asserts the success of medical treatment in terms of objective criteria.

3. Design of a System for the Analysis of Snore Signals

Snoring acquisition can be performed in clinical sleep laboratories and/or at home. Signals are acquired with a stereo-electret microphone connected to a digital portable audio recorder. In the first implementation Micro Track II, as recording system, was used. The recording system permits to performs an acquisition with 16 bits resolution and 48 kHz sampling frequency. Patients with suspected sleep apnoea syndrome underwent to the recording. They were asked to put the digital recorder near the body and to sleep. The duration of sound acquisition can be chosen and it is only limited by the storage capacity of the used recorder.

3.1. System Architecture

Figure 1 shows the flow of data from patients to doctor and the overall system architecture. Signals coming from microphone were pre-amplified and, then, digitized and stored in a CompactFlash memory available on the recorder. Data (WAV files) can be transferred to PC for further elaborations through USB 2.0 interface.

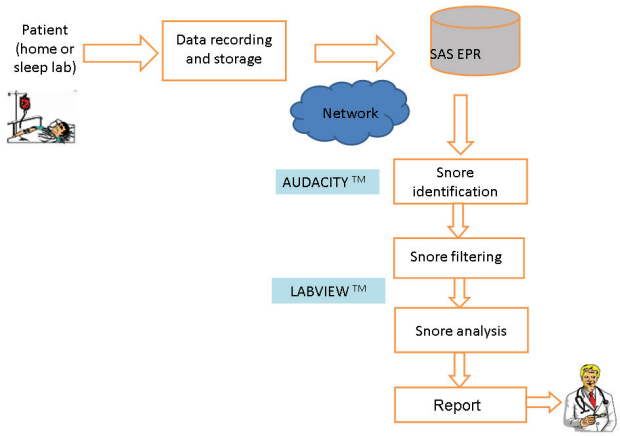

Figure 1: Architecture of the proposed system

Snoring signals contains not only snore events, but also breathing sounds and background noise. It is needed to perform a sound segmentation to separate snore from other recorded events. In our case, sound segmentation in breathing and snoring intervals has been performed with the help of Audacity^{TM} software. It is an open source software for recording and editing audio.

The extracted set of snoring intervals has been analyzed with National Instruments LabVIEW^{TM} software. LabVIEW is a graphical programming environment to develop measurement, test, and control systems using intuitive graphical icons and wires that resemble a flowchart. It, also, provides hundreds of built-in libraries for advanced analysis and data visualization. We choose to use LabVIEW because of its intuitive visual interface and ability to integrate with thousands of hardware devices and to process real-time signals The LabVIEW-based modules perform a data pre-processing and analysis aimed to the extraction of a set of useful signal parameters (see Figure 2). These parameters will help the clinician to better discriminate sleep apnoea. In particular, snoring signals is filtered through a FIR band-pass filter. It is possible to specify different filter parameters such as filter band cut-off frequencies in Hz and the ripple level in decibels in the pass-band and in the stop-band.

After signal filtering, the system performs a time and frequency domain analysis. In the time-domain, the module evaluates the crest factor and the peak and root-mean square value (RMS) of the snoring signal. In parallel, the system calculates the power spectrum based on Fast Fourier Transform (FFT) elaboration. A set of spectral parameters (power in band, peak values, median frequency) are then extracted from power spectrum. The numerical and graphical results of these elaborations can be viewed by clinicians thanks to the simple and intuitive LabVIEW interface. Alternatively, all these parameters can be saved in a text or comma-separated values file.

3.2. Snoring signal analysis technique

3.2.1. Filtering

Finite impulse response (FIR) filter was implemented because it can achieve linear phase thanks to filter coefficient symmetry in the realization and stability. FIR filters, also known as non-recursive filters and convolution filters, are digital filters that have a finite impulse response. FIR filters operate only on current and past input values and are the simplest filters to design. FIR filters perform a convolution of the filter coefficients with a sequence of input values and produce an equally numbered sequence of output values. Equation defines the finite convolution that a FIR filter performs:

$$y_i = \sum_{k=0}^{n-1} h_k x_{i-k} \,, \tag{1}$$

where x is the input sequence to filter, y is the filtered sequence and h is the FIR filter coefficients.

