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Sleep-Wake Identification in Infants: Heart Rate Variability Compared to Actigraphy

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Abstract—**Heart rate variability and actigraphy offer alternative techniques for sleep-wake identification compared to manual sleep scoring from a polysomnograph. The advantages include high accuracy, simplicity of use, and low intrusiveness. These advantages are valuable for determining sleep-wake states in such highly sensitive groups as infants. A learning vector quantization neural network was tested as a predictor. The accuracy of the neural network was compared to "gold standard" hand-scored polysomnographs. The prediction results are in agreement with other studies, thus validating the suggested methodology.**

Keywords— **actigraphy, heart rate variability, neural network**

I. INTRODUCTION

Identification of asleep/awake states is used in several areas of medical science. For infants, sleep state identification in combination with other parameters may be useful in prediction of life-threatening events such as the Sudden Infant Death Syndrome (SIDS) [1]. Polysomnography (PSG), which includes an electroencephalogram (EEG), electrooculogram (EOG) electromyogram (EMG), and electrocardiogram (ECG), is the most accurate procedure for determining sleep states and is considered to be the "gold standard". The largest shortcoming of PSG is that it is rather expensive and too complex to be used by an untrained person. Relatively high intrusiveness of the PSG method is also the cause of its low tolerance by nursing-home patients and infants. An appealing alternative is presented by the actigraphic and electrocardiogram methods.

Heart rate and heart rate variability (HRV) is one of the commonly used cardiorespiratory signals in studies of infants. HRV is determined by a complex interaction of the sympathetic and parasympathetic divisions of the autonomic nervous system (ANS). It is considered a noninvasive and inexpensive way to analyze the ANS. Many types of parameters have been used to measure heart rate variability, including time domain, frequency domain, time-frequency domain, and nonlinear methods. Heart rate and heart rate variability are sleep state dependent variables. It is assumed that awake state has the highest heart rate and heart rate variability, and quiet sleep (QS) has the lowest value of heart rate and variability. The value for rapid eye movement (REM) sleep is in between. Landes et al. found that heart rate is the slowest and contains the highest frequencies in quiet sleep [2]. Sleep state differences are also shown in the frequency analysis of HRV. Medigue et al. found that the high frequency component of HRV (HF) dominates during QS, while low frequency component of HRV (LF) dominates in REM [3]. Kantelhardt et al. used ECG to test the correlation between sleep states [4].

An actigraph is a wireless portable device usually worn on a wrist or an ankle. It includes a motion sensor (an accelerometer), a microprocessor with analog/digital circuitry and a memory chip. The motion patterns are recorded throughout the day and are analysed for the information of interest. Usually, actigraphy doesn't aim at identifying sleep states; rather it is traditionally used for determining asleep-awake patterns. Actigraphy provides sleep detection results comparable to those of polysomnography and behavioural response monitoring [5] when applied to different population groups like adults [6], demented nursing-home patients [7], young children and infants [8,9], etc. Such a wide spectrum of subjects can be covered due to the actigraphy's non-invasiveness. Asleep/awake identifications made in adults using actigraphy have shown 85-95% agreement rates with polysomnography [10]. In infants, agreement rates varied from 54% to 87% at different ages [9].

This study aims at validating the use HRV in Asleep/Awake identification by making a comparison to a dataset previously analysed using activity-based identification [11,12]. A soft computing method (neural network) performs classification using a set of HRV features. The ECG and multi-axial accelerometer were recorded as a part of the Collaborative Home Infant Monitoring Evaluation (CHIME) NIH study, which studied home infant monitors for apnea and bradycardia for over 1000 infants [13,14,15]. Sleep state information would be helpful in analysing the over 700,000 hours of data recorded on the home monitor where traditional PSG information is not available [15].

