AN EFFICIENT AND FAST METHOD OF SNORE DETECTION FOR SLEEP DISORDER INVESTIGATION

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ABSTRACT

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Snores are breath sounds that most people produce during sleep and they are reported to be a risk factor for various sleep disorders, such as obstructive sleep apnea syndrome (OSAS). Diagnosis of sleep disorders relies on the expertise of the clinician that inspects whole night polysomnography recordings. This inspection is time consuming and uncomfortable for the patient. There are surgical and therapeutic treatments. However, evaluation of the success of these methods also relies on subjective criteria and the expertise of the clinician. Thus, there is a strong need for a tool to analyze the snore sounds automatically, and to produce objective criteria and to assess the success of the applied treatment by comparing these criteria obtained before and after the treatment.

In this thesis, we proposed a new algorithm to detect snoring episodes from the sleep sound recordings of the individuals, and created a user friendly interface to process snore recordings and to produce simple objective criteria to evaluate the results. The algorithm classifies sleep sound segments as snores and nonsnores according to their subband energy distributions. It was observed that inter- and intra-individual spectral energy distributions of snore sounds show significant similarities. This observation motivated the representation of the feature vectors in a lower dimensional space which was achieved using principal component analysis. Sleep sounds can be efficiently represented and classified as snore or nonsnore in a two dimensional space. The sound recordings were taken from patients that are suspected of OSAS pathology while they were connected to the polysomnography in Gülhane Military Medical Academy Sleep Studies Laboratory. The episodes taken from 30 subjects (18 simple snorers and 12 OSA patients) with different apnea/hypopnea indices were classified using the proposed algorithm. The system was tested by using the manual annotations of an ENT specialist as a reference. The system produced high detection rates both in simple snorers and OSA patients.

Keywords: Snoring, Apnea, OSAS, Classification, Spectrogram

ÖZ

UYKU BOZUKLUKLARI ARAŞTIRMASI İÇİN ETKİN VE HIZLI BİR HORLAMA TESPİT YÖNTEMİ

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Horlama, çoğu insanın uyku sırasında çıkardığı nefes sesleridir ve obstrüktif uyku apnesi sendromu (OSAS) gibi pek çok uyku bozukluğu için bir risk faktörü olduğu belirtilmiştir. Uyku bozukluklarının teşhisi, polisomnografi kayıtlarının alınması ve hekim tarafından incelenmesi gibi zaman alıcı, klinik uzmalık gerektiren ve hastayı rahatsız eden bir süreci içerir. Cerrahi ve terapatik tedaviler geliştirilmesine rağmen, apnenin ve horlamanın tedavisi için hastaya yapılan müdahalelerde karşılaşılan en önemli sorunlardan birisi, uygulanan yöntemin hasta üzerinde ne kadar etkin olduğunun objektif kriterlere dayandırılarak belirlenememesidir. Bu kriterlerin belirlenmesini ve tedavi öncesi ve sonrası karşılaştırılarak başarı performansının belirlenmesini sağlayacak bir sisteme ihtiyaç vardır.

Bu çalışmada, uzun süreli solunum seslerini analiz etmek amacıyla, bölütlenmiş horlama sesleri için bir sınıflandırma sistemi, ve sonuçları objektif olarak değerlendirmek amacıyla klinik personeli tarafından kolaylıkla kullanılabilen bir arayüz geliştirilmiştir. Algoritma uyku sesleri bölütlerini alt-bant enerji dağılımlarına göre 'horlama' ve 'horlama değil' şeklinde sınıflandırır. Hem aynı hastanın tüm kaydı boyunca, hem de hastadan hastaya kayıtlar karşılaştırıldığında önemli benzerlikler gözlenmiştir. Bu gözlem, öznitelik vektörlerinin daha düşük bir boyutta temsil edilmesine motivasyon oluşturmuştur. Bu şekildeki bir temsil de 'ana bileşen analizi' yöntemiyle mümkün olmuştur. Uyku sesleri 'horlama' veya 'horlama değil' olarak iki boyutlu bir uzayda başarıyla temsil edilebilmişlerdir. Ses kayıtları, Gülhane Askeri Tıp Akademisi Uyku Çalışmaları Labaratuvarı'nda OSAS patolojisinden şüphelenilen hastalardan gece uykusu boyunca, hastalar polisomnografi cihazına bağlı iken alınmıştır. Farklı apne/hipopne indeksine (AHI) sahip 30 hastadan (18 basit horlayan, 12 OSA hastası) alınan episodlar geliştirilen algoritma ile sınıflandırılmıştır. Sonuçlar bir KBB uzmanı tarafından yapılan değerlendirmelerle karşılaştırılmıştır. Sistem hem basit horlayanlarda hem de OSA hastalarında yüksek belirleme oranları göstermiştir.

Anahtar kelimeler: Horlama, Apne, Sınıflandırma, Spektrogram

To my parents

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CHAPTER 1

INTRODUCTION

Snoring can be defined as a respiratory noise that is generated during sleep when breathing is obstructed by a collapse in the upper airway. It is a widely encountered condition that has a number of negative social effects and associated health problems. Snoring can be treated by therapeutic and/or surgical methods; however, there is strong need for objective and non-invasive criteria to evaluate the success of these treatments. One way to assess the success of the applied medical treatment is by analyzing the snoring sounds. These sounds are often recorded throughout the whole night and include not only the snoring sounds, but also other respiratory sounds. Manual processing of a whole night respiratory sound recording is a time-consuming and operator dependent task. Therefore, automatic processing of these sound recordings is necessary. One can also extract snoring related parameters by automatic processing, which makes it possible to evaluate the severity of snoring, and to assess the success of the applied treatment. In order to extract snore related parameters from the signal, first each snoring episode must be detected automatically, while discarding undesired sounds such as cough, nasal congestion, speaking and other environmental noises. Once these snoring episodes are detected, it is possible to compute some useful statistics such as the ratio of the snoring time to the total sleeping time, mean and maximum time between two snoring episodes, intensity of the snoring episodes and regularity of the snoring. An objective assessment of the applied medical treatment can be obtained from the comparison of these statistics computed pre and post operatively.

In this thesis, we proposed a new and efficient method for detecting snoring episodes from long duration respiratory sound recordings based on the spectrogram of the acoustic snoring signals. Principle component analysis (PCA) was applied to reduce the dimensionality of the problem. We also developed a MATLAB based graphical user interface to run this algorithm and compute snoring related statistics.

1.1 Definition and Significance of Snoring

The American Sleep Disorders Association (ASDA) defines snoring as "Loud upper airways breathing, without apnea or hypoventilation, caused by vibrations of the pharyngeal tissues. It can be classified as mild, moderate and severe on the basis of frequency, body position, and disturbance for other people (spouse, bed partner)" [1]. Snoring is known to affect over 60% of adult men and 44% of women over the age of 40 in the world [1]**.** The noise of snoring can disrupt sleep for the snorer, the bed partner and other members of the household, and more importantly, it is the earliest and most consistent sign of upper airway (UA) dysfunction leading to sleep apnea/hypopnea syndrome.

Hoffstein *et al*. [2] and Dalmasso *et al.* [3] have emphazised the necessity of an accurate definition of snoring in terms of objective measurement. Recent studies of snoring and asthma [4,5] have also reached the same conclusion. These studies raise the question of distinguishing between snoring and other nocturnal sounds, detected on the chest wall. Furthermore, simple monitoring of sound intensity on the sternal notch is not sufficient, and more complex techniques of acoustic analysis need to be employed to properly define and measure snoring. From the acoustical point of view, snoring has been analysed and measured on the frequency and time domain, and it must be defined with these parameters. Snoring has also been used, with a particular acoustic technique, as a means to evaluate the cross-sectional area (CSA) of the UA [6].

1.2 Obstructive Sleep Apnea and Polysomnograhy

Sleep apnea is defined as cessation of airflow to the lungs during sleep for 10 s or more. [7,8]. There are mainly two causes of sleep apnea, mechanical and neurological. Mechanical cause is the upper airway collapse, and the resulting apnea is called as obstructive sleep apnea (OSA). Neurological cause is the lack of neural input from the central nervous system to the diaphragm, and the resulting apnea is known as central sleep apnea [8]. OSA is the mostly encountered form of the sleep apnea. Common symptoms of OSA are fatigue, reduction in cognitive functions, daytime sleepiness, heart problems, and systemic hypertension [8,9]. It is usually associated with loud, heavy snoring [8]. In OSA, the upper airways are obstructed during sleep, resulting in the decrease of oxygen flow to the lungs. Patients suffering from OSA often wake up frequently. When there is a full closure of airways, the problem is termed “apnea” and when there is a partial closure, it is known as “hypopnea”. OSA is a serious public health concern throughout the world. An estimated 9% of the women and 24% of the men of 30-60 years are reported to have more than five apnea or hypopnea per hour of sleep and daytime hypersomnolence (excessive sleepiness), which constitute the minimal diagnostic criteria for the sleep apnea syndrome [10].

Untreated OSA is very expensive to society; OSA patients are known to utilize national health resources at twice the usual rate before treatment [1]. However, studies have shown that 93% of women and 82% of men with at least moderate sleep apnea did not receive diagnosis [1]. The most important reason for this situation is that simple, low-cost instruments for mass screening of the population do not yet exist.

PSG, performed over a full night sleep, is presently the standart method for diagnosis of sleep apnea [11,12,13]. It consists of recording the patient’s physiological signals such as electroencephalogram (EEG), electrooculogram (EOG), electrocardiogram (ECG), electromyogram (EMG) of chin, EMG of legs, oral airflow using thermistors, intensity of snoring sound (or breathing sound) using an external pharyngeal microphone, thoracic and abdominal movement using inductive plethysmography, and blood oxygen saturation (S_pO_2) measured by oximetry. By reviewing these signals, the sleep disorders specialist or technician can determine the type of sleep apnea and other sleep disorders [14,15]. However, since analysis using a PSG device requires spending the night at the hospital with many measurement electrodes connected to the body, it is time consuming and uncomfortable for the patient. There is an enormous need for a simplified diagnostic instrument capable of convenient and reliable diagnosis/screening of OSA at a home setting [10].

There has been a number of recent activities to develop portable technology to address this need [11]. The proposed systems varied from two channels (airflow and oximetry) to four channels (oximetry, airflow, effort and position) to full PSG with more channels. Their major disadvantage is that they require an experienced medical technologist at the site of the test for an acceptable sensitivity/specificity performance. Furthermore, all the devices evaluated in the comprehensive study, have at least one sensor connected to the body. This makes the devices difficult to use by untrained persons, and hard to use on children [11].

1.3 Anatomical and Pathophysiological Aspects of Snoring

The UA extends from the lips and nostrils to the vocal chords. It can be modeled as a combination of numerous cylindrical segments that have different cross section areas and lengths; and therefore, from the physical point of view, the UA acts as "tubes" of Venturi [16]. The passage of an airflow through these airways should satisfy the equation of Bernoulli and the law of Poiseuille [16]. The airflow can be laminar or turbulent as a function of the value of the Reynolds number [16]. The UA only partially satisfies these formulae, because of its particular anatomical and functional features; the UA behaviour, in a particular way, is based on different characteristics of its segments, which can be stiff (rigid) or collapsible, and on their compliance, which depends on morphology and trophicity. A median section of the pharynx is presented in Figure 1.1.

In general, it is sufficient to consider three segments:

1. The first (proximal) segment is formed by the nasal cavities and rhinopharynx. It has an osseous-cartilaginous structure, is rigid, and not deformable or collapsible under the effect of the inspiratory pressure (suction pressure activated by inspiratory muscles).
2. The second (medium) segment is the oropharynx, a typical collapsible structure which can decrease its CSA with the approach of the walls under sufficient inspiratory negative pressure. The collapsible part of this segment is formed anteriorly by the soft palate, the lymphoidamygdalic apparatus and the hyoid-lingual apparatus.
3. The third (distal) segment is formed by the larynx, a cartilaginous and rigid structure which is neither deformable nor collapsible under inspiratory pressure.

The flow of air through the UA is regulated by the activity of numerous muscles, which act as dilators or constrictors. In particular, the decrease of air flow in the oropharynx segment depends on the activity of three groups of muscles. The pharyngeal duct, which extends posteriorly from the nasal cavities and mouth to the larynx and oesophagus, has a muscular wall. There are five pharyngeal muscles, three of which are constrictors and two elevators. During contraction, the constrictors, acting as a sphincter, bring the posterior wall close to the anterior and lateral walls, and so reduce the CSA. The tongue plays an important role with its seventeen muscles, having four pairs of symmetric muscles plus a single median muscle to regulate its movement [17].

In a very schematic way, three main groups of muscles are involved in the loss of air flow in the oropharynx:

1. The muscles of the soft palate
2. The muscles of the back tongue
3. The pharyngeal uvular muscles.

In pathophysiological conditions, the different sites of anatomical or functional narrowing from nose to larynx are, therefore, represented in all three segments. The segment that is typically collapsible is the second one, i.e. the oropharynx.

Some simultaneous factors have to be present to produce snoring such as sleep, flow limitation, vibrating structure, which is represented by the soft palate and other soft parts of the oropharynx behaving like a Starling resistor [16], reduction of CSA of the UA and thorax bellows, which act with suction inspiratory pressure.

The causes which determine snoring are the same as those which can lead to upper airway resistance syndrome (UARS) and/or OSAS on the basis of their degree of severity. Possible causes are [17]:

1. General causes (metabolic, in particular obesity which involves almost 100% of snores, hormonal, and ageing),
2. Local causes (congenital and acquired, correction of which an eliminate the trouble),
3. Non demonstrable causes (a high percentage of which induces oropharyngeal dysfunction).