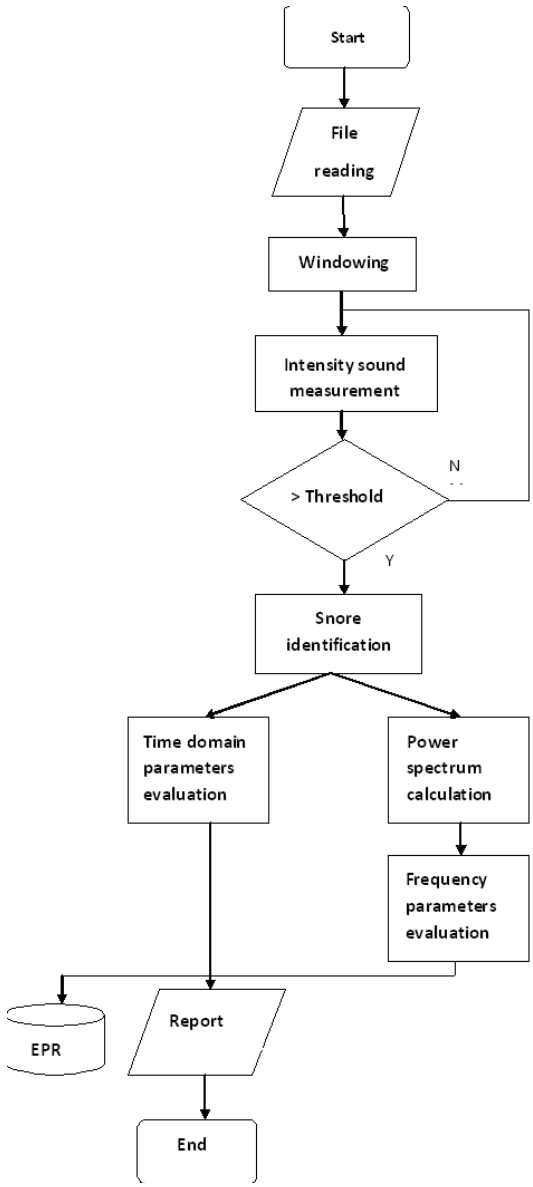

Figure 2: Block diagram of LabVIEW-based analysis

3.2.2. Snore identification

Time-domain analysis. Crest factor (FC) of the snoring signal is defined in the following way:

$$FC = \frac{V_{PK}}{V_{RMS}}, \tag{2}$$

$$V_{RMS} = \sqrt{\frac{1}{T}\int_0^T |V|^2\, dt} \tag{3}$$

Where V_{RMS} is the root-mean square of the signal and V_{PK} is the peak level.

Frequency-domain analysis. Snoring signals were transformed in the frequency domain by using the Fast Fourier Transform (FFT). LabVIEW and its Virtual Instrument (VI) analysis library provide a complete set of tools to perform Fourier and spectral analysis. The Fast Fourier Transform (FFT) and Power Spectrum VIs are optimized and their outputs adhere to the standard DSP format. FFT is a powerful signal analysis tool, applicable to a wide variety of fields. Power spectra of snoring signals have been evaluated by using real part of the FFT. Then a peak search on power spectra for finding the most relevant snoring signal components has been implemented. The algorithm can detect single or multiple peaks above a defined threshold. The algorithm returns the amplitude and corresponding frequency, and the number of peaks (in the case of multiple search). The system finds all the peaks within the spectrum and performs amplitude/frequency estimation on each individual peak.

The system is able to perform other spectral parameters calculations. It computes the total power in the frequency range of interest from power spectra. It is possible to measure the total power in band within the specified range based on the input signal. This method permits to compare and eventually discriminate snores from their power distribution along different frequencies (e.g. normal from apnoeic snores or apnoeic from post-apnoeic snores).

4. A First Prototype of System

Generally in the clinical practice, doctors examine in a manual way the acquired signals for detecting sleep apnoeas problems. Some PSG commercial software give out some indicators, such as AHI, but they do not permit further signal analysis. The Graphical User Interface (GUI) of the prototype is shown in Figure 3. In particular the GUI is composed of four windows, named Signal Loading, Signal Filtering, Crest Factor Computing and Power Spectrum Analysis, that respectively implements the loading and filtering of the signal, the individuation of snores and, through the power spectrum analysis, the discrimination between snores and post-apnoeic snores.