II. METHODOLOGY

A. Data

Data used in this study were collected from infants as part of the CHIME study [14]. Each infant had a standard, monitored 8-hour PSG performed with EEG, EOG, and EMG for calculation of sleep state. Additionally electrocardiogram, respiratory volume, pulse oximetry and an accelerometer were recorded from the same equipment as used in the home-based recording [14].

PSG-based sleep state identification was performed by trained technicians on the infants with 30-second intervals (epochs) [16]. The PSG-identified sleep states (Awake, Active sleep, Quiet sleep and Indeterminate) were used as a baseline for training of the neural network. For this study the Active and Quiet sleep states were combined into "Asleep" (ASP) state, the Awake state remained "Awake" (AWK), and the indeterminate states were discarded.

The CHIME home monitor recorded a 50 Hz accelerometer signal and a 1000 Hz R-wave to R-wave (RR) signal. This data is preprocessed to create reliable data as follows:

RR interval signal:

1. An ECG artifact rejection routine was run to find artifactual heartbeats and correct the data [17].
2. Both the beginning and end of the RR interval recording were synchronized in time with the PSG data on an epoch (30 seconds) boundary.
3. The following measures were extracted from the signal for each epoch: mean, standard deviation of normal to normal (SDNN), root mean square of successive differences, high frequency wavelet (HFW), low frequency wavelet (LFW), LFW/HFW, approximate entropy, poincare plot, fractal dimension, and detrended fluctuation analysis.
4. A fuzzy C-means clustering algorithm [18] was run to find which of the features best separated the data into clusters of sleep and wake. The parameter selected is: mean.

Accelerometer signal:

1. Both the beginning and the end of the accelerometer recording were synchronized in time with the PSG data on an epoch (30 seconds) boundary.
2. An artifact of unknown origin with a period of 1.7 min was removed from the signal.
3. Position-related DC levels in the ACC signal were removed by applying Discrete Fourier Transform (DFT) to an epoch of the signal (50Hz x 30 seconds = 1500 data points), zeroing the DC harmonic and applying the inverse DFT to the data.
4. The maximum accelerometer reading (maxACC) was computed for each epoch [11,12].

B. Prediction

The PSG records of AWK or ASP represent the response variable during each 30-second epoch.

For HRV, the mean was taken for the last n consecutive periods, thus giving respectively M_{-n} , … , M_{-2} , M_{-1} , M_0 as separate predictors. For the accelerometer, the maxACC measure was taken for the last n consecutive periods, thus giving respectively ACC_{-n}, … , ACC_{-2}, ACC_{-1}, ACC_0 as separate predictors.

Utilization of lagged metrics as predictors was based on a simple reasoning that there could be no sudden change in the awake/asleep state. Similar lagged models were used in related studies on adults [10].

A Learning Vector Quantization (LVQ) neural network [19], a subclass of so-called Kohonen networks, was used to build the neural predictor. The LVQ networks are primarily used as non-linear classifiers, which make this method a perfect candidate for the task at hand. Initially, the network was trained on half the dataset (13 infants). The second half of the dataset (13 infants) was used to validate the results from the training of the network. One of the validation infants could not be used for the HRV analysis because of corrupted data, thus the HRV validation set consists of 12 infants. The neural predictor was initially trained utilizing the LVQ-1 algorithm and fine-tuned with LVQ-3.

Classification by both LVQ-1 and LVQ-3 is based on a codebook of vectors m_i, where each codebook vector belongs to a certain class. The input vector X is compared to each codebook vector m_i and assigned to the same class to which the closest codebook vector belongs. The distance d between X and m_i is calculated according to the following formula:

$$d = \min_i \left\| X - m_i \right\| \qquad (1)$$

More information on the LVQ neural networks can be found in [20].

III. RESULTS

A. Heart rate variability

The LVQ network of 16 codebook vectors (8 ASP and 8 AWK) was trained by the data from 13 infants combined into a single data set. Nine input features were used (the mean of the epoch and the mean of the previous 8 epochs). The network was trained for 100,000 iterations and fine-tuned by LVQ_3 for 100,000 iterations.