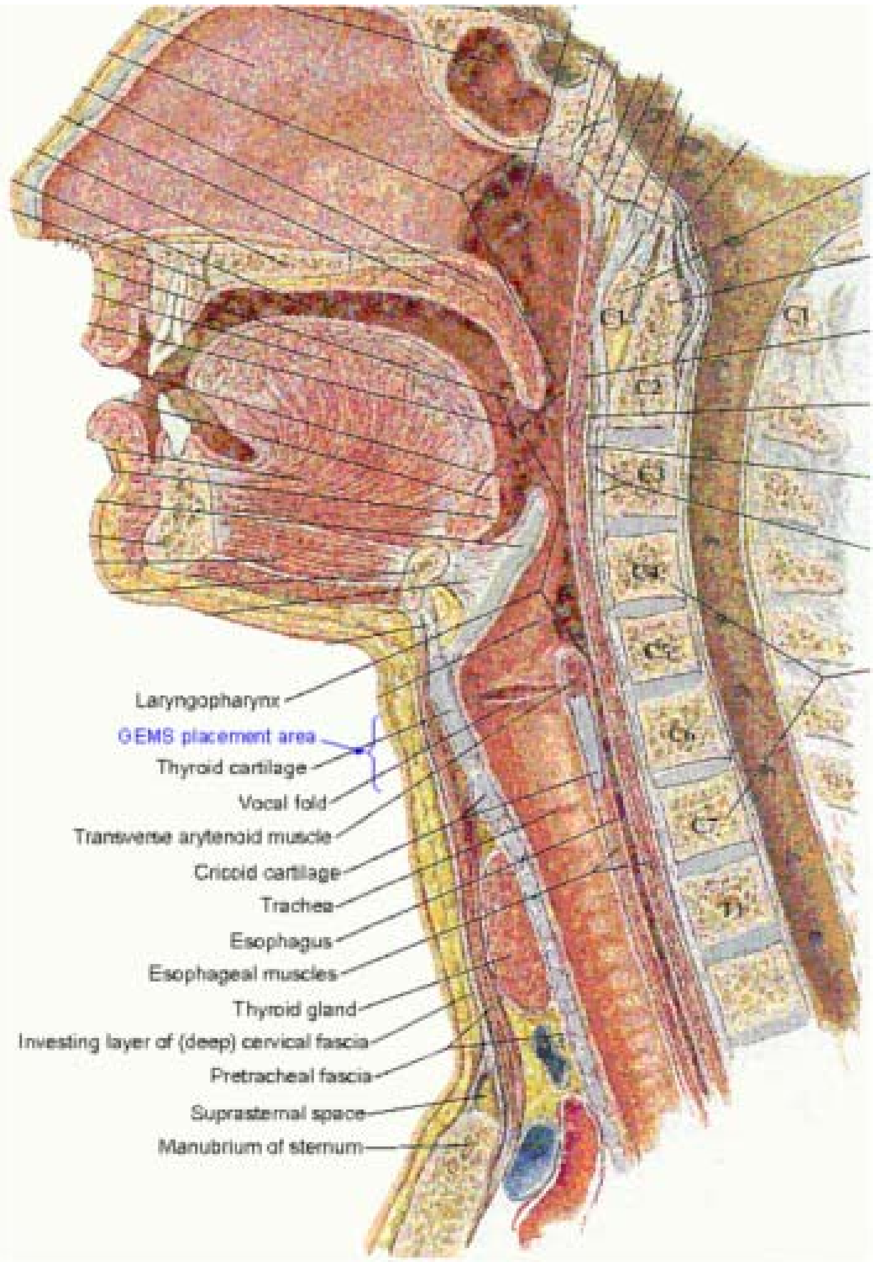

Figure 1.1 A median section of the pharynx (atlas of Human Anatomy, by Frank H. Netter, M.D.)

1.4 Snoring Effects on the UA: Snoring and Sleep Relationship

Several factors influence UA resistance. For example it decreases with the increase of lung volume and breath rate [18,19] and increases with head flexion, mucous congestion [20] and, particularly, during sleep. The most important effect of sleep is the decrease of activity of all of the muscles of the UA and its variability, according to the muscular group and sleep phase. The contraction of dilator muscles of the UA, during inspiration, anticipates the closing trend of the collapsible segment of the UA [21,22]. During sleep, the decreasing activity of these muscles makes the two segments of UA less stable which can explain the increasing resistances.

In healthy individuals, no direct correlation has been found between the increased resistance of the UA and variation in the activity of the genioglossus and geniohyoideus muscles during sleep [23,24]. This fact could demonstrate that the reduction in CSA, which determines the increase in resistance, is not located at the level of the back tongue. Recently, it was reported that the significant decrease in activity of the tensor palatini muscle during sleep, demonstrated a good correlation with increased resistance [25].

In snoring subjects, there are some anatomical and functional abnormalities, and the intensity and frequency of snoring correlate with these [26]. A flow limitation such as constant or decreasing flow independent of the driving pressure, during sleep has been reported by several authors in healthy nonsnorers [27], in healthy snorers [28], and in OSA patients. In these situations, sleep seems to provoke a flow limitation [29], with a decrease in the tone of the muscles of the UA.

Listro *et al*. [30], in heavy snorers without OSAS and in OSA patients, found that low limitation precedes the snoring action during sleep, in all cases. They recognize two main patterns of snoring, with cineradiographic technique, which can differ in heavy snorers and in OSA patients.

A study by Hoffstein *et al*. [2] showed that snoring did not influence the sleep "architecture" in general. Evaluating snoring distribution among the various stages of sleep, they found that light snorers snored evenly throughout all stages while heavy snorers tended to snore more during slow-wave and rapid eye movement (REM) sleep than in other sleep stages. The snoring frequency of light snorers was the same in all sleep stages, whereas it was significantly higher in slow-wave sleep in heavy snorers. These data agree with the recent observations of Skatrut and Dempsey [28], who showed that total pulmonary resistance depended on the sleep stage, and that snorers demonstrated an increase in resistance during the deeper stages of sleep [17].

Perez-Padilla *et al* [31] also found that snoring distribution was irregular throughout the sleep stages; in particular, it occurred only in stage II and in slow-wave sleep of normal young adults. They found, however, that heavy snorers snored longer in stage II, probably because this is the longest sleep stage.

1.5 Acoustics of snoring

1.5.1 Snoring Sound Generation

Snoring sounds originate in the upper airway, which behaves as a collapsible tube tending to collapse predominantly in the inspiratory phase. Therefore, the production of snoring sounds has been compared to the production of wheezes in the bronchial tree, represented by a series of collapsible tubes, which tend to collapse predominantly in the expiratory phase. This inversion of phases of collapsibility of the upper vs central airway is due to the mechanism of inspiration-expiration. Mathematical and biochemical simulation models have been employed to explain sound generation during snoring [32,33].

Two main models for interpreting snoring sounds can be considered [17]. One model is that of "relaxation oscillations" of a collapsible tube described by Bertram [34]. The oscillations produce a partial or complete closure of the lumen with maximal constriction which moves upstream along the tube. The partial or total closure of the lumen, opening with a sudden qualization of upstream-downstream pressure could generate an explosive sound. This model of the mechanism is similar to that which is applied for crackles generation in the peripheral airways. According to Perez-Padilla [35], this type of explosive feature of snoring, in frequency and time domain, is more common in the snoring of patients with OSA. The second model [33,36], based on the "flutter theory", employs a long corrugated channel, changing in CSA, with elastic walls and resistance which interacts with a gas flow. This model fits well with the shape and characteristics of the bronchial and pharyngeal wall. On the basis of this second model, the fluttering walls of the collapsed segment, where there is flow limitation, are the source of snoring. The flutter frequency tends to decrease as the CSA becomes smaller or the thickness increases. The two theoretical models for explaining snoring sound generation meet with the observations of fluoroscopic imaging of vibrating uvula, soft palate and pharyngeal wall [30,37].

1.5.2 Acoustic Investigations

Snoring is an acoustic signal and can be described in terms of quality and quantity by means of acoustic analysis techniques, which can give information on the mechanism, loudness, intensity, CSA and sites of obstruction of the UA. Snoring sounds can be easily and precisely detected by a microphone, hung in front of the patient's mouth at a distance of 15–20 cm, and/or by microphones directly applied above the suprasternal notch, or on the neck or chest wall. The signal can be recorded to a digital audio tape recorder, or sent through an analogue-digital converter directly to a computer system for subsequent analysis. The snoring signal can be detected alone or with other parameters, such as in polysomnographic and/or fluoroscopic investigations or in ambulatory, home monitoring devices. Snoring can be also picked up by a condenser microphone placed at 15–20 cm from the mouth [17].

Generally, the pathological importance of snoring has been related to its intensity (dB), maximum and mean snoring intensity (dBmax and dBmean, respectively), timing (continuous or interrupted), and the length of time during sleep (snoring index: numbers of snores per hour of sleep; snoring frequency: numbers of snores per minute of snoring time). Acoustically, snoring is due to vibration of the walls of the oropharynx when the patency of the upper airway is altered by some of the numerous factors which regulate it [17].

1.5.3 Leq-Equivalent Continious Sound Level

Equivalent sound level (Leq) is the A-weighted energy mean of the noise level averaged over the measurement period. It can be considered as the continuous steady noise level which would have the same total A-weighted acoustic energy as the real fluctuating noise measured over the same period of time, and is defined as:

$$Leq = 10\log\frac{1}{t}\int_0^{\tau}(\frac{P_A(t)}{P_0})^2\,dt \qquad (1.1)$$

where t is the total measurement time; $P_A(t)$ is the A-weighted instantaneous acoustic pressure; P_0 is the reference acoustic pressure (20 Pa); and A is an electrical filter "A" of sound level meter internationally standardized [37].

The statistical analysis of the snoring signal during night by Leq technique reports the data on Leq, L5, L95. The quantities L5 and L95, expressed in dB (A), are the sounds levels which are exceeded in 5% and 95% of the test period and are representative of the highest levels (5%) and of background levels (95%), respectively. The duration of the evaluation takes place in about 8 hours and data are produced every 10 min, so that the evolution time can be well evaluated. The global value of Leq (7 h) is 55.7 dB (A). The lower values of L95 indirectly confirm the low level of the background noise in the test room. The complete Leq study has been reported previously [6,38].

The results of the analysis of snoring in terms of Leq confirm that snoring can be quantified in terms of the sound energy emitted during sleep, and can be correlated to other parameters measured with polysomnography (PSG). When a larger number of subjects and patients are studied, this technique could help to differentiate the population of pathologic patients, guide the therapeutic approach, and follow the results of treatment. On the other hand, this technique provides only quantitative and objective data and not further information on the anatomy and pathophysiology of the upper airway. The technique measures noisiness, annoyance, and damage to the partner's hearing. In addition, it allows verification of possible damage to the snorer's hearing. For these reasons, Leq analysis can be useful in forensic medicine to judge cases of requested separation and damage claims [17].

1.6 Clinical Aspects of Snoring

1.6.1 Snoring as a sign of abnormality

In each patient's history, the presence or absence of snoring should always be considered, in particular if he complains about some disturbances. Obviously, this is not easy to obtain from the patient himself. If snoring is present, the history and related diagnostic tests help to determine whether:

1. The patient is just a snorer without other disorders (nonhabitual, habitual, simple snorer)
2. The patient presents not only snoring but also sleep disorders or breathing disturbances during sleep
3. The patient or the partner report apneas during sleep and other daytime disturbances.

When snoring is reported by the patient, the patient's history must be recorded accurately and, consequently, some investigations must be made by a specialized doctor. The patient’s history should indicate the functional nocturnal and daily disturbances, and the onset of these disturbences as far as possible. Falling asleep during the day can suddenly arouse suspicion. The reported characteristics of snoring are important, i.e. habitual or not, recent or longstanding, continuous or intermittent, in dorsal supine position or in other positions. Also the type of sleeping, i.e. quiet or not, with arousal, the presence of choking or the sensation of unrest, the presence of restless movements of the legs are fundamental to precisely define the respiratory disorders, together with snoring. In addition, reports of headache in the morning and excessive daytime sleepiness, which is typically after noon but also may occur in the early morning or while driving the car, should be noted. It is important to record previous or unreported diseases from the patient, life-style and consumption of smoke, alcohol and sleeping pills. A complete, objective physical examination of signs must be performed, including weight (using Lorentz formula or body mass index (BMI), which equals $(\text{weight in kg}) / (\text{height in cm})^2$, and neck size [17].

1.6.2 Snoring and the Cardiovascular System

Snoring leads to alterations that can reduce the life expectancy of the people afflicted by it. The most dangerous consequences appear to involve the cardiovascular system. The investigations that have been carried out involving large numbers often use questionnaires or techniques less complex than polysomnography. For this reason, it is not always easy to discriminate snoring alone from snoring with sleep apnea. Moreover, haemodynamic monitoring was much less frequently performed than polysomnography in snorers and in snorers with OSAS to investigate the direct effect of snoring on the cardiovascular system. In addition, other risk factors for systemic hypertension, such as age, obesity, smoke, diabetes, etc., overlap and cause confusion [39, 40]. Waller and Bhopal [41] have underlined the discrepancies that sometimes occur between various studies.

Partinen and Palomaki [42] found a three times greater percentage of habitual snorers in 50 consecutive cases of male patients afflicted with cerebral infarct, when compared to a group of neurology in-patients with other pathologies. The studies of Lugareasi *et al* [43] on the whole population of San Marino, repeated on the inhabitants of a whole quarter of Bologna [43,44], were first to point out the prevalence of arterial hypertension among heavy snorers, in whom, unlike normal subjects, the systemic arterial pressure does not decrease during the night, but on the contrary slightly increases. The most accepted mechanism by which snoring directly determines cardiovascular effects is that during sleep, snoring develops a more negative intrathoracic pressure, even if the upper airway obstruction is not complete [17].

Smirne *et al.* [45] showed that habitual snoring carries a significant risk factor for stroke and myocardial infarction, even after adjusting for other confounding variables, such as age, gender, body mass index, diabetes, dyslipidaemia, smoking, alcohol and hypertension. The association of habitual snoring and acute vascular disease is probably explained by the occurrence of OSAS in habitual snorers.

Snoring is, obviously, not only a disturbance for the bed partner and a significant social problem, but also, definitely, a sign of pathology which can range from "of little importance", as in light and initial forms of snoring, to "extremely important" when it is continuous (every night) and heavy. Snoring assumes particular characteristics; besides being a sign of pathology it can also be a trigger or a causative factor. There have been no systematic studies on its acoustic features to indicate what kind of snoring can become a trigger or cause of cardiovascular diseases [17].

1.6.3 Snoring and Nasal Obstruction

Partial or total nasal obstruction can variously affect sleep, ventilation and snoring. Olsen [46] and Zwillich [47] demonstrated sleep and breathing disorders in normal subjects with nasal obstruction. Lavie [48] reported respiratory disorders in the sleep of patients with allergic rhinitis [17]. Bilateral nasal obstruction determines an increase in the number of apneas and of their duration in healthy subjects [47]. It has also been demonstrated [49,50] that nasal stimulation or obstruction determines an increase of the lung airways resistance. In normal subjects, nasal obstruction, partial or total, due to various causes (septal deviation, turbinate hypertrophy and other nasal abnormalities) provokes snoring in a high percentage of cases [46,50]. In particular, Fairbanks [51] found that 80% of nasal anomalies caused obstruction in healthy snorers.

The nasal obstruction itself does not make the nose the site of origin of the snoring and/or of sleep apnea. It typically determines an increase of the velocity of airflow with the effect of an increased pressure of aspiration and/or an oral breathing; these are factors which can favour pharyngeal collapse and, consequently, snoring up to apneea. Accurate examination of the nasal cavities is, therefore, mandatory. During direct endoscopic visualization, with instruction of the patient to speak, to simulate snoring, and to carry out the Müller manoeuvre, careful observation of the oral-pharyngeallaryngeal cavity can provide useful information for the expert observer. The analysis of snoring with LPC technique, starting from acoustic and fluoroscopic studies of simulated snoring, makes it possible to distinguish prevalently nasal, oronasal and oral snoring. The shape of the acoustic airway and the spectral analysis become typical when the nasal obstruction is important or total [17].