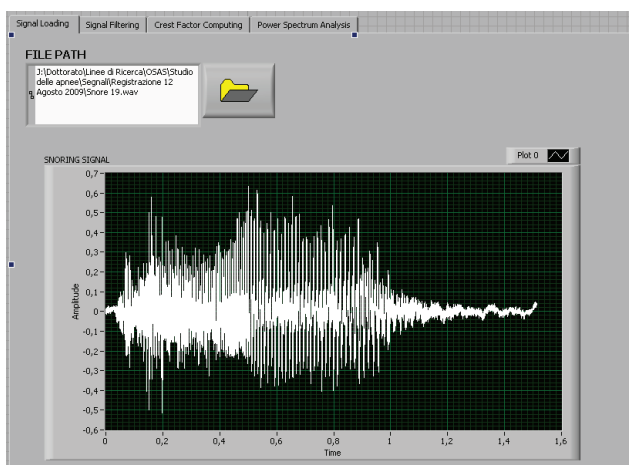

Figure 3: System Interface

The rest of the Section shows the different steps of analysis applied to a dataset generated into the Electroencephalography/Polysomnography Laboratory of the Institute of Neurology of the University Magna Graecia of Catanzaro (Italy). In particular Figure 3 represents the acquisition section of the GUI prototype. Users can load the input WAV file that contains recorded data and display it in the time domain. Figure 4 shows the filter parameters that the user can modify according to signals characteristics. In particular it is possible to exclude the filtering operation through a specific button and indicate the filter type (band-pass, high-pass, low-pass and stop-band) and the relative cut-off frequencies.

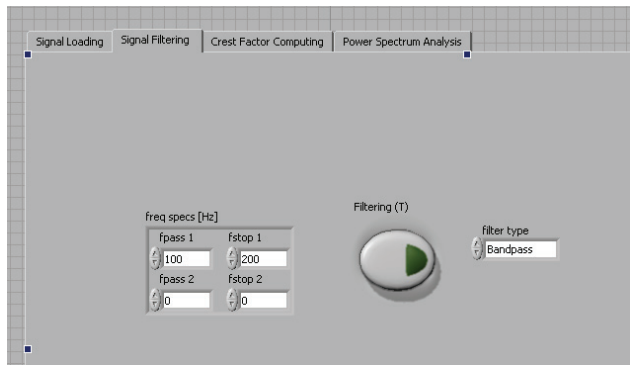

Figure 4: Filtering Section

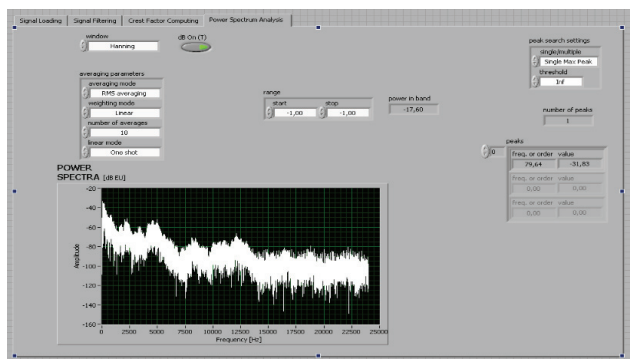

Figure 5: Frequency Analysis Section

The frequency analysis section is illustrated in Figure 5. The user can set FFT elaboration parameters and analyze power spectrum. Then it is possible to choose power in band and peak search parameters and visualize relative results for each selected snore.

Results obtained through snoring signal analysis can be inspected by doctor for follow-up procedure and for eventual statistical analysis or populations studies.

5. Conclusions

This work, that largely extends the work described in [22], presents a system for the analysis of snoring signals for supporting doctors in SAS diagnosis. A first prototype has been implemented: the system permits the clinicians to record, collect and analyze snoring signals from possible apnoeic patients. In particular the system allows to evaluate not only clinical parameters, such as the number of snores or apnoeas events, but it extracts significant signal parameters in the time and frequency domain. The collected data and results related to signal processing can

be viewed by clinician thanks to the simple user interface of the system or saved for patients follow-up and further statistical analysis and data mining.

Future work will regard (i) an extensive experimentation and validation of the software on clinical data, (ii) implementation of novel signal processing techniques to improve SAS diagnosis and (iii), due to the modular design of the software, the hardware implementation on a portable device for personal signal collection and monitoring.

