

Most Discriminative Atom Selection for Apnea-Hypopnea Events Detection

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- Motivation

2 Materials and methods

- Proposed method
- Database
- Sparse representations
- Learning and inference problems

3 MDAS method

4 Experiments and results

5 Discussion and conclusions



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- The Obstructive Sleep Apnea-Hypopnea (OSAH) syndrome is characterized by repetitive episodes of airway narrowing during sleep.
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Medical criteria

- *apnea*: if the amplitude of the airflow signal decreases below 25 % of the “baseline” breathing amplitude and it remains below that level for more than 10 seconds.
- *hypopnea*: if the amplitude of the respiratory signal decreases below 70 % of the “baseline” breathing amplitude, it remains so for more than 10 seconds for more than 2 breathe periods.



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Apnea-Hypopnea Index (AHI) = average number of AH events per hour.

- $5 < \text{AHI} \leq 15$, mild.
- $15 < \text{AHI} \leq 30$, moderate.
- $\text{AHI} > 30$, severe.



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Polysomnography



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Proposed method



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SHHS: Sleep Heart Health Study

The SHHS database contains 1000 PSGs of the “Sleep and Epidemiology Research Center (SERC)¹” at the “Case Western Reserve University”.

- Biomedical signals:
 - Nasal airflow
 - SaO₂
 - OXStat
 - EEG

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Signals of interest



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Dictionary

$$\mathbf{s} = \sum_{j=1}^M \phi_j a_j = \Phi \mathbf{a}$$

$$\mathbf{s} \in \mathbb{R}^N$$

$$\Phi \in \mathbb{R}^{N \times M}, M \geq N$$

$$\mathbf{a} \in \mathbb{R}^M$$

Sparse representation problem:

- *learning*.
- *inference*.



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Learning and inference

- Noise Overcomplete Independent Component Analysis (NOCICA)

$$\mathbf{s} = \sum_{j=1}^M \phi_j a_j + \epsilon = \Phi \mathbf{a} + \epsilon. \quad (1)$$

Then:

$$\Delta \Phi = \eta \Lambda_{\epsilon} ((\mathbf{s} - \Phi \mathbf{a}_{MAP}) \mathbf{a}_{MAP}^T - \Phi H^{-1}). \quad (2)$$

- Orthogonal Matching Pursuit (OMP)

$$\min \|\mathbf{s} - \Phi \mathbf{a}\|_2 \text{ subject to } \|\mathbf{a}\|_0 \leq T, \quad (3)$$

where $\|\cdot\|_0$ denotes the zero-norm.



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Most Discriminative Atom Selection

The idea behind this method is to select the most discriminative atoms of Φ in order to improve the classifier's performance.

Main steps:

- 1 Compute the atom activation frequency n_{ci}^j given the class i and the atom j .
- 2 Select the most discriminative atoms of Φ by $D = |n_{c1}^j - n_{c2}^j|$.



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Substeps:

- 1 Improve the neural network performance.
- 2 Obtain the optimal configuration of the classifier.



Database

Training set:

AHI	Total studies
$AHI \leq 5$	5
$5 < AHI \leq 10$	5
$10 < AHI \leq 15$	5
$AHI > 15$	5

Test set:

AHI	Total studies
$AHI \leq 5$	21
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AH events detection



Scatter plots



Tables of results

MDAS method (Multilayer perceptron):

	OAD	CD
Inputs	24	30
Neurons (hidden layer)	14	14

Studies:

	OAD	CD
Total studies	84	84
Sensibility (%)	74.52	68.86
Specificity (%)	76.73	67.69
Correlation (%)	90.04	74.57



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¡Thank you!

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