1.6.4 Snoring : Sign to Screen Sleep Related Breathing Disorders

Snoring is a central sign, around which various factors and disorders can be found as causes and effects. In particular, loud continuous (every night), intermittent (during the night) snoring is very common in sleep-related breathing disorders with obstruction of the upper airway (i.e. obstructive snoring with arousal and OSA). Early diagnosis of sleep selated breathing disorders (SRBD) is not easy, but important for therapeutic intervention [17]. For an accurate diagnosis, polysomnography obviously represents a gold standard. This technique is, however, hard to apply, time-consuming and expensive. In Europe, only a small number of sleep laboratories are present, and they cannot admit all suspected patients. The recording of tracheal sounds on the sternal notch allows monitoring of the snoring and breath sounds, and also of sleep apnea. For these and other reasons, snoring is the constant parameter to be recorded [17].

Some portable devices were developed and applied for ambulatory and home monitoring of sleep, to screen and/or select patients for more complex investigations (such as polysomnography). Recently, Penzel and Peter [52] have worked out a concept of stepwise diagnosis of sleep disorders and sleep-related breathing disorders to manage this health risk factor using the “Non-Laboratory Monitoring System (NLMS)”. Evaluation of a questionnaire, clinical investigation and functional tests are accompanied by ambulatory measurements with NLMS. These measurements are heart rate, snoring, O2-saturation, and body position. If the patient’s history and ambulatory recordings with NLMS show that the patient is high risk, long-term recordings for diagnosis and treatment are obtained immediately in the sleep laboratory. If the patient is medium or low risk, further investigation and treatment is performed later in the sleep laboratory or using NLMS. Ambulatory systems are also very useful for long-term observation [17].

In 1987, Hida *et al*. [53] developed a device to record and play back nasal flow, tracheal sound and electrocardiogram during sleep at home. In an epidemiological study of 168 workers, they found that the percentage of patients with OSAS in the general population was 17%. This value was unexpectedly higher than the values presented in a previous study [44] that surveyed middle-aged men. The present results indicate that there are many undetected patients with sleep apnea syndrome, and that the portable home sleep monitoring test is helpful in order to find patients with sleep-disordered breathing in a mass survey.

Penzel *et al* [52] developed a device, MESAM II, based on snoring and heart rate analysis to monitor sleep apnea. Stoohs and Guilleminault [54] used the same device to screen subjects for OSAS and compared their findings with simultaneous polysomnography. Researchers who have used the MESAM devices have compared the discriminant power of the variables digitally analysed, with the objective data of the polysomnography [55].

The variable snoring, calculated on its energy variation and heart rate have demonstrated a poor correlation with apnea hypopnoea index (AHI) derived from polysomnography. The sensitivity of these variables is good (96 and 58%) but the specificity is bad (27 and 39%). Using MESAM II, Stoohs and Guilleminault [56] with "hand scoring" found a specificity of 72% and a sensitivity of 92%. The variable with the highest performance was S_pO_2. DSA model I and II portable systems were further devices for recording tracheal sounds, such as snoring, wheezing and cough. These devices have been used by Lens and Postiaux [57,58] since 1987. With Sleepsound II, a recently developed portable device, the authors found 16 snorers with OSAS by sonogram vs 5 diagnosed clinically, and 4 vs 3 by S_pO_2. Another portable device, CID 102, applies the detection of tracheal sounds by two electret sensors and evaluates the sound signal as a function of its frequency range and intensity (dBA). A good correlation was found using this device between the automatic detection of apnea, and hypopnoea by CID 102 and those evaluated by flow tachograph [59,60]. Also, Issa *et al*. [61] developed a new portable digital device (Snoresat), which uses the sound of snoring and S_pO_2 to monitor respiratory disturbance (RD). Data were played back and analysed by a PC program. Using the RD index, they found a sensitivity and specificity of the device in detecting OSAS of between 79–90% and 90–100%, respectively, depending on the RD index value used to define OSA. .

The availability of this portable small compact system offers great advantages for the general and specialized physician and patients. These devices fill the big gap in the screening of SRBD. They are, in particular, developed for out-patient use, and enable the physician to make a prompt screening of SRBD, to obtain a diagnosis of sleep apnea syndrome, and to screen children or infants with snoring, daytime sleepiness, fatigue and poor school performance, in order to ascertain the UARS [62,63]. All these five mentioned devices are based on monitoring of snoring and recording of the snoring signal as present or absent, without additional analysis or measurement. Only when these devices can analyse and measure snoring, will they improve knowledge of it. The systems described make it possible to avoid time-consuming and expensive polysomnography, which can be reserved for problematic cases. Their versatility, in addition to diagnostic use, can be helpful in monitoring drug and continuous positive airway pressure (CPAP) treatments. Long-term surveillance of patients, who are not at acute risk, can be accomplished at home. Another important point is the application of snoring monitors to epidemiological studies. These systems can provide an earlier diagnosis of SRBD and facilitate accurate estimation of percentage of occurance of OSAS [53], substantially modifying the epidemiological data so far reported in the literature, as already indicated by Hida *et al*. [53].

1.7 Review of the Snoring Signal Processing

Detection of snoring episodes in a full-night recording of sleep sounds is a fundamental step in all these tasks. Until recently, related studies were based on manual segmentation of snoring episodes. There is a very limited amount of work on automatic detection of snoring episodes. Abeyratne *et al.* [64], in 2005, used the energy and the zero crossing rate as the features in a minimum-probability-of-error approach to identify snoring episodes. Energy and zero-crossing rate are commonly used for audio signal activity detection, however they are not known as having strong discriminative capabilities in classification. Duckitt *et al.* [65] adopted speech processing techniques for snore detection. Mel-Frequency-Cepstral Coefficients (MFCC) were used as the features in a Hidden Markov Model (HMM) based classification framework. Speech is a sequence of phonemes with evolutionary transitions (loose boundaries) from one to another. The characteristics of a speech waveform in a transition segment between two phonemes may deviate considerably than those observed over the core segments of the neighboring phonemes. Phonemes are commonly modeled by three state HMMs in order to represent initial, core and final segments distinctively. However, sleep sounds are of dominant discrete nature. Furthermore, snoring sounds remain quite stationary over their intervals of existence. These observations suggest the possibility of using computationally less intensive classification approaches. Mel frequency cepstral coefficients (MFCC) are low level acoustic descriptors of speech. They extract the acoustic filter characteristics of the human vocal tract by homomorphic deconvolution of the vocal tract response and the source signal produced by the vocal folds. However, sleep sound recordings contain not only sounds produced by humans but also sounds from other sources having different mechanisms in the environment. Furthermore, the production mechanisms of snoring sounds, which have not been investigated as widely as speech sounds, are not completely similar to speech sounds. In case of snoring, the location of the source along the vocal tract and its dynamics are different than that of speech.

Therefore, sound feature definition and classification methods in automatic snoring episode detection still appear as a ground of exploration.

1.8 Scope of the Study

The scope of the study and the objectives are listed below:

- Recording the patients sounds during their whole night sleep accurately with a proper recording setup
- Creating a snore data base
- Determining the time and frequency domain charachteristics of the snoring signal
- Developing a segmentation system to find the boundaries of the episodes
- Spectogram based feature extraction
- Application of pricipal component analyses (PCA) to the feature set
- Defining a subspace by using principal components
- Seperating snore episodes from other sounds by using robust fitting with bisquare weights based on iteratively reweighted least squares algorithm.
- Developing snore related statistics calculation algorithms
- Design and implementation of a user interface for clinical application

1.9 Contributions of the Thesis

The contributions of this thesis are listed below which were not available in the literature:

1) Spectogram based classification of snoring sounds
   - Feature extraction for segmentation of snoring signal,
   - Representation of the snore signals in a two dimensional space using PCA,
   - Determining a decision boundary by using robust regression with iteratively least squares method.

2) A user interface for clinical applications

- Developing a fast an efficient algorithm for clinical applications including patient file and registration operations,
- Computing snore related statistics with high accuracy,
- Comparison of the results pre and post operatively,
- Supporting the software with visual graphics for easy understanding of the medical staff,
- Output page for storing the results both as a hard or a soft copy.

3) Simple snorer - OSAS decision parameters

- Determining the regularity of the snoring with a high accurate and fast method,
- Intensity, time and episode parameters block for pre and post operative comparison.

4) Integration with polysomnography

- The system is integrated with polysomnography in order to determine the efficient sleeping time and to provide the system with Apnea/hypopnea index.

5) Including OSA patients in the study

- Determining snoring episodes for OSA patient is a difficult task for a number of reasons that will be explained in the following chapters. In this thesis we determine the snoring sounds and do all the analysis for OSA patients with a high accuracy.

1.10 Outline of the Thesis

As described above, there are two main works in this study. First one is developing an algorithm to detect the snoring episode and the second work is design and implementation of a user interface for clinical application.

In Chapter 1, the definition of the snoring is given. The clinical side and the anatomical and physiological aspects of snoring are expressed in detail. The acoustics of the snoring and origin of the snoring sound are introduced. A review of the signal processing of snore signals is also presented.

In Chapter 2, snore detection algorithm development procedure is described. In its subsections, the properties of the sound recording system and the patient profile are given. After expressing the types of testing and training datasets, the frequency domain characteristics of the snoring are given. The feature extraction methods are introduced. The application of principal component analyses and robust fitting with bisquare weights based on iteratively reweighted least squares algorithms are also given in chapter 2.

In Chapter 3, the stages and the flow chart of the algorithm are illustrated. The results of the system and the performance measurements are the subsections of this chapter.

In Chapter 4, the implementation details of the user interface are given. Each part of the interface is expressed as the subsections of chapter 4.

Finally, Chapter 5 is the Conclusion chapter.

CHAPTER 2

DETECTION OF SNORING EPISODES

Several methods are available for the treatment of snoring, depending on the location of pathology such as uvulopalatopharyngoplasty (UPPP) for uvuloal snoring and radiofrequency tissue volume reduction of the tongue for tongue based snoring. Despite the existence of different treatment methods, determination of the treatment success is a common problem for both snoring and apnea patients**.** It is possible to assess the medical treatment by analyzing the snoring sounds. However, manual inspection of a whole night respiratory sound recording is a time-consuming and operator-dependent task. It is possible to process these recordings automatically, and compute related statistics. In order to extract snore related parameters from the signal, we developed an algorithm that detects each snoring episode automatically, while discarding undesired sounds such as cough, nasal congestion, speaking and other environmental noises, and that computes some useful statistics. These statistics can include the ratio of the snoring time to the total sleeping time, the mean and maximum time between two snoring episodes, the intensity and distribution of the snoring episodes with respect to sleep stages. These statistics can be computed pre and post operatively, and an objective assessment of the medical treatment can be obtained from their comparison.

In this chapter, we present the recording setup for snore sound recordings, created snoring database and snore signal characteristics are presented. Then, the content of training and testing datasets are given. Finally the feature extraction methods for segmentation, the basics of PCA and application of PCA, and robust regression with iteratively reweigted least squares method to our problem is presented.

2.1 Recording Setup

A Sennhiser ME 64 condenser microphone with a 40–20000 Hz ± 2.5 dB frequency response was used for recording sounds. This microphone has a cardioid pattern which helps to suppress some of the echoes from the environment. It was placed 15 cm over the patient's head during sleep. The signal was fed via a BNC cable to the Edirol UA-1000 model multi-channel data acquisition system connected to a personal computer via universal serial bus. The computer was placed outside the sleeping room to avoid its noise in the recording. The acquired signal was digitized at a sampling frequency of 16 KHz with 16 bit resolution. The data were stored in the computer together with the patient information. Figure 2.1 shows a 25 second long snoring signal.

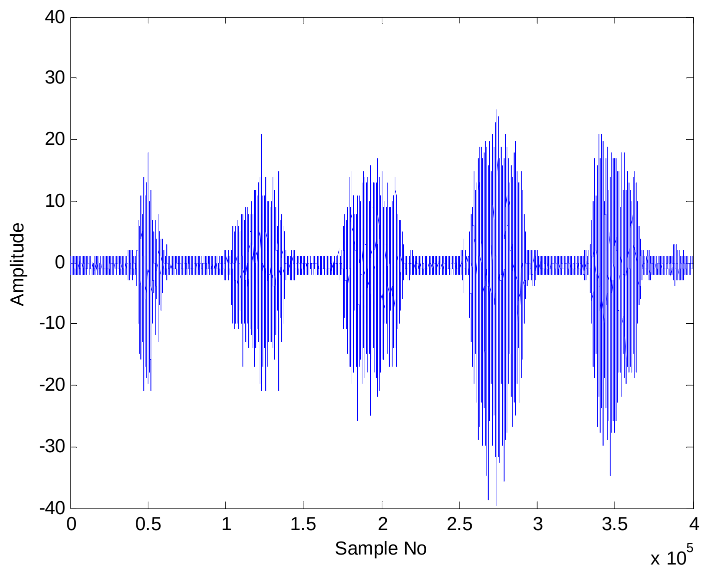

Figure 2.1 25 second long snoring signal from an OSA patient.

2.2 Snoring Database

A database has been created from the sound recordings taken from patients who were suspected of OSAS pathology. These patients were connected to the polysomnography in Gülhane Military Medical Academy (GMMA) Sleep Studies Laboratory during their whole night sleep. The position of the microphone is shown in Figure 2.2.a and an OSA patient that is connected to the polysomnography is shown in Figure 2.2.b.

(a)

(b)

Figure 2.2 (a) The position of the microphone with respect to the patient's bed in sleep studies laboratory
(b) OSA patient under polysomnography

The sound recordings were taken synchronously with polisomnography in order to determine the Apnea/Hypopnea index of the patient and to be able to study the relationship between the physiological signals and snoring. The database is composed of whole night respiratory sounds recorded from 30 individuals. Each of the recordings has approximately 6 hours duration. There are 12 patients with OSAS and 18 simple snorers, with different AHI and body mass index. Table 2.1 indicates the number of patients and the mean of their age, AHI and BMI.

Table 2.1 Number of patients and the mean of their age, AHI and BMI in OSA patients and simple snorers

Patient Info	OSAS	**Simple snorers**
# patients	12	**18**
Age	53.26	**46.92**
Sex	Male	**16 male**
AHI	39.21	**4.29**
BMI	32.76	**27.66**

2.3 Characteristics of the Snoring

In order to develop a snore recognition algorithm, it is crucial to investigate the power spectrum of the snoring signal and determine the frequency domain characteristics. In literature, Dalmasso [17] had firstly investigated the power spectrum of the snoring signal. The frequency domain characteristics of the snoring signal will be examined in this section.

Figure 2.3.a shows the snoring signal in one snorer over a period of 10 s, where four respiratory cycles are present. Figure 2.3.b shows the "power spectrum" of the snoring signal corresponding to section 1 and Figure 2.3.c shows the "frequency spectrum" of the snoring signal corresponding to section 2.

The greater part of the energy content is below 5,000 Hz and the main components lie in the low frequency range, at about 130 Hz, and in the mean frequency range, at about 1060, 2200 and 3500 Hz.