References

[1] Pataka A., Riha R., The obstructive sleep apnoea/hypopnea syndrome- An overview, Respiratory Medicine CME 2, 2009

[2] Al-Shawwa B. A., Badi A.A.,Goldberg A. N., Woodson B. T., Defining common outcome metrics used in obstructive sleep apnea, Sleep Medicine Reviews (2008) 12, 449-461

[3] Epstein L. J. et al., Clinical Guideline for the Evaluation, Management and Long-term Care of Obstructive Sleep Apnea in Adults, Journal of Clinical Sleep Medicine, Vol.5, No. 3, 2009

[4] Collop N. A. et al., Clinical Guidelines for the Use of Unattended Portable Monitors in the Diagnosis of Obstructive Sleep Apnea in Adult Patients, Journal of Clinical Sleep Medicine, 2007

[5] Su S., Baroody F.M., Kohrman M., Suskind D., A comparison of polysomnography and a portable home sleep study in the diagnosis of obstructive sleep apnea, Otolaryngology Head and Neck Surgery, 2004

[6] Lee Y.K., Bister M., Blanchfield P., Salleh Y.M., Automated detection of obstructive apnea and hypopnea events from oxygen saturation signal, in Proc. Of 26th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, 2004, pp. 321 - 324

[7] Khandoker A.H., Palaniswami M., Karmakar C.K., Support Vector Machines for Automated Recognition of Obstructive Sleep Apnea Syndrome From ECG Recordings, IEEE Transactions on Information Technology in Biomedicine, Vol. 13 , No. 1, pp. 37 48, 2009.

[8] Jane R., Fiz J.A., Sola-Soler J., Blanch S., Artis P., Morera J., Automatic snoring signal analysis in sleep studies, in Proc. Of the 25th Annual International Conference Engineering in Medicine and Biology Society, 2003, pp. 366 369

[9] Pevernagie D., Aarts R.M., De Meyer M., The acoustics of snoring, Sleep Medicine Reviews, 2009 1-14

[10] Countera P., Wilson A., The management of simple snoring, Sleep Medicine Reviews (2004) 8, 433441

[11] Sol-Soler J., Jan R., Fiz J.A., Morera J., Variability of snore parameters in time and frequency domains in snoring subjects with and without Obstructive Sleep Apnea, in Proc. Of the 27th Annual International Conference of the IEEE EMBS, 2005

[12] Abeyratne U.R., Patabandi C.K.K., Puvanendran K., Pitch-jitter analysis of snoring sounds for the diagnosis of sleep apnea, Proc. Of the 23rd Annual International Conference of the IEEE EMBS, 2003

[13] Yadollahi A., Moussavi Z., Formant Analysis of Breath and Snore Sounds, in Proc. Of 31st Annual International Conference of the IEEE EMBS, 2009

[14] Perez-Padilla JR, Slawinski E, Difrancesco LM, Feige RR, Remmers JE, Whitelaw WA. Characteristics of the snoring noise in patients with and without occlusive sleep apnea. Am Rev Respir Dis 1993; 147: 635644.

[15] Fiz J.A., Abad J., Jan R., Riera M., Mananas M.A., Caminal P., Rodenstein D., Morera J., Acoustic analysis of snoring sound in patients with simple snoring and obstructive sleep apnoea, Eur Resp J 1996

[16] Sol-Soler J., Jan R., Fiz J.A., Morera J., Formant frequencies of normal breath sounds of snorers may indicate the risk of Obstructive Sleep Apnea Syndrome, in Proc. Of the 30th Annual International Conference of the IEEE EMBS, 2008

[17] Ng A. K., Koh T. S., Baey E., Puvanendran K., Speech-like Analysis of Snore Signals for the Detection of Obstructive Sleep Apnea, International Conference on Biomedical and Pharmaceutical Engineering, 2006

[18] Hsu Y.L., Chen M.C., Cheng C.M., Wu C.H., Development of a portable device for home monitoring of snoring, in Proc. Of IEEE International Conference on Systems, Man and Cybernetics, 2005

[19] Cheng C. M, Hsu Y. L., Young C. M. and Wu C. H., Development of a portable device for telemonitoring of snoring and obstructive sleep apnea syndrome symptoms, Telemedicine Journal and E-Health , vol. 14, no. 1, pp. 55-68, 2008

[20] Yadollahi A., Moussavi Z., Acoustic Obstructive sleep apnea detection, in Proc of 31st Annual International Conference of the IEEE EMBS 2009

[21] Cavusoglu M., Kamasak M., Erogul O., Ciloglu T., Akcam T., Serinagaoglu Y., SASA: a software system for sleep and snoring analysis, International Symposium on Health Informatics and Bioinformatics, 2007.

[22] Calabrese B., Pucci F., Sturniolo M., Veltri P., Gambardella A., Cannataro M., Automatic detection of obstructive sleep apnea syndrome based on snore signals, 6th International Workshop on Models and Analysis of Vocal Emissions for Biomedical Applications (MAVEBA2009), December 14 - 16, 2009, Firenze, Italy