To obtain the correct number of codebook vectors a relative-operating curve (ROC) was created. The ROC graphically shows when over training occurs. This is seen by a decrease in the test set accuracy while the training set continually increases in accuracy. The value of 16 codebook vectors was decided from figure 1.

The 13 training infants were then tested individually to see how each infant influenced the training of the network. The average ASP agreement was 92.7% and the average AWK agreement was 51.4%. The overall training weighted average was 80.6% correct agreement (Table 1).

The validation set for the heart rate variability consists of 12 infants. Each of the 12 infants was tested on codebook vectors obtained from the training procedure. The average ASP prediction was 89.5% and the average AWK prediction was 56.5%. The overall validation weighted average was 78.7% correct prediction.

B. Accelerometer

The LVQ network of 32 codebook vectors (16 ASP and 16 AWK) was trained by the data from 13 infants combined into a single data set. Nine input features were used (the mean of the epoch and the mean of the previous 8 epochs). The network was trained for 100,000 iterations and fine-tuned by LVQ_3 for 100,000 iterations [11,12].

The 13 infants were then tested individually to see how each infant influenced the training of the network. The average ASP agreement was 94.6% and the average AWK agreement was 48.2%. The overall training weighted average was 80.7% correct agreement (Table 2).

Each of the 13 training infants was tested on codebook vectors obtained from the training procedure. The average ASP prediction was 92.3% and the average AWK prediction was 42.4%. The overall validation weighted average was 75.3% correct prediction.

TABLE 1. AGREEMENT AND VALIDATION RATES (%) BY THE LVQ PREDICTOR FOR HRV

Group (rate)	Accuracy of sleep prediction	Accuracy of awake prediction	Weighted Average
Training (agreement)	92.7	51.4	80.6
Validation	89.5	56.5	78.7
Average	91.1	54.0	79.7

TABLE 2. AGREEMENT AND VALIDATION RATES (%) BY THE LVQ PREDICTOR FOR THE ACCELEROMETER

Group (rate)	Accuracy of sleep prediction	Accuracy of awake prediction	Weighted Average
Training (agreement)	94.6	48.2	80.7
Validation	92.3	42.4	75.3
Average	93.5	45.3	78.0

C. Comparison

From figure 2 and figure 3 it can be seen that HRV and accelerometer offer similar overall results. HRV has better results for AWK validation.

IV. DISCUSSION

The determination of sleep state using heart rate parameters in previous studies has a range from 82% (25 infants with different discriminant functions at 1, 2, 3, 4, and 6 months of age) [21] to with wavelet packet modeling 75%-90% (1 infant at 2, 3, 4, and 5 months of age) [22]. Both studies account for age by creating different classifiers for different age groups. Our study uses one general classifier on a population with mean post conception age (PCA) of 46 weeks and a range from 33.6 PCA to 58.1 PCA with an average of ~80%. Lisenby et al. use heart rate data to separate REM from non-REM states [23]. Other studies have been done to see how heart rate changes during sleep [24, 25, 26]. Our results confirm that an automated technique is plausible to distinguish between AWK and ASP in infants. Further research will consider age-based models, along with an expanded set of HRV inputs.

Previous actigraphy studies showed prediction rates of ASP/AWK identification of 85%-95% in a population of 41 infants [10]. The neural predictors of this study provide ASP/AWK identification of 58%-89% in a population of 26 infants, which is comparable to those in other studies.

Lower results for AWK identification are most likely due to the fact that the accelerometer is placed on the diaper. In general, lower AWK results may also be due to the method for training the model where the number of ASP epochs was much larger than the AWK epochs, giving greater weight to ASP identification. In some cases, it may be difficult to predict the AWK state due to lack of motion and low, steady HR.