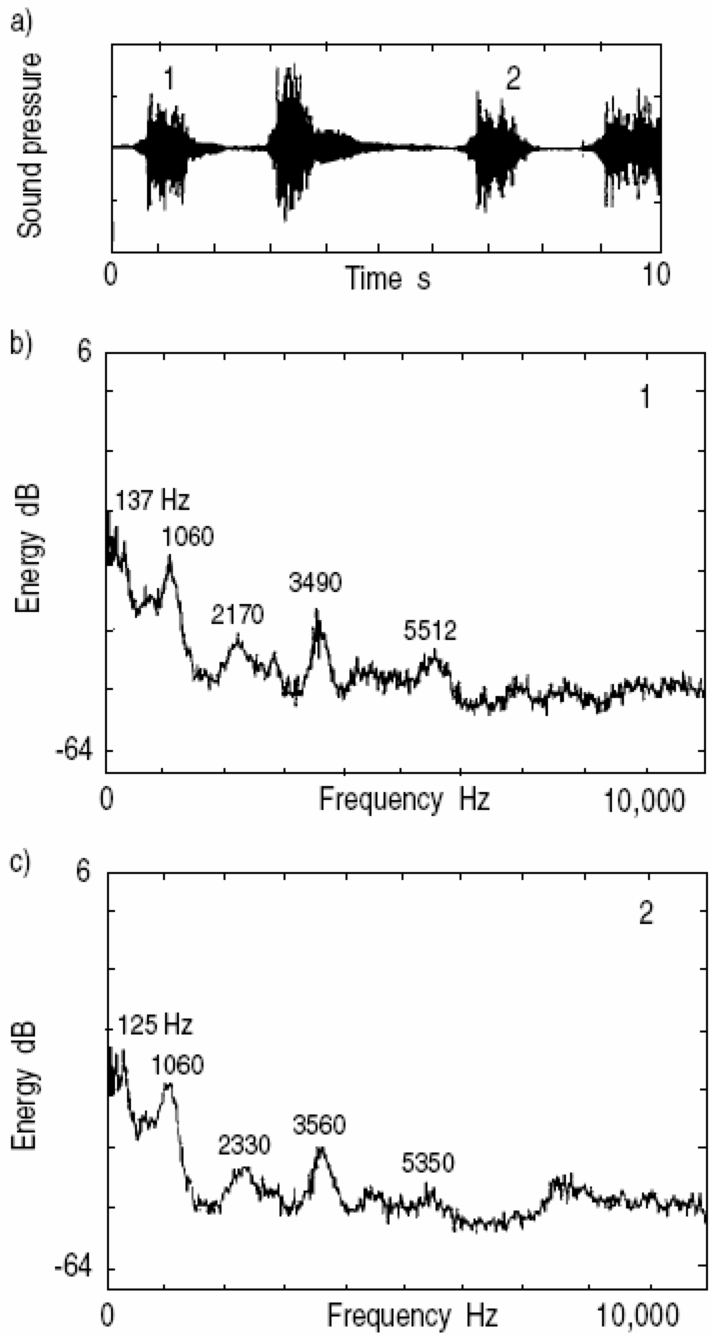

Figure 2.3 a) A graphic representation of waveforms of snoring events,
b) the avaraged spectrum shaped of event 1 in Figure 2.3.a
c) the avaraged spectrum shaped of event 1 in Figure 2.3.a

(Adapted from Dalmasso et al.: Snoring: analysis, measurement, clinical implications and applications Eur. Respir. J.9 146–59)

Since the distribution of energy of the frequency spectrum changes within a single event or during a respiratory cycle, a three-dimensional representation of snoring was performed. This allowed visualization of the time evolution of the spectrum. [17]

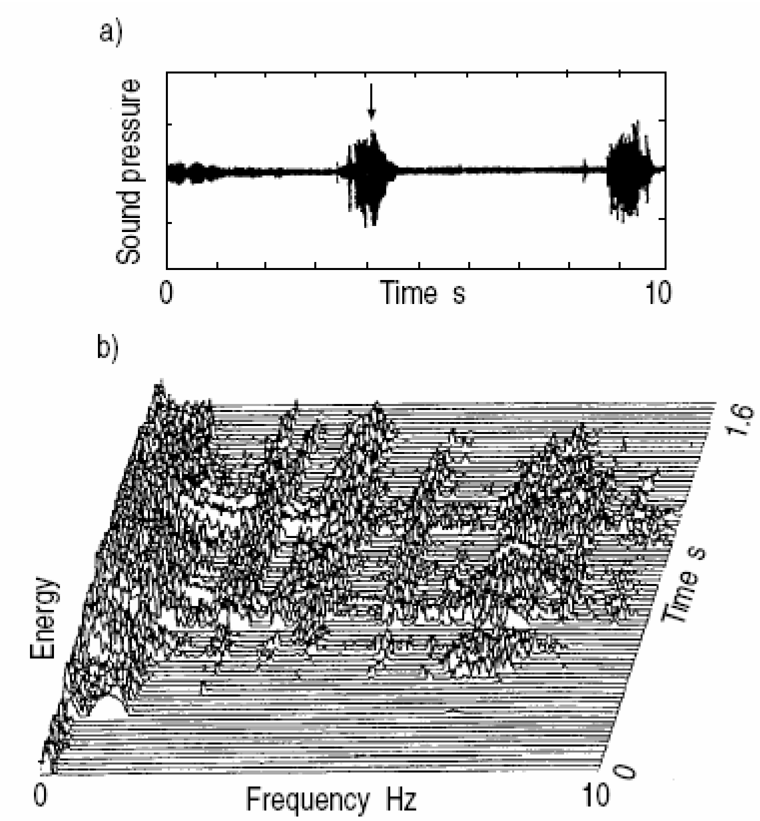

Figure 2.4 a) Time variation of the snoring sound pressure
b) Time variation of the frequency spectrum of the event marked in (a)

(Adapted from Dalmasso et al.: Snoring: analysis, measurement, clinical implications and applications Eur. Respir. J.9 146–59)

As it is seen from Figure 2.4, energy was mainly concentrated in the low frequency range at the beginning of snoring, and at middle and high frequencies (up to 7 kHz) at the end. In Figure 2.5 the spectogram of the snoring signal including four snoring episodes is shown.

The structure of the spectrum results being of formantic type, practically identical in every cycle of the sequence examined [17]. The spectrum shows a fundamental frequency and a "formants type" structure [17]. In experimental phonetics, the formants are the acoustic analogue of the shape and size of the vocal duct. Each "formant" is characterized by frequency, bandwidth and amplitude level, and its range depends on the shape of the resonant cavities. The different conditions in which the subjects and the patients who snore can affect the formants range in the frequency spectrum.

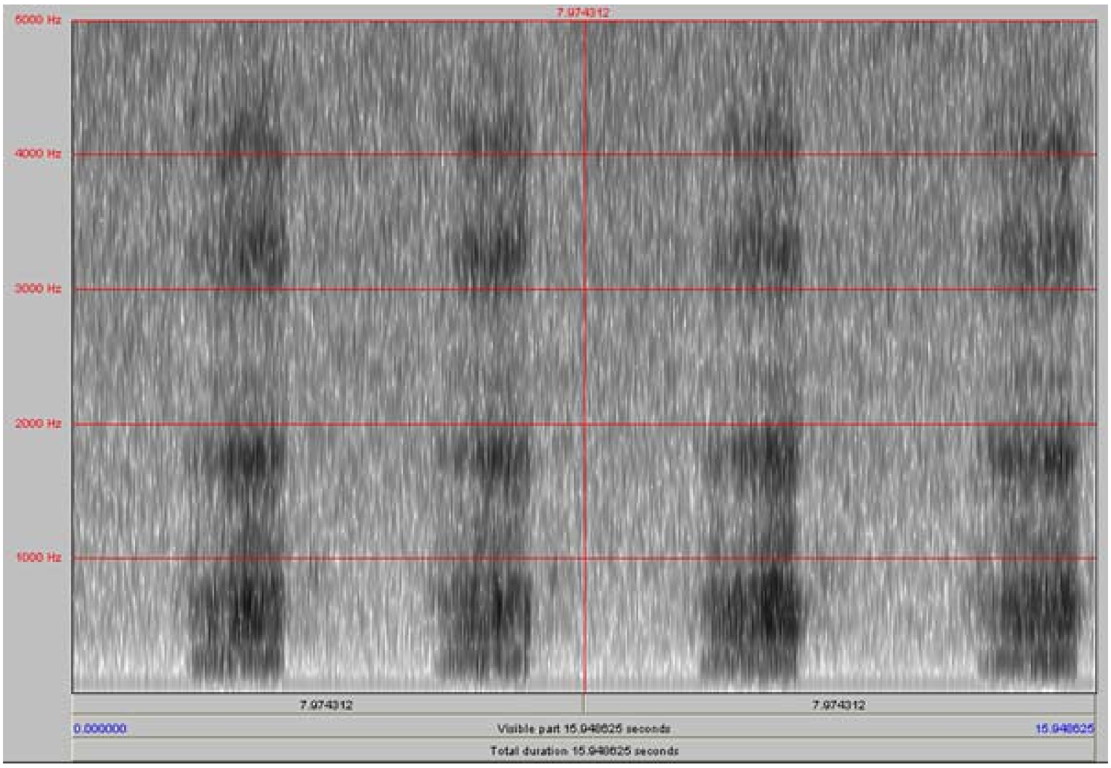

Figure 2.5 Spectogram of the snorign signal including four snoring episodes

Meslier *et al*. [43], monitoring tracheal breath sound in snoring patients with OSAS, found no significant change in frequency spectrum with sleep stages. They found evolution of fundamental frequency during a snore (stability, increase of fundamental frequency,sudden variations of frequency). Perez-Padilla and Remmers [39] found, in spontaneous snorers, three main patterns of snoring (nasal, oral and oronasal) which present characteristic spectra. They may make it possible to recognize the type of respiration [17].

The same author [46], found the most different spectra in OSA patients; in particular, the first post-apnea snore constituted by white noise with more power at higher frequency. Therefore, he proposed that the ratio of power above 800 Hz to power below 800 Hz could distinguish simple snorers from those with OSAS. Spencee *et al*. [47], in patients who underwent standard polysomnography, recorded snoring on the sternal notch and examined snores during Stage II sleep using the FFT technique. They found a significant correlation between median frequency of snore and apnea-hypopnoea index. This fact may be related to intrathoracic pressure changes or differing sites of UA obstruction. Thus, the spectral analysis values, the "formants type" structure and the shape of spectrum help to distinguish simple snoring from loud snoring with OSAS, even though with a certain overlap of data [17].

2.4 Testing and Training Datasets

To create the testing and training datasets for the classification problem, the snoring episodes were first manually labeled by a medical doctor. Then, three different experiments were performed:

Snore detection tests for only simple snorers (Exp-1): The individuals in the training and testing datasets are different. The training dataset contains randomly selected 300 snoring episodes from each of 12 simple snorers (a total of 3600 snoring episodes). The testing dataset was composed of 6 simple snorers. For each of these subjects a randomly selected recording interval containing 300 snoring episodes was included into the testing dataset.

Snore detection tests for both simple snorers and OSA patients (Exp-2A): The individuals in the training and testing datasets are the same, however the recording intervals in each of these datasets are different. The first half of the recordings (first three hours) was used to compose the training dataset and the second half (the last three hours) to compose the testing dataset. The training dataset contains randomly selected 150 snoring episodes from each of the 30 subjects. The testing dataset contains a randomly selected recording interval that includes 150 snoring episodes from each the 30 subjects.

Snore detection tests for both simple snorers and OSA patients (Exp-2B): The individuals in the training and testing datasets are different. Each dataset involves 9 simple snorers and 6 OSA patients (two disjoint datasets of 15 subjects). The training dataset contains randomly selected 300 snoring episodes from each of 15 training subjects (a total of 4500 snoring episodes). For each of the 15 subjects in the testing dataset, a randomly selected recording interval containing 300 snoring episodes was included into the testing dataset.

Table 2.2 summarizes the compositions of the testing and training datasets in these experiments.

Table 2.2 Compositions of testing and training datasets in the experiments.

	EXP-1		*EXP-2A*		***EXP-2B***	
	Training	*Testing*	*Training*	*Testing*	*Training*	***Testing***
Simple Snorers	***12 subjects 3600 snoring episodes***	***6 subjects 1800 snoring episodes***	***18 subjects 2700 snoring episodes***	***18 subjects 2700 snoring episodes***	***9 subjects 2700 snoring episodes***	*9 subjects 2700 snoring episodes*
OSA Patients	-	-	*12 subjects 1800 snoring episodes*	*12 subjects 1800 snoring episodes*	*6 subjects 1800 snoring episodes*	*6 subjects 1800 snoring episodes*

2.5 Segmentation Subsystem

The first step in snoring detection is to identify the intervals of sound activity. Energy and zero crossing rate (ZCR), conventional measures for determining boundaries of sound activity, were used to determine the boundaries of sound segments. Energies and ZCRs of signal frames of length 100 ms, with 50 ms overlaps, are calculated. The energy, E_k, in the k^{th} frame of the signal is computed as

$$E_k = \sum_{i=0}^{N-1} s_k^2\left[i\right] \tag{1}$$

where $s_k\left[i\right]$ is the signal in the k^{th} frame of length N samples. Figure 2.6 shows a sample recording and the corresponding energy and ZCR patterns.

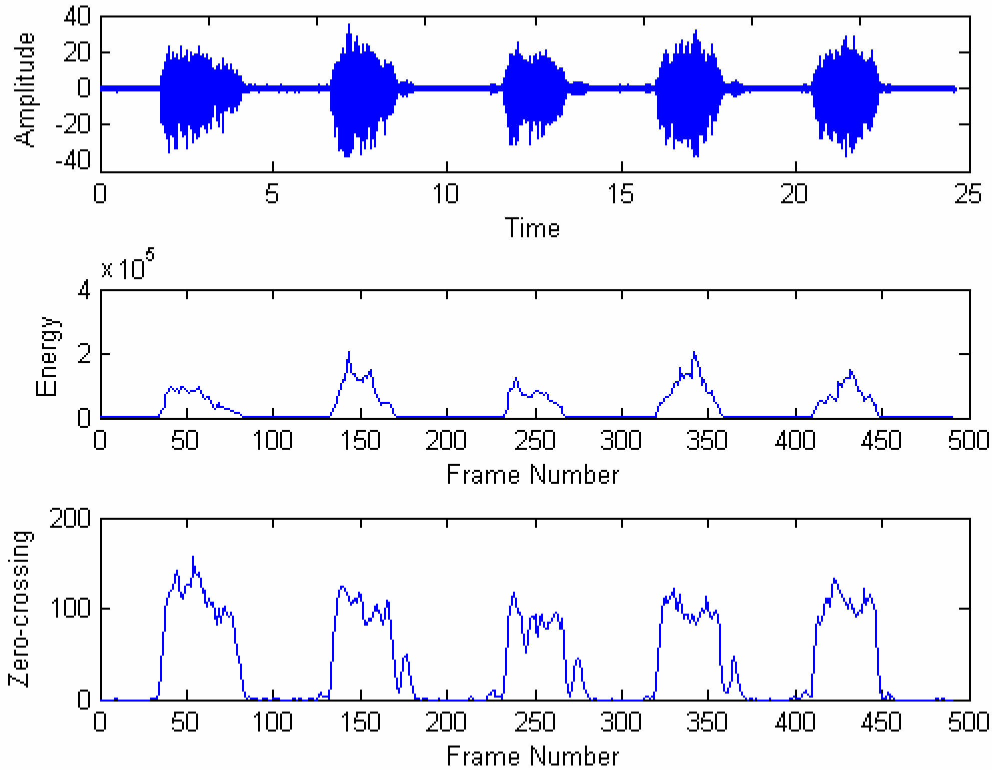

Figure 2.6 A signal sample (top), its energy pattern (middle) and its ZCR pattern.

