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An automatic apnea screening algorithm for children

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ABSTRACT

Sleep Disordered Breathing (SDB) is a group of diseases that affect the normal respiratory function during sleep, from primary snoring to obstructive sleep apnea (OSA) being the most severe. SDB can be detected using a complex and expensive exam called polysomnography. This exam monitors the sleep of a person during the night by measuring 21 different signals from an Electrocardiogram to Nasal Air Flow. Several automatic methods have been developed to detect this disorder in adults, with a very high performance and using only one signal. However, we have not found similar algorithms especially developed for Children. We benchmarked 6 different methods developed for adults. We showed empirically that those models' performance is drastically reduced when used on children (under 15 years old). Afterwards, we present a new approach for screening children with risk of having SDB. Moreover, our algorithm uses less information than a polysomnography and out performs state-of-the-art techniques when used on children. We also showed empirically that no signal alone is a good SDB screening in children. Moreover, we discover that combinations of three signals which are not used in any other previous work are the best for this task in children.

1. Introduction

Several health systems from different countries have agreed on the need of tackling public health by the means of a more preventive, personalized and anticipatory health service. This requires to encouraging patients and caregivers to make them protagonists of their healthcare, assuming responsibility to keep themselves on controlled states without collapsing healthcare centers.

In Chile, we have a severe case of air pollution, which produce episodes where hospitals collapse during autumn and winter. This is why; Health Ministry is developing several programs that aim to treat patients at home. But to do so, we need to know exactly a patient, for example, what is their normal biomedical signals values (mean and standard dev.) or what happens with humidity during winter inside their home or other environmental conditions. Based on specific data and other information from the patients and knowledge extracted from experts we can develop an expert system similar to Echeverría, Jimenez-Molina, and Ríos (2015) that aid patients and caregivers to take better decisions (even from their homes).

This article focuses in the creation of an automatic screening method for Sleep Disordered Breathing (SDB) which are a group of chronic diseases that affect the normal respiration function during the night. These can affect people at any age and are due to different causes: in newborns and young children they are related to congenital defects or premature birth; in older children and adults they may be related to obesity, morphological causes, and hypertension (Goodwin et al., 2003a; 2003b; Levy, Bonsignore, & Eckel, 2009; Rosen, Palermo, Larkin, & Redline, 2002).

The diseases -from least to most severe- considered as SDB are: primary snoring, upper airway resistance, and obstructive sleep apnea (OSA). For example, a newborn with OSA can experience short episodes of apnea, total absence of airflow during night and live a relatively normal life, while a severe OSA may lead to sudden death (Goldstein et al., 2004).

Symptoms of SDB are abnormal day sleepiness, sudden naps during the day (for example, at a red light while driving), general tiredness, fatigue, trouble sleeping, and other related diseases (de la Luz Alonso Álvarez et al., 2008). It has been shown that in children SDBs are closely related to obesity and learning problems (Goodwin et al., 2003a).

The diagnosis of SDB is accomplished through a clinical study called polysomnography (PSG) which collects over 20 different biomedical signals during sleep, including: electrocardiography, electroencephalography, electromyography, plethysmography, oronasal airflow, chest movement, abdominal movement and leg movement among others.

Several automatic methods have been developed in the form of expert systems to detect these disorders in adults, with a very high performance (Álvarez-Estévez & Moret-Bonillo, 2009; De Chazal et al., 2003; Driver et al., 2011; Jarvis & Mitra, 2000; Khandoker, Palaniswami, & Karmakar, 2009). However, we showed empirically

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by Erazo and Ríos (2014) that those models' performance is drastically reduced when used in children (under 15 years old).

This time we present a new algorithm able to classify children into two groups: the group at risk of having an SDB, and the group with no risk (or very little risk) of having an SDB. Moreover, our algorithm uses less information than a polysomnography and surpasses state-of-the-art techniques when used on children. This is very important factor since in order to develop a non-invasive solution (to be used at home, for example) we need to reduce the amount of signals used by screening methods.

We showed empirically that no signal alone can be a good OSA predictor in children and also we showed that only three signals: EMG-Chin, EOG and Leg Movement are very good predictors. We need to remark this result, since until today, none of these signals have been used on their own or in combination with other signals for screening in any documented study reviewed in this research.

This work is based on data collected by Pablo E. Brockmann M.D. and his research team in the Sleep Study Center of Clinical Hospital of Catholic University of Chile. This dataset consists in 78 whole night polysomnographies from patients under 15 years old. This is the largest dataset of this characteristics used for OSA screening.

2. Related work

Our main interest is to develop an algorithm that can distinguish between OSA and non-OSA individuals with the least amount of signals from the PSG. In adults, several researchers (Álvarez-Estévez & Moret-Bonillo, 2009; Driver et al., 2011; Flemons et al., 2003) have shown that some signals from PSG have enough predictive power to perform this task. In fact, one-signal screening methods have been successfully tested in adults and children (Roche et al., 2003; Tsai et al., 2013), but those methods still require attending personnel and overnight dedicated systems. Most of them also required a medical evaluation afterwards.

