

# Chapter 11

## An Intelligent Algorithm for Home Sleep Apnoea Test Device

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### ABSTRACT

*This chapter describes the application of an intelligent machine learning technique (Support Vector Machines, SVM) to diagnose the patients with sleep apnoea syndrome using Electrocardiogram (ECG) signal. Sleep apnoea syndrome is a medical condition caused by sleep apnoea which is defined as the cessation of breathing for short periods during sleep. First, the importance of early diagnosis and treatment of sleep apnoea syndrome are presented. This is followed by an introduction to the design of a home diagnostic model for predicating sleep apnoea syndrome from electrocardiogram recordings. Examples are presented using SVM to build a reliable model that utilizes key indices of physiological measurements (ECG signals). A number of recommendations have been proposed for assessing a classifier model in recognizing patients with sleep apnoea. The chapter concludes with a discussion of the importance of machine intelligence and signal processing techniques in developing medical diagnostic device.*

### INTRODUCTION

Obstructive sleep apnoea syndrome (OSAS) is a common problem defined by frequent cessation of breathing due to the partial or complete obstruction of upper airway for short periods during sleep. This is typically accompanied by a reduction in blood oxygen saturation and leads to wakening from sleep in order to breathe. It is a common sleep related

breathing disorder with a reported prevalence of 4% in adult men and 2% in adult women (Young, 1993). Excessive daytime sleepiness is the most common complaint. The fragmented sleep due to OSAS can result in poorer daytime cognitive performance, increased risk of motor vehicle and workplace accidents, depression, diminished sexual function, and memory loss (Coleman, 1999; Neito, 2000). Undiagnosed OSAS is now regarded as an important risk factor for the development of cardiovascular diseases (e.g. hypertension, stroke, con-

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gestive heart failure, left ventricular hypertrophy, acute coronary syndromes) (Young, 1997). OSAS can be treated by applying continuous positive airway pressure (CPAP) through the nose which prevents upper airway from collapsing. If patients are identified and then treated at an early stage of OSAS, the adverse health effects can be reduced (Dimsdale, 2000). Therefore, early recognition of subjects at risk of OSAS is essential.

The severity of OSAS is typically quantified by the number of apneas and hypopneas per hour of sleep, a quantity that has been termed Apnea-Hypopnea Index (AHI). Different populations have different AHI values. Specific cutoffs are typically used to establish the diagnosis of OSAS (Polysomnography task force, 1997; Flemons, 2003). For example, as of this writing, the Medicare criteria for reimbursement of continuous positive airway pressure (CPAP) therapy are  $AHI \geq 15$  events/hour, or  $AHI \geq 5$  events/hour associated with symptoms (e.g., daytime somnolence and fatigue). However, a variety of AHI thresholds ranging between 5 and 40 have been used as suggestive of OSAS in different studies (Khandoker, 2009a). Approximately two to four percent of middle-aged women and men, respectively, have been estimated to have an  $AHI \geq 15$  events/hour and excessive daytime somnolence in the population-based Wisconsin Sleep Cohort Study (Young, 1993). Using an AHI cutoff of  $\geq 5$  events/hour without the symptoms of excessive daytime sleepiness puts the prevalence at 9% for women and 24% for men. The symptom of excessive daytime sleepiness is quite variable and not always present in patients with OSAS. Thus, most people suffering from OSAS remain undiagnosed and untreated (Khandoker, 2009a). More recent studies also suggest a high prevalence (i.e., prevalence of  $AHI \geq 5$  in adults age 30-69 of 17%), perhaps due to increasing obesity rates in later years (Young, 2005).

The standard measurement of AHI (and the diagnosis of OSAHS by extension) requires a comprehensive, technologist-attended sleep

study with multichannel polysomnography (PSG), which is performed in specialized sleep laboratories (Polysomnography task force, 1997; Flemons, 2003). Laboratory-based PSG records a variety of neurophysiologic and cardiorespiratory signals and is interpreted by trained technologists and sleep physicians after the sleep study has been completed. Because of the high demand, the associated costs and the need for timely diagnosis, portable devices have been developed to substitute for laboratory-based PSG (Flemons, 2003). Due to the scarcity of sleep laboratories, vast majority of patients remain undiagnosed (Young, 1997). Therefore, if OSAS could be diagnosed using only ECG recordings, it would be possible to diagnose OSAS simply and inexpensively from ECG recordings acquired in the patient's home. There are different types (classes) of portable monitors (Ferber, 1994). Each gathers different neurophysiologic and respiratory information and may synthesize the accumulated data differently (Ferber, 1994). Depending on the data they record, portable monitors are classified in different categories (which are discussed in more detail later in this technology assessment) (Ferber, 1994). Portable monitors can be used not only in the home setting, but in the hospital and clinics other than specialized sleep units.

In this chapter, we will systemically review how an intelligent algorithm can be applied for screening sleep apnoea and recognizing the OSAS subjects with sleep apnoea using ECG signals. Based on our previous works (Khandoker, 2009a,b), we will demonstrate the step by step procedures of training and validating support vector machines (SVM) for automated recognition of OSAS subjects and estimation of the severity of OSAS based on overnight ECG signals.

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