Sound activity episodes were determined in three steps. First, those frames for which the energy and the ZCR values are above certain thresholds simultaneously were marked as activity frames. Then, the starting and ending points of episodes were found by searching for continuities of activity frames. Finally, those episodes separated by less than a certain duration were merged.

The energy threshold, T_E , was determined as,

$$T_E = \min(I_1, I_2) \tag{2}$$

where

$$I_1 = a \times \left[\max(E_k) - \min(E_k)\right] + \min(E_k)$$

$$I_2 = b \times \min(E_k) \,.$$

ZCR threshold, T_Z , was determined as

$$T_Z = c \times \overline{ZC} \tag{3}$$

where $\overline{ZC}$ is the average ZCR of snoring episodes in the training dataset. The values of constants *a*, *b* and *c* were set experimentally.

2.6 Classification of the Episodes

Classification of the episodes, as snore or nonsnore, was carried out in two steps. In the first step, spectral features are computed and the feature space is reduced. In the second step, episodes are classified by finding a linear boundary between the two classes. The developments of these steps are described in the following two subsections.

2.6.1 Feature Extraction

When the spectograms of snoring sound waveforms and those of other sound waveforms (cough, breath, sounds of vehicles/doors/animals, sounds due to the motion of the subject) are examined, it is observed that the energy distributions differ over the frequency spectrum. In particular, snoring sounds' spectra have been observed to exhibit a significant coherence while displaying discriminative characteristics relative to other sounds' spectral patterns. The spectrogram of a sequence of snoring and some other sound episodes is shown in Figure 2.7. The regularity of snoring episodes and their distinction from some other sound patterns can be observed in this figure. The disparity of spectral energy distributions among snoring and other sounds suggests the use of spectral features in order to distinguish among snoring sounds and other waveforms.

The spectral features in this study have been obtained by dividing the 0-7500 Hz frequency range into 500 Hz subbands and calculating the average normalized energy in each subband for each episode. To cope with inter- and intra-patient variation of sound intensity the energy of each 500 Hz subband was normalized by the total energy of the episode.

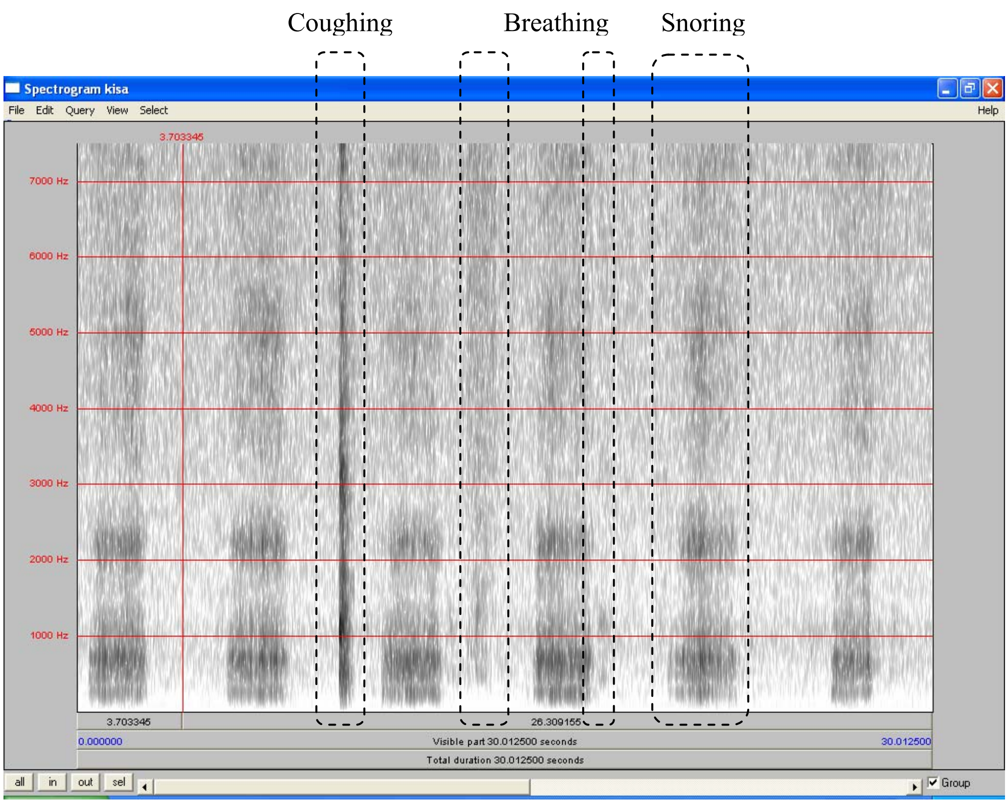

Figure 2.7 Spectrogram of a sample recording.

For the k^{th} episode consisting of N_k subframes, the i^{th} element, ξ_i^k, of its feature vector, ξ^k, is computed as,

$$\xi_i^k = \frac{\sum_{j=1}^{N_k} \sum_{f=500(i-1)}^{500i} |y(j,f)|^2}{\sum_{j=1}^{N_k} \sum_{f=0}^{7500} |y(j,f)|^2} \qquad i = 1,2,...,15 \qquad (4)$$

where $y(j,f)$ is the short time Fourier transform of j^{th} frame of the episode.

2.6.1.1 Principal Component Analyses

Principal component analysis involves a mathematical procedure that transforms a number of (possibly) correlated variables into a smaller number of uncorrelated variables called principal components [int]. The first principal component accounts for as much of the variability in the data as possible, and each succeeding component accounts for as much of the remaining variability as possible.The objectives of principal component analysis can be listed as follows:

- To discover or to reduce the dimensionality of the data set.
- To identify new meaningful underlying variables.

We assume that the multi-dimensional data have been collected in a “Table Of Real data matrix”, in which the rows are associated with the cases and the columns with the variables.

Traditionally, principal component analysis is performed on the symmetric covariance matrix or on the symmetric correlation matrix. These matrices can be calculated from the data matrix. The covariance matrix contains scaled sums of squares and cross products.

The eigenvectors with the largest eigenvalues of this covariance matrix correspond to the dimensions that have the strongest correlation in the dataset. Principal components are obtained by projecting the multivariate data vectors on the space spanned by these eigenvectors.

PCA is a linear transformation that transforms the data to a new coordinate system such that the greatest variance by any projection of the data comes to lie on the first coordinate (called the first principal component), the second greatest variance on the second coordinate, and so on. In other words, PCA can be used for dimensionality reduction in a dataset while retaining those characteristics of the dataset that contribute most to its variance, by keeping lower-order principal components and ignoring higher-order ones. Such low-order components often contain the "most important" aspects of the data.

The steps of PCA can be summerized as follows:

- Find the eigenvalues and eigenvectors of a square symmetric matrix with sums of squares and cross products. (Covariance matrix)
- The eigenvector associated with the largest eigenvalue has the same direction as the first principal component.
- The eigenvector associated with the second largest eigenvalue determines the direction of the second principal component.
- The sum of the eigenvalues equals the trace of the square matrix and the maximum number of eigenvectors equals the number of rows (or columns) of this matrix.

2.6.1.2. Application of PCA to the Classification Problem

The dimensionality of snoring sound feature vectors was studied via principal component analysis. The principal components are found by first computing the covariance matrix, $\mathbf{C}$, of all snoring sound feature vectors, $\boldsymbol{\xi}^k$, in the training database

$$\mathbf{C} = \frac{1}{K}\sum_{k}\left(\xi^{k} - \overline{\xi}\right)\left(\xi^{k} - \overline{\xi}\right)^{T}. \tag{5}$$

where $\overline{\xi}$ is the mean of snoring feature vectors obtained from the training data set and K is the total number of snoring feature vectors. The principal components of this covariance matrix are computed as follows.

$$W_{opt} = \arg\max_{W} \det(W^{T} C W) \tag{6}$$

The eigenvectors corresponding to the largest eigenvalues of the covariance matrix are the basis vectors of the subspace. These eigenvectors span the new classification space. By examining the eigenvalues of the covariance matrix (See Figure 2.8), it is seen that the largest two eigenvalues are much higher than the others. This implies that two dimensional classification subspace is sufficient for this problem.

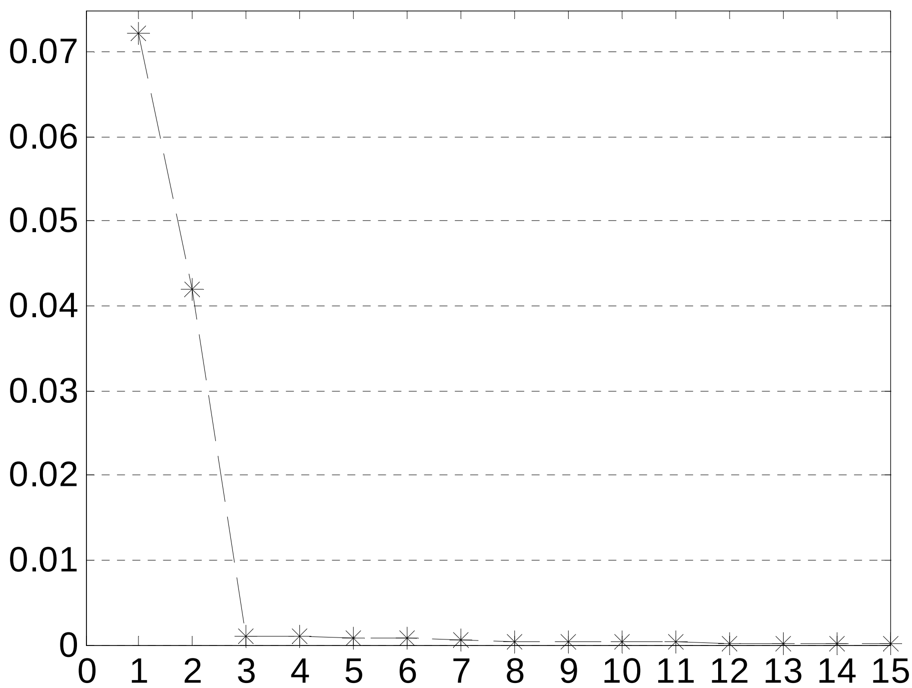

Figure 2.8 The eigenvalues of the covariance matrix sorted in descending order.

New features can be computed by projecting the feature vectors onto this subspace. These projection vectors are computed as

$$\hat{\xi}^k = \mathbf{W}_{\mathbf{opt}} \xi^k \tag{7}$$

Figure 2.9 shows a typical distribution of two dimensional projection vectors of simple snorers. Two useful observations can be made. First, the projection vectors obtained from snoring and other sound episodes are distributed almost in a completely separable manner. Second, the projection vectors of snoring episodes are confined into an almost linear strip.

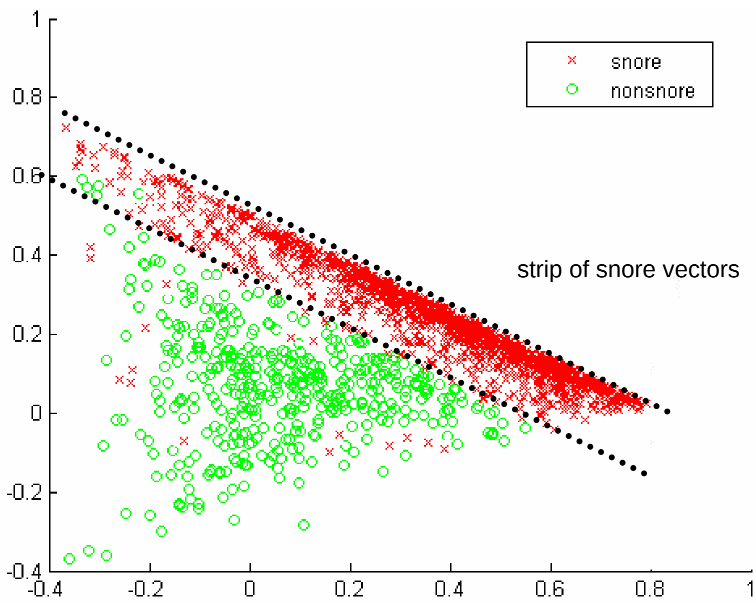

Figure 2.9 Typical distribution of two dimensional projection vectors of simple snorers.

2.6.2 Finding the Classification Boundary by Robust Linear Regression

The idea behind the classification method is to identify the boundary separating the strip where snore vectors are mainly clustered from the region where nonsnore vectors are distributed. The simplest way would be to fit a straight line aligned with the strip and to define a range around this line. However, the existence of outliers (sparsely distributed red crosses among green circles) complicates the identification of this straight line. To overcome this difficulty robust linear regression (RLR) was used **[**66**]**. RLR attempts to minimize the effects of outliers by a weighted least square formulation in which those samples yielding large errors are weighted less.

Let $\hat{\boldsymbol{\xi}}^k = \left[x_k \;\; y_k\right]^T$, $k = 1, 2, \ldots, K,$ be the projection vectors obtained from the training set. The problem is to find the coefficients *a* and *b* in the equation $y_k = a\,x_k + b$ such that

$$w_1\left[y_1 - (ax_1 + b)\right]^2 + w_2\left[y_2 - (ax_2 + b)\right]^2 + \ldots + w_N\left[y_N - (ax_N + b)\right]^2 \tag{8}$$

is minimized. In this problem, the weight, w_p, values depend on the coefficients *a* and *b* so they are not known in advance. They have to be found together with the coefficients iteratively. In general, to suppress the effect of outliers, a weight value w_p decreases as $\left|y_p - \left(ax_p + b\right)\right|$ increases. There are a number of weighting functions proposed for iterative solution in the literature [67]. In this study, we used “bisquare function” **[67]** according to which w_p at the k^{th} iteration is defined as:

$$w_{p,k} = \left|r_{p,k-1}\right|(1 - r_{p,k-1}^2)^2 \tag{9}$$

where $r_{p,k}$ is

$$r_{p,k} = \frac{\text{residual}_p \text{ in the } k^{\text{th}} \text{ iteration}}{tune \times s \times \sqrt{1 - h_{p,k}}} \tag{10}$$

where *tune* is the tuning constant, $h_{p,k}$ is the leverage value from the least squares fit for the p^{th} weight, and s is an estimate of the standard deviation of the error term. [66,67].