Automated classification methods aim to avoid unnecessary resource consuming screening methods. The most important contribution to this respect was made by the Computers in Cardiology Challenge of 2000. In that work the task was to automatically tag, minute by minute, a single ECG signal as OSA or non-OSA and get to a final diagnosis: OSA or non-OSA for every record (De Chazal et al., 2003; Jarvis & Mitra, 2000; Khandoker et al., 2009; Mendez et al., 2007). Some of these methods reached a precision of 100% in the binary diagnosis and over 85% in minute-by-minute tagging. Unfortunately, none of these studies on automatic classification was performed on children. Besides, most of the algorithms were trained and tested on databases specially designed for this task. In particular, models tested on the Computers in Cardiology 2000 database can not be compared, because this database has been preprocessed to obtain clean, but not realistic data.

This is why we performed a benchmark with real data from 78 children and compared the results among them. This was published by Erazo and Ríos (2014) and a summary of methods tested is shown in Table 1. The best classifiers from all approaches tested were those based on: a Support Vector Machine (SVM), an Artificial Neural Network (ANN). Besides we implemented a Logit classifier to evaluate a simple model, though it is not in the literature. We also selected the three signals that reported best results in the literature, which are: Electrocardiography (ECG or ECGI channel), Air Flow (Patient Airflow channel) and Oxygen Saturation (SpO_2 channel).

Afterwards, we pre-processed ECG, Air Flow and SpO_2 with wavelet transform to extract features. All algorithms were trained with all 14 features generated. Then we trained the models with a cross-validation approach with 70% of the dataset to train the models and 30% to test; and finally, experiments were performed 30 times to generate the final benchmark results computing several measures shown in Section 3.3.

The best performing models were the ANN applied over oronasal Air Flow signals, with $Sensitivity = 84.36\%$. The second best model was the SVM with Air Flow signal that resulted in a $Sensitivity = 75.64\%$. Both classifiers were far from the 90% sensitivity considered as the clinical minimum for a successful classifier. We demonstrated experimentally that state-of-the-art models for OSA screening in adults are not good enough to be used in children.

3. Model construction methodology

After performing our benchmark by Erazo and Ríos (2014), we could not find a good predictor for OSA+ and OSA- in children's data. However, models using Air Flow signal had an outstanding sensitivity, over 80% and regular accuracy (in the Neural Network models). ECG based models, on the other hand showed high specificity, meaning that they have the ability to detect healthy people. This suggests that a combination of these signals may lead to a successful model.

This section describes a novel approach to this task. From a purely mathematical point of view, signal selection is performed in order

Table 1
Automated OSA screening approaches tested in our previous work (Erazo & Ríos, 2014).

Author, Year	Brief description	Results	Comments
Jarvis and Mitra (2000)	Apnea diagnosis based on ECG signal. Features used derived from spectral analysis. Classification based on threshold criteria.	Acc=100%	Tested on Computers in Cardiology 2000 database. 75 records tagged minute-by-minute. All registers corresponding to adults.
De Chazal et al. (2003)	Apnea diagnosis based on ECG signal. Features extracted using black-box methods. Classification methods: linear discriminant, quadratic discriminant.	Acc=100%	Tested on Computers in Cardiology 2000 database. 75 records tagged minute-by-minute. All registers corresponding to adults.
Mendez et al. (2007)	Apnea binary diagnosis based on ECG signal. Features extracted: derived signals (EDR, HRV) coefficients. Classification method: K-Nearest Neighbour.	Acc=85,5%, Sens=83,9%, Spec=88,5%	Tested on Physionet Apnea ECG Database (50 registers) tagged as OSA+ or OSA-.
Álvarez-Estévez and Moret-Bonillo (2009)	A fuzzy reasoning is used to detect apneic events; Air flow signal and Oxygen Saturation signals are used	Sens=87%, Spec=89%	Tested on a 12 patients database (Sleep Heart Health Study), it does not diagnose OSA, it only detects apneic events. All registers corresponding to adults.
Khandoker et al. (2009)	Apnea binary diagnosis (OSA+, OSA-) based on ECG signal. Features extracted: Wavelet Transform coefficients. Classification method: Support Vector Machine.	Acc=100%	Tested on three combined databases: Sleep Research Unit Database, Physionet Apnea ECG Database and Saint Vincent's University Hospital/University College Dublin Sleep Apnea Database. All 125 registers corresponding to adults.
Driver et al. (2011)	Validation of MediByte (portable monitor) as screening method.	Sens=80%, Spec=87%	This monitor requires a clinician to perform the diagnosis.