V. CONCLUSION

This study compared two methods, heart rate variability and actigraphy, to offer alternative techniques for sleep-wake identification compared to manual sleep scoring from a polysomnograph. The methods have advantages that are valuable for determining sleep-wake states in such highly sensitive groups as infants. A learning vector quantization neural network was tested as the predictor. The prediction from the neural network was compared to "gold standard" hand-scored polysomnographs. The results are in agreement with other studies, thus validating the suggested methodology. In conclusion, both the HRV and accelerometer offer similar results for asleep/awake prediction from the LVQ neural network.

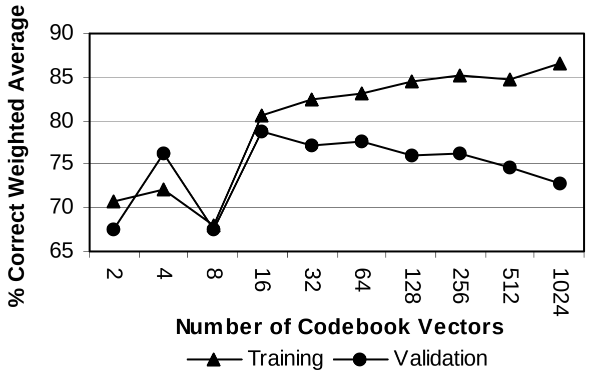

Fig. 1. ROC curve for HRV LVQ.

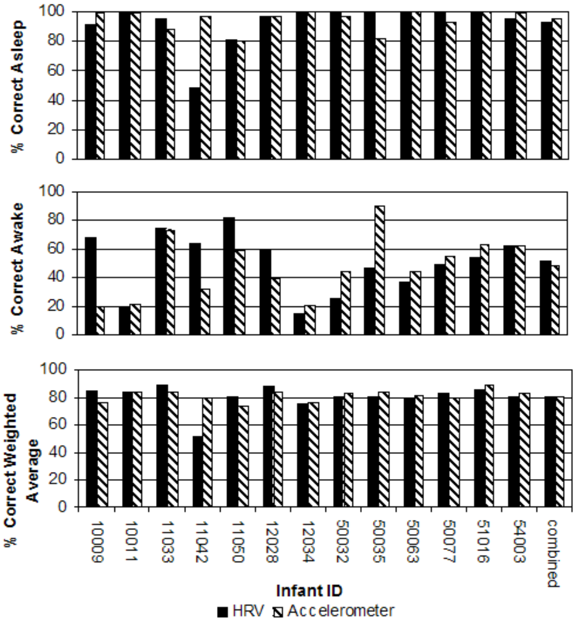

Fig. 2. LVQ agreement rates.

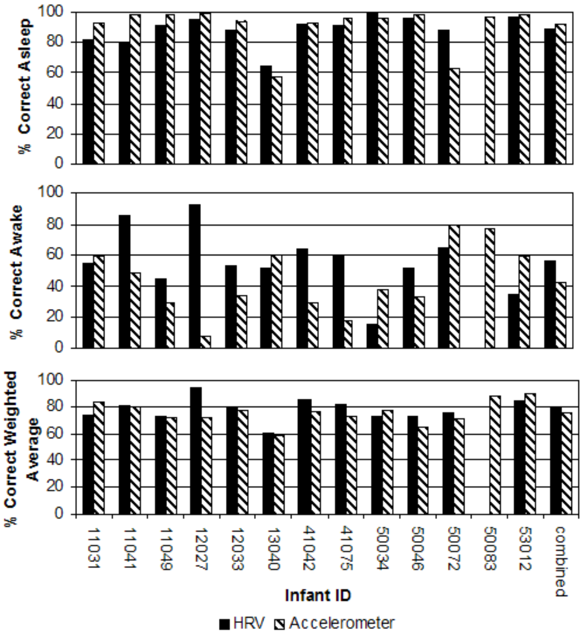

Fig. 3. LVQ validation rates.

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