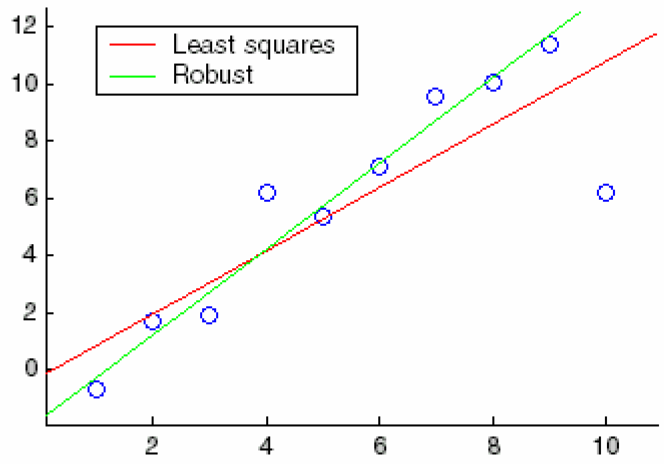

Figure 2.10 Two fitted lines. One line is the fit from an ordinary least squares regression and the other is from a robust regression.

Figure 2.10 shows two lines fit to the same data, one obtained by ordinary least squares and the other by robust linear regression. The influence of outliers is diminished in robust regression.

After fitting a line to the snore train data, a parallel line at some distance below is determined empirically and is used as the classification boundary between snore and nonsnore episodes. Figure 2.11 shows the distribution of snore and nonsnore data, the line fit according to robust linear regression and the classification boundary line.

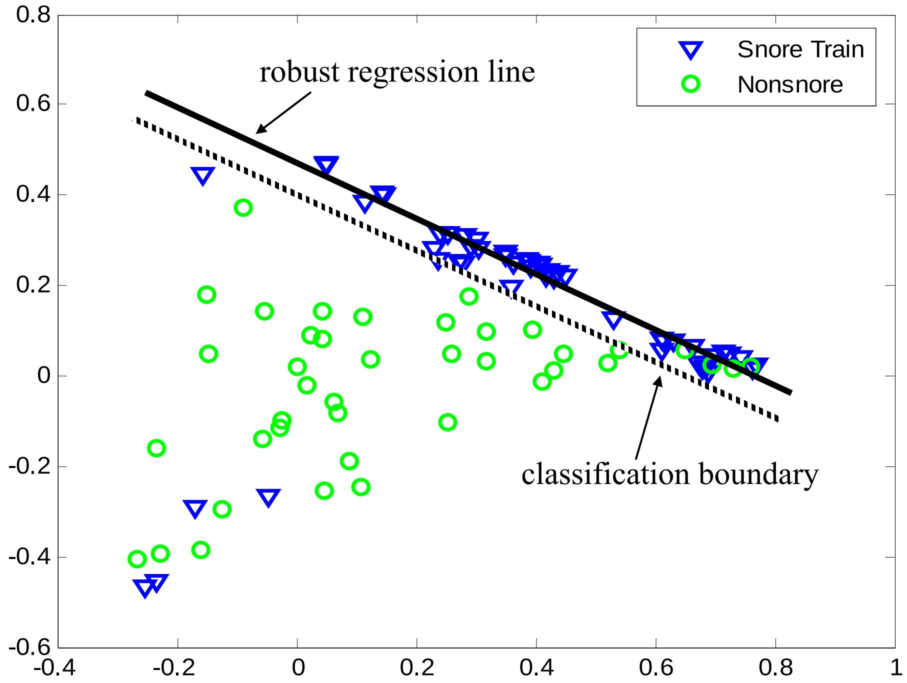

Figure 2.11 The distribution of snore and nonsnore data, the illustration showing line fit according to robust linear regression and the classification boundary line.

The robust linear regression with iteratively reweighted least squares algorithm is summarized step by step as follows:

- Solve the regression problem by using least squares method, so define the initial weighting coefficients as a unit vector
- Fit the corresponding line that is acquired from the least squares solution
- Find the residual of each data to the fitted line
- Define the weighting function for the solution based on how you want to smooth the least square solution (in this thesis we used bisquare function)
- Define the weighting coefficients for each term according to its residual value
- Solve the new regression problem defined by new weighting coefficients (New Iteration)
- Iterate the solution until the leverage value is below a certain threshold

CHAPTER 3

RESULTS

3.1 Flow of the Algorithm

After we calculate the principle components from the training data, and define the region corresponding to snoring episodes, we apply the following algorithm to a new snoring sound recording. The steps of the algorithm are charted in Figure 3.1.

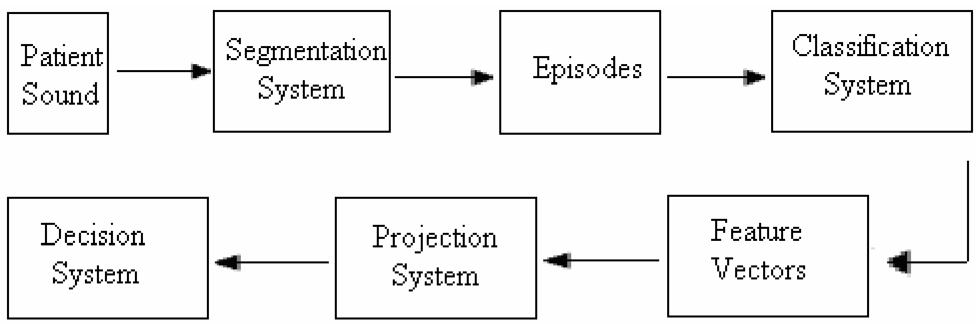

Figure 3.1 The steps of the developed algorithm.

- read the patient's sound
- segment these sound recordings
    - window length = 100 ms
    - overlap length = 50 ms

- slide the 100 ms window with 50 ms overlaps on the signal
- compute two feature values in each window:
  - energy
  - number of Zero-Crossings
- define certain threshold values for energy (T_E) and zero-crossings (T_z)
- if energy of the k^{th} frame > T_E & zero-crossing of the k^{th} frame > T_z, then determine the frame as a segment
- determine the starting points and ending points of all the segments (episodes)

- classify the episodes
  - calculate the value of the spectrogram for an episode
    - define the frequency range 0-7500 Hz
    - define the fft size as 256 point
  - divide the 0-7500 Hz frequency range into 500Hz subbands
  - compute the value of the spectrogram in each subband
  - normalize the each subbands energy with the total energy of the episode
  - get the 15-D feature vector for the k^{th} episode $\xi^k = \left[\xi_1^k \ \xi_2^k \ldots \xi_{15}^k\right]^T$
  - multiply the feature vector with W_{opt} matrix which is defined from PCA
  - get a 2-D vector corresponding to the coordinates of the projection on to defined subspace
- determine whether the projection is in the snoring range or out of the snoring range and make a binary decision for the episode as snore or not

3.2 Performance Measurement of the System

The detection method described in the previous section has been tested using the snoring signal database. The system produced high detection rate both in simple snorers and OSA patients.

Figures 3.2 and 3.3 depict the detection of snoring episodes of two simple snorers. Figure 3.4 shows the detection of snoring episodes of an OSA patient. Sound activity segments identified by the system are shown in rectangular pulses. Then, those which are classified as snore episodes are marked by a second rectangular pulse above the first one. In these figures, we show parts of recordings where there are no false negatives (*i.e.*, missed snore episodes) and no false positives (*i.e.*, nonsnore episodes marked as snore).

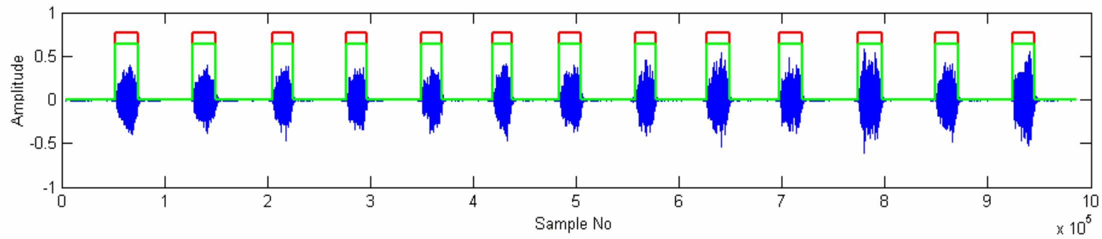

Figure 3.2 Detection of snoring episodes that belong to a simple snorer

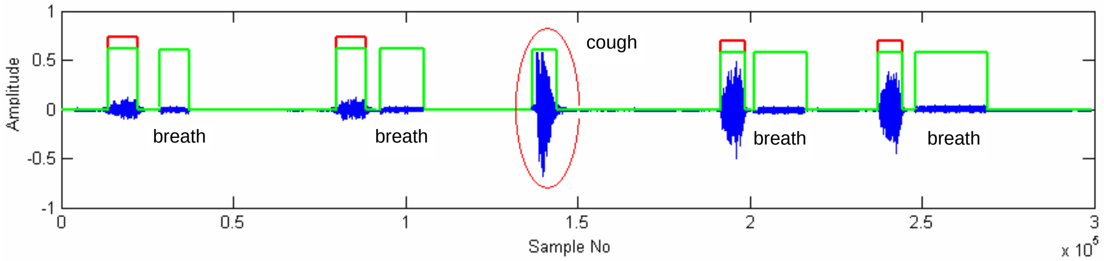

Figure 3.3 Output of the detection system to a cough episode

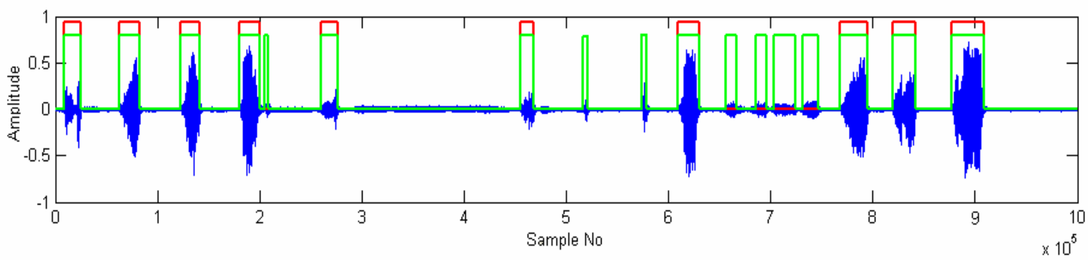

Figure 3.4 Detection of snoring episodes taken from an OSA patient.

In Section 2, we stated that three different experiments were performed. In this section, the performance of the system will be given for each of the datasets separately.

The results of **Exp-1, Exp-2A and Exp-2B** are shown in Tables 3.1, 3.2 and 3.3, respectively. Numbers of true positive (TP), false positive (FP) and false negative (FN) detections are given in these tables. Detection performance was evaluated in terms of accuracy, which is defined as $100 \times \mathrm{TP} / (\mathrm{TP+FN})$, and the positive predictive value (PPV), which is defined as $100 \times \mathrm{TP} / (\mathrm{TP+FP})$.

Following observations can be made in the detection of snores of simple snorers: The best detection performance was achieved in **Exp-1** where both the training and the testing datasets contain only simple snorers. Accuracy dropped by 4.6% (from 97.3% to 92.8%) in **Exp-2A** where snores of OSA patients were included in the training dataset, even though the testing and training datasets are obtained from the same individuals. Accuracy dropped by 7.3% in **Exp-2B** (from 97.3% to 90.2%). On the other hand, PPV values are in general higher than, and do not decrease as much as the accuracy values in this sequence of experiments.

In the detection of snores of OSA patients, accuracy and PPV values are less than those of the simple snorers. However, the accuracy values in Exp-2A and Exp-2B are still high enough (89.2% and 86.8%, respectively) to be considered for clinical applications.

Table 3.1 Results of **Exp-1**.

	TP	**FP**	**FN**	**Accuracy**	PPV
Simple snorers	1752	6	48	97.3 %	**99.6 %**

Table 3.2 Results of **Exp-2A**.

	TP	**FP**	**FN**	**Accuracy**	PPV
Simple snorers	2505	19	195	92.8 %	**99.2 %**
OSA patients	1607	87	24	89.2 %	**94.8 %**

Table 3.3 Results of **Exp-2B**.

	TP	**FP**	**FN**	**Accuracy**	PPV
Simple snorers	2438	32	262	90.2 %	**98.7 %**
OSA patients	1564	103	236	86.8 %	**93.8 %**

CHAPTER 4

A USER INTERFACE FOR SLEEP AND SNORE ANALYSES

In Chapter 2, we introduced a fast and efficient algorithm for analyzing the whole night respiratory sound recordings automatically. In this chapter, we present a user interface that is designed for the clinical applications. Designing a user interface for the clinic is a difficult task for a number of important necessities:

- The system must be fast enough for clinical applications. The sampling frequency of the signal is 16 KHz. This means, there are 16000 samples in a one second interval of the signal. If we code each sample with 2 bytes, the size of a one second signal will be equal to 32 KB. The system must analyze the whole night sleep of the patient which is approximately 6 hours long (700 MB). Furthermore, during the analysis, the system performs several time consuming complex calculations such as taking Fourier Transforms, and extracting snore related statistics.
- The system must compute the snore related statistics with a high accuracy. Sensitivity is crucial if we consider the effect of the system on the diagnostic and treatment process of the patient.
- The system must give the outputs that can easily be understood by the medical doctors and that can be comparable pre and post operatively.
- The system must easily be used by the medical doctors and clinical staff.

Hence we updated our previously developed algorithms and we increased the implementation speed of the developed algorithms for clinical applications. We also designed and implement our system by taking feedback from the ENT clinic.

4.1 System Outline

The system consists of six blocks:

1. patient information,
2. analyzing selection,
3. time parameters,
4. episode parameters,
5. regularity block,
6. intensity block.

In addition to these blocks, a screen with a slider is available for monitoring the snoring signal. There are also “play” and “print” buttons exist. The user interface of the system is shown in Figure 4.1. The following sections introduce each of the blocks and their functions.

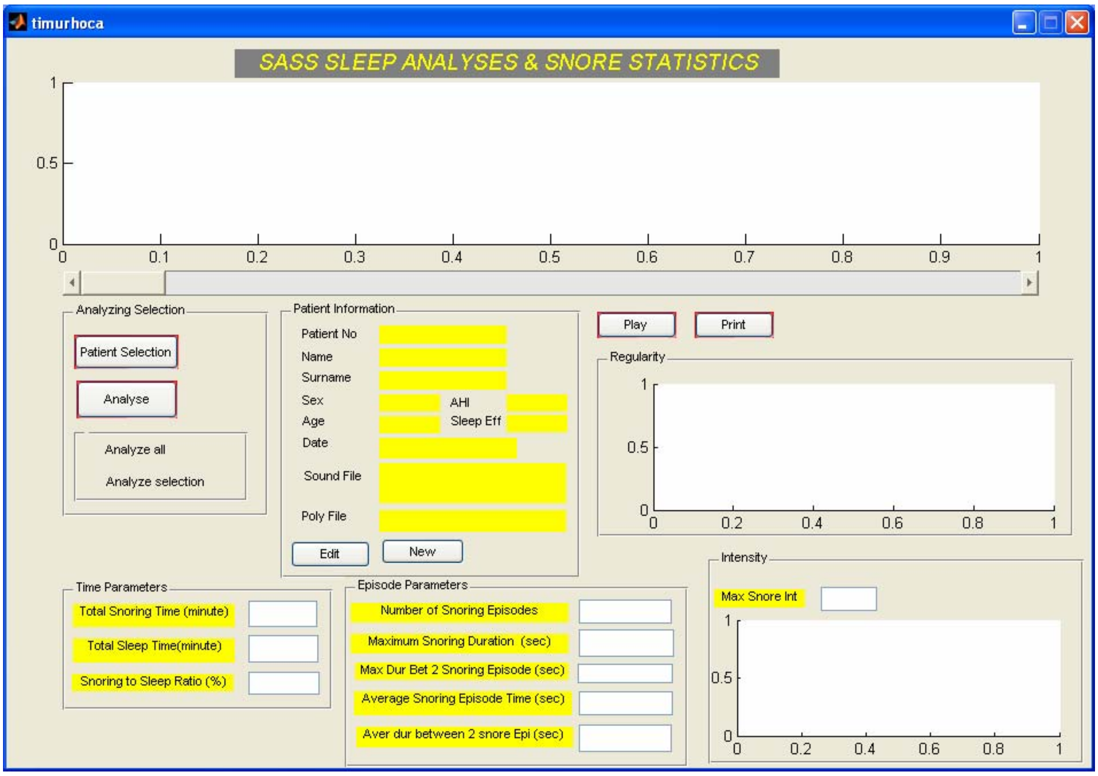

Figure 4.1 The user interface of the system

4.2 Patient Information Block

This block was designed for file operations. When a patient applies to the clinic, the system allows the doctor to create a specific file for that patient. When you click on the "New" button to create a file for a patient, the system allows you to enter the patient information. This includes patient identification number, name, surname, sex, age, AHI and sleep efficiency of the patient and the date of the recording. AHI and the sleep efficiency parameters are obtained from the PSG recordings. The sound file of the patient can be loaded from the computer. The aim of the "Poly File" will be explained in Section 4.4. When the "save" button is clicked on, the system creates a text file with the extension .hst that includes this patient information. The system allows to make edit, save or clear operations on any file. Figure 4.2 shows the patient information interface and a sample file with the .hst extension.

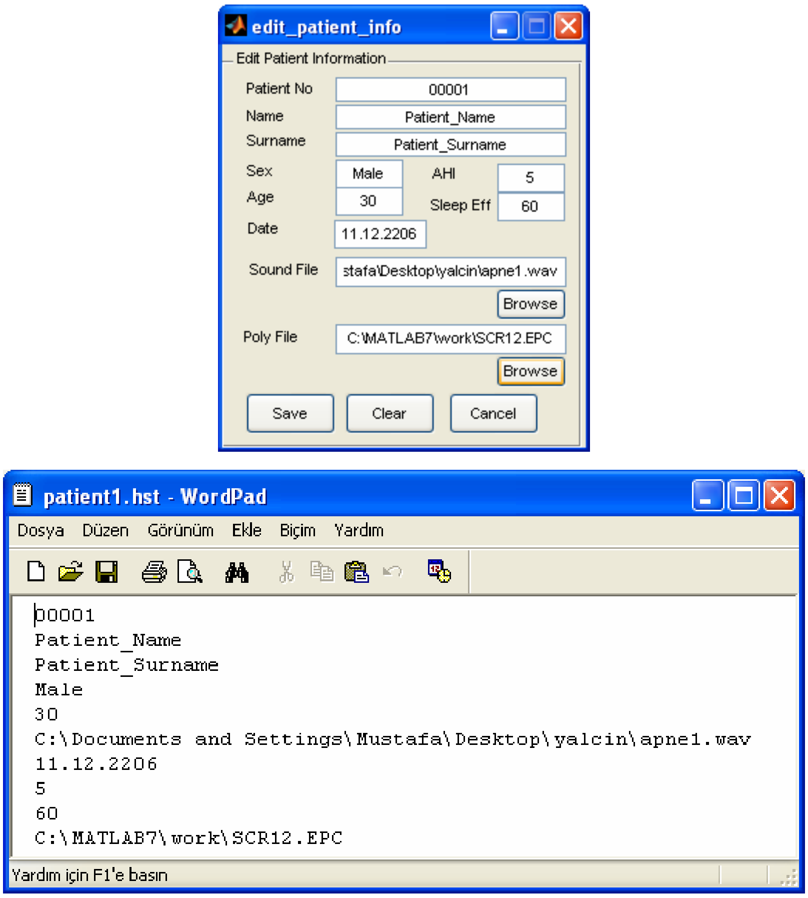

Figure 4.2 Top: Patient information interface. Below: a sample text file with .hst extension.

4.3 Analysing Selection Block

This block was designed in order to initiate the analysis. When you clicked the "Patient selection" button, a dialog box is opened in order to select a pre-created file to initiate the analyze. The "Analyzing Selection" block and the pation selection dialog box is shown in Figure 4.3.

When you select the patient whom you want to analyse, all the information of the patient is shown on the main interface and the snoring signal of the patient is loaded and monitored on the screen. If you click the "Analyse" button after selecting the

"Analayse all", the system analyses all the data and extracts the parameters from the whole night sleep.

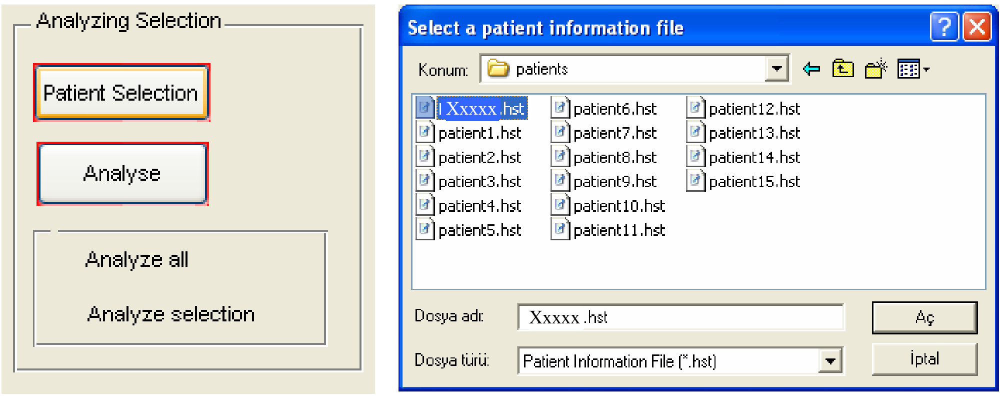

Figure 4.3 The "Analyzing Selection" block and the patient selection dialog box

In some cases the doctor wants to see the statistics that are extracted from only a part of the signal such as the sleep stage 2 data. It is possible to analyse the selected signal by clicking "Analyse" button after selecting the "Analyse selection" button. Figure 4.4 shows a 20 second long snoring signal on the screen of the interface. It is possible to examine all the signal by using the slider.

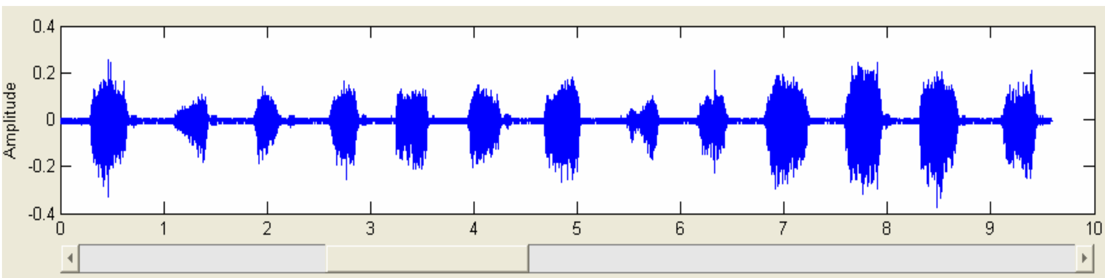

Figure 4.4 20 second long snoring signal on the screen of the interface

4.4 Time Parameters Block

This block was designed for monitoring the time parameters such as total snoring time, total sleeping time and snore to sleep ratio. Total sleep time gives the doctor the how many minutes does the patient sleeps. In this point, it is important to determine the efficient sleep time of the patient accurately. Because the lenght of the signal that corresponds to the time in bed may not be equal to the patient's total sleep time. In order to get rid of this problem, we integrate the system with polysomnography and we take the recordings simultaneously. Current polysomnography systems gives the sleep stage information in every 30 second length epoch as a text file and it is possibile to determine the wake time of the patient from there. Hence, we designed the system that allows to load the "Poly File". Computing the wake time from this file lets us to determine the total sleep time accurately. In order to extract this kind of parameters from the sound recordings, an automatic detection system for real acoustic snoring signals has been designed. The proposed algorithm is based on the spectrogram of the acoustic snoring signals. The objective is to determine whether the episode is snoring or not in order to reject undesired waveforms. After detecting each snoring episode, we compute the total snoring time and snoring to sleep ratio. Actually the most useful blocks of the system are the "Time Parameters" block and the "Intensity" block. The comparision of the snoring to sleep ratio pre and post operatively is the fundamental parameter for the clinician in determining the treatment success. Figure 4.5 shows the "Time Parameters" block and a sample "Poly File". The first column of the "Poly File" depicts each 30 second length epoch and the second coloumn is the corresponding sleep stage of that epoch. The letters "W" indicates that the patient is wake in that epoch.

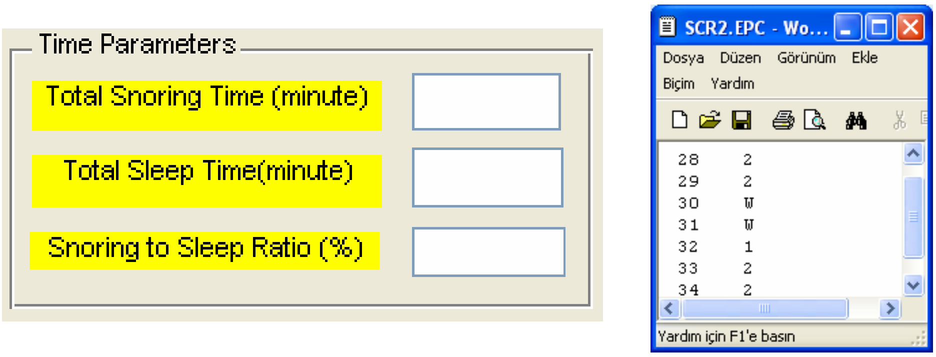

Figure 4.5 “Time Parameters” block and a sample “Poly File”.

4.5 Intensity Block

Observing the changes in the intensity of the snoring signals pre and post operatively is essential in determining the treatment success. The intensity of the snoring signal can be varied either from patient to patient or at different episodes of a single patient. Hence, the system computes the intensity of each snoring episode and gives the histogram of it. It is possible for doctor to see the maximum snoring intensity of a patient for comparision. The distribution of the intensity values of a patient also gives information about the regularity of his/her snoring. The importance of this concept will be explained in detail in the “Regularity Block” section. In Figure 4.6. a sample snoring intensity histogram is displayed.

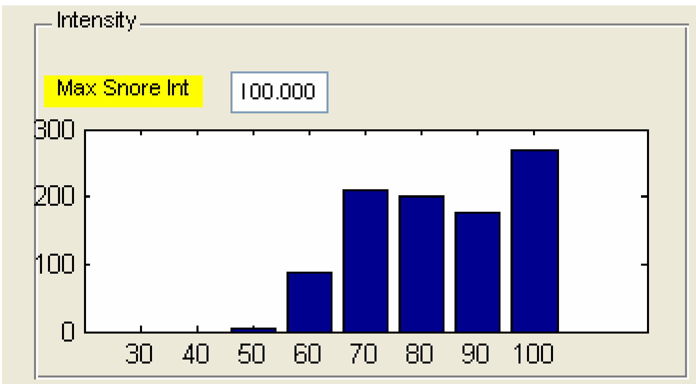

Figure 4.6 A sample snoring intensity histogram.

4.6 Regularity Block

The regularity of the snoring can be used to identify whether the patient is a simple snorer or an OSA patient. If we compare the snoring signals of simple snorers and OSA patients, we see that the snoring episodes of simple snorers are more similar to each other than, those of OSA patients. In other words, while simple snorers are regular snorers, OSA patients are non-regular snorers in general. This situation is illustrated in Figure 4.7.a and Figure 4.7.b. As it is seen, while the episodes of simple snorers are highly correlated, there is no such kind of correlation exits between the episodes of an OSA patient.

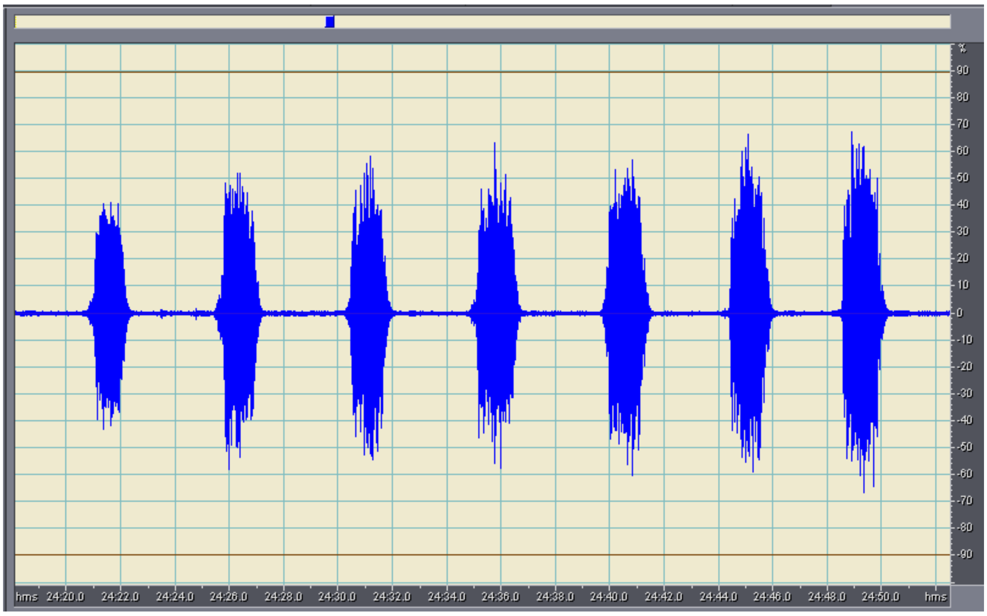

Figure 4.7.a Snoring episodes taken from a simple snorer.

In order to extract the information about the regularity of the snorings of a patient we designed the "Regularity" block. It is possible to determine the regularity of the snoring by computing the correlation between the episodes of a patient. But this method is time consuming and computationally inefficient.

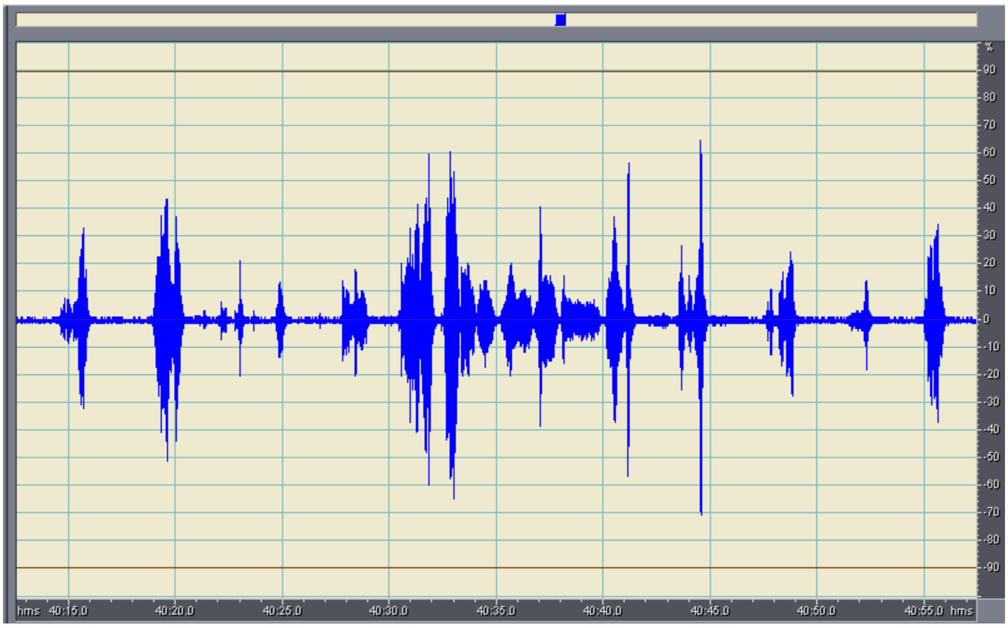

Figure 4.7.b Snoring episodes taken from an OSA patient.

If we plot the graph of absolute energy versus number of episodes, the flatness of the mid-points of each energy value gives us information about the similarity of the episodes. This situation is depicted in Figure 4.8. The flatness of the red curve is a measure of regular snoring. Figure 4.8.a shows the regularity plot of a snoring signal taken from a simple snorer and Figure 4.8.b is the regularity plot of a snoring signal taken from an OSA patient. It is clearly seen that the regularity curve is flatter in simple snorers. This phenomenon is important in the diagnostic process of a patient. An other regularity parameter is the intensity histogram. The distribution of the intensity values over a wide range implies a non-regular snoring.

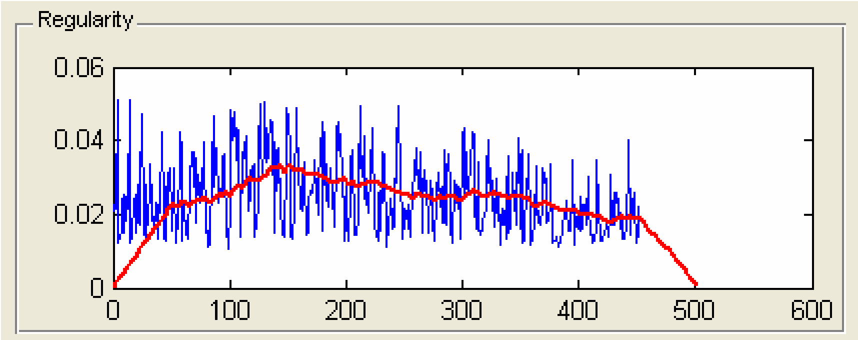

Figure 4.8.a Regularity plot of a snoring signal taken from a simple snorer.

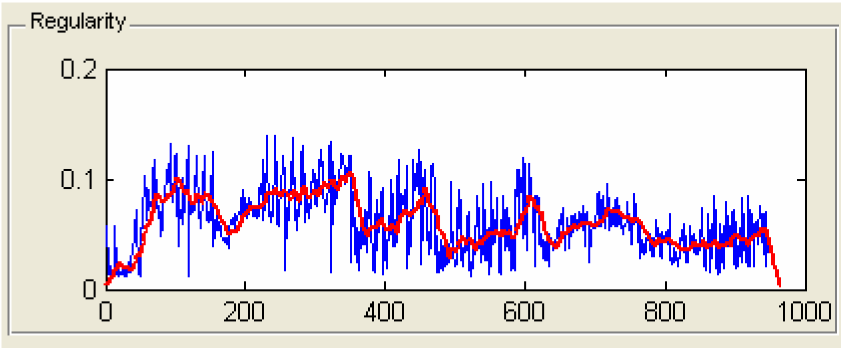

Figure 4.8.b Regularity plot of a snoring signal taken from an OSA patient.

4.7 Episode Parameters Block

This block was designed to extract the parameters related to the episodes such as number of snoring episodes, maximum snoring duration, maximum duration between two snoring episodes, average snoring episode time and average duration between two snoring episodes. These parameters are also useful in deteremining the treatment success by making pre and post-operative comparision. Figure 4.9 shows the "Episode Parameters" block. These values are also differ in simple snorers and OSA patients.

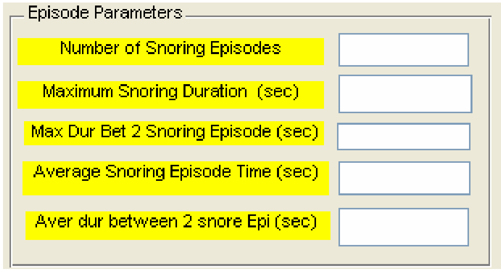

Figure 4. 9 “Episode Parameters” block.

4.8 Output of the System

By analaysing the whole night respiratory sound recordings and computing related statistics, it is possible to assess the medical treatment. Figure 4.10 shows the analysis result of an OSA patient. In the screen of the program, the snoring episodes are selected with the upper red lines. It is also possible to play or listen the selected signal.

After analysing the sound recording of a patient, the system allows to save the results or take print out for comparision pre and post-operatively. The print out page of the computed statictics is given in appendix A

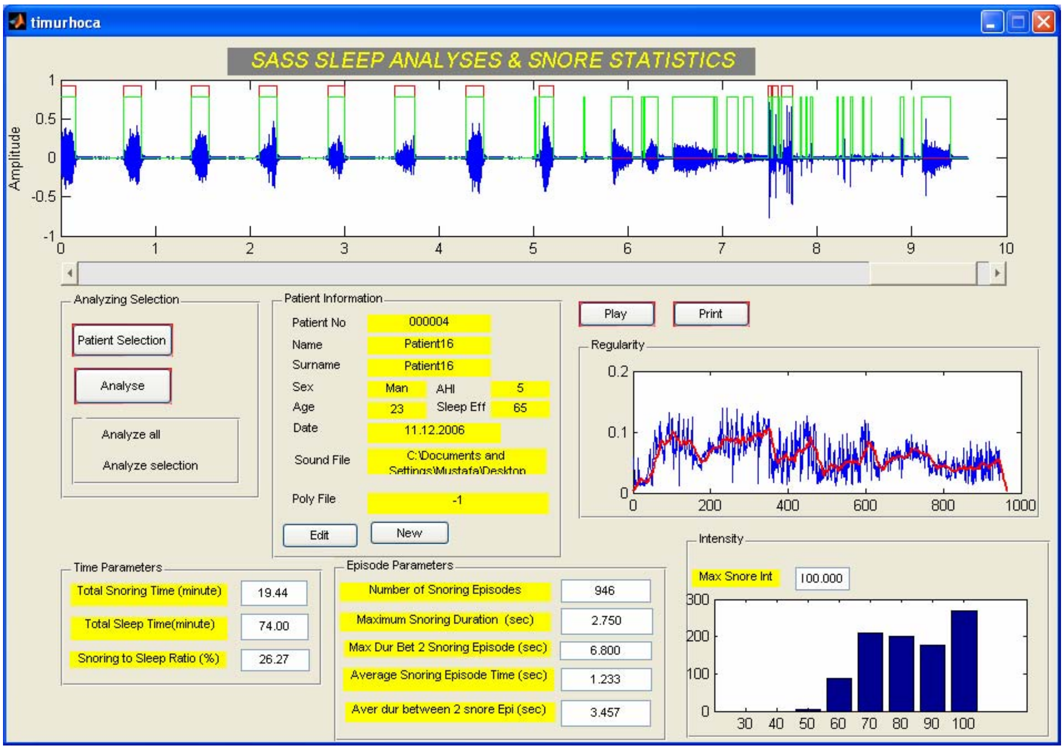

Figure 4.10 The analyze result of an OSA patient

CHAPTER 5

CONCLUSION

Snoring is a respiratory sound that originates during sleep, and can be nocturnal or diurnal. It is a typical inspiratory sound, even though a small expiratory component can be heard or recorded (especially in OSA patients) with different spectral features. It must be distinguished from all the other sounds that can be heard, recorded and analysed during sleep. In this thesis, we proposed a new algorithm to detect snoring episodes from the sleep sound recordings of the individuals. The algorithm classifies sleep sound segments as snores and nonsnores according to their subband energy distributions. It was observed that inter- and intra-individual spectral energy distributions of snore sounds show significant similarities. This observation motivated the representation of the feature vectors in a lower dimensional space which was achieved using principal component analysis. Sleep sounds can be efficiently represented and classified as snore or nonsnore in a two dimensional space. The proposed system was tested by using the manual annotations of an ENT specialist as a reference. In addition, a user interface was developed and certain sleep statistics are calculated to make the system available for clinical purposes.

The sound recordings were taken synchronously with polisomnography during their whole night sleep in order to determine the Apnea/Hypopnea index of the patient and to be able to study the relationship between the physiological signals and snoring. The recording system was set up to acquire high SNR so that there is no need for extra processing to increase the SNR. The tests were carried out on a dataset formed by the 6 hour recordings of 30 individuals (18 simple snorers and 12 OSA patients with different apnea-hypopnea indices and body mass indices). The size of this dataset can be assumed to be sufficient for the reliability of the results of the particular binary classification problem.

We have composed the testing and training datasets in three different ways. In the first experiment (**Exp-1**), both the testing and the training datasets come from simple snorers, but individuals in each set differ. In the second experiment (**Exp-2A**), both simple snorers and OSA patients are included in the testing and training datasets; the same individuals are included in both sets, however testing and training sets are obtained from different intervals of the 6-hour recordings. Finally in the third experiment (**Exp-2B**), again there is a mixture of simple snorers' and OSA patients' recordings, however, this time testing and training datasets are formed from recordings of different individuals.

The accuracy for simple snorers was found to be 97.3 % when the system was trained using only simple snorers' data. It drops to 90.2 % when the training data contain both simple snorers' and OSA patients' data. (Both of these results were obtained by using training and testing sets of different individuals.) This suggests that, in a practical setting, the individual can first be roughly identified as a simple snorer or OSA patient using a composite training dataset and then the results can be refined by using a system trained with the specific type of data. In the case of snore episode detection with OSA patients the accuracy is 86.8 %. Some of the missed snores were post-apneic type with complex content that include several types of sounds. Some other missed snoring episodes have very low energy that can not be distinguishable from the background noise. All these results can be considered as highly acceptable values to use the system for clinical purposes including the diagnosis and treatment of OSAS.

The information such as total snoring time, snore-to-sleep ratio, variation of snoring rate and regularity of snoring episodes in time and in amplitude may be useful for diagnosis of sleep disorders. These kinds of information can be obtained by detecting

snore episodes. This fact and the need for reasonable processing time of night-long recordings justify a binary classification scheme as snore or nonsnore.
The classification boundary in this work was found heuristically. It may be possible to improve the performance by using boundaries generated in a more systematic and optimal manner via large margin classification methods like support vector machines.

The user interface was composed of various blocks. These blocks are: patient information, analyzing selection, time parameters, episode parameters, and regularity and intensity blocks. The most useful block of the system is the "time parameters" block. The comparison of snoring to sleep ratio values pre and post-operatively is the fundamental parameter in determining the treatment success. Observing the intensity changes in the snoring signal is also meaningful. We see that while the snoring intensity of the simple snorers is in the range of 40-60 (db), this range becomes wider such as 50-100 (db) in OSA patients. Another difference between simple snorers and OSA patients appears in the similarity of the snoring episodes. Contrary to highly correlated form of the snoring episodes in simple snorers, it is impossible to observe such kind of correlation in OSA patients. Hence, examining the regularity of the snoring episodes is a useful method of estimating whether the patient is a simple snorer or an OSA patient before the polysomnography. The system also extracts a number of useful statistics about the episode parameters. The numbers of snoring episodes are also different between simple snorers and OSA patients. While it is approximately 600 in simple snorers it is almost over 1000 in OSA patients. The episode parameters are also important for the comparison of pre-operative and post-operative situation. The system enables the user to perform all kind of file operations and gives a print out if it is desired. Integrating the system with polysomnography allows us to determine the sleep time accurately and to make advanced researches on sleep studies. It takes only six minutes to analyze six hours of data (whole night sleep recordings) that were sampled at 16 KHz (each sample is coded with 2 bytes). This can be considered as a reasonable processing time of night-long recordings.

The proposed system can be applied to the following problems as future work:

- Testing the treatment effectiveness of sleep disorders by comparison of snore statistics obtained before and after treatment.
- Studying the relationship between the nightlong recordings of physiological signals (polysomnography) and corresponding snoring profiles, e.g., the relationship between sleep stages and snore characteristics.
- Identifying the physiological sources, such as palatal/nonpalatal, of snoring to guide the treatment strategy.

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Appendix

The print out page of the computed statictics

Patient Information	
Patient No	000004
Name	Patient16
Surname	Patient16
Sex	Man
Age	23
Date	11.12.2006

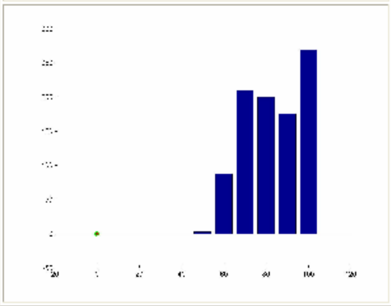
Time Parameters	
Total Snoring Time	19.4433
Total Sleeping Time	74
Snoring to Sleep Ratio (%)	26.2748

Episode Parameters	
Number of Snoring Episodes	946
Maximum Snoring Duration (sec)	0
Max Dur Bet 2 Snoring Episode (sec)	6.8
Average Snoring Episode Time(sec)	1.2332
Average Dur Bet 2 Epi (sec)	3.4566

Polysomnography Parameters	
AHI	5
Sleep Efficiency	

Snore Intensity

Max Snore Int (dB) 100



Snore Intensity Change In Time