Bio-inspired algorithms based on sparse representations of signals for apnea-hypopnea events detection

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IMAL seminar

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Organization

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Objectives

General

The main objective of this research is the development, use and evaluation of advanced biomedical signal processing techniques and machine learning algorithms for identifying pathologies associated to sleep disorders.

Specifics

- Develop methods based on sparse representations of pulse oximetry signals by using optimization techniques and inverse problems for the detection of obstructive sleep apnea-hypopnea syndrome.
- Include discriminative information to sparse representations for biomedical signals classification.
- Use of databases with real studies for applying and validating the proposed methods.
- Compare the proposed method with those well-know traditional ones.
- Analyze and validate the results.

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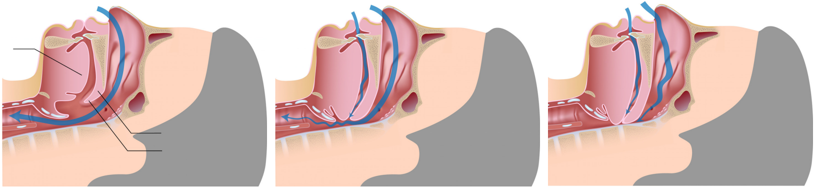
Motivation
OSAHS

Obstructive Sleep Apnea-Hypopnea Syndrome (OSAHS)

OSAHS is one of the most common sleep disorders, which is caused by repeated events of partial (hypopnea) or total (apnea) obstruction of the upper airway while sleeping.

OSAHS illustration



(a) Normal (b) Partial obstruction (c) Total obstruction

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Motivation
OSAHS

OSAHS

- Is a highly prevalent syndrome in the general human population.
- Affects up to 5 % of men and 3 % of women.
- The diagnosing method is normally very limited as well as costly in terms of both time and money.
- Aging, being male, snoring and obesity are all factors increasing the risk of suffering this pathology.
- Sleep fragmentation, intermittent hypoxemia, increased sympathetic tone and hypertension are main causes of mortality and morbidity.
- There is evidence that close to 93 % of women and 82 % of men with moderate to severe OSAHS remain undiagnosed.

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Some definitions

- Apnea event: Cessation of airflow at least 10 seconds.
- Hypopnea event: Reduction of airflow accompanied by a desaturation of at least 4 %.
- Desaturation: Blood oxygen reduction.
- Apnea-hypopnea index (AHI): Represents the average number of apnea-hypopnea events per hour of sleep.

OSAHS severity

- Healthy if AHI $\in [0, 5)$.
- Mild if AHI $\in [5, 15)$.
- Moderate if AHI $\in [15, 30)$.
- Severe if AHI $\in [30, \infty)$.

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Nocturnal polysomnography (PSG)

Importance of simplified studies!

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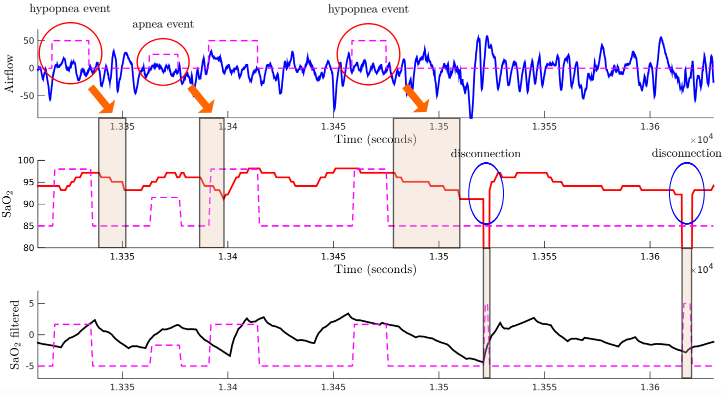
Biomedical signals coming from a polysomnography



It is possible to detect the apnea-hypopnea events by "analyzing" only the pulse oximetry signal?

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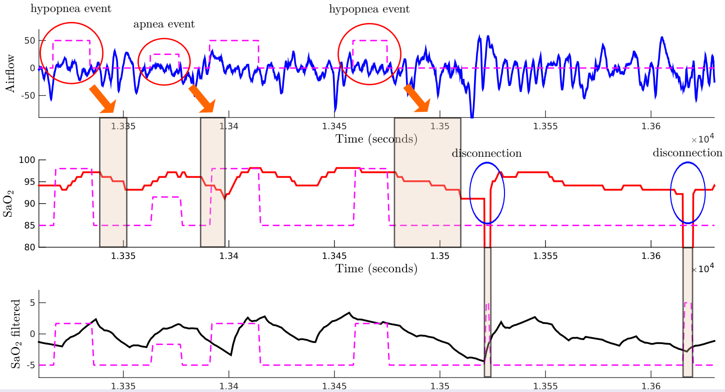

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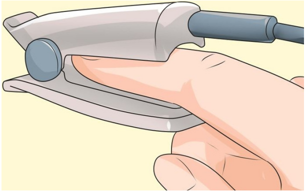
OSAHS

Hypothesis 1
It is really possible to detect OSAHS using only the pulse oximetry signal.

Pulse oximetry



Hypothesis 2
The inclusion of *discriminative information* in the sparse representation of pulse oximetry signals allows for improving the performance and providing robustness in the detection of OSAHS.

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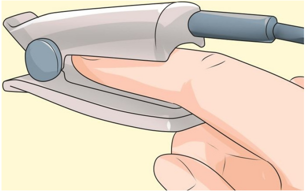
Pulse oximetry



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The inclusion of *discriminative information* in the sparse representation of pulse oximetry signals allows for improving the performance and providing robustness in the detection of OSAHS.

Organization

1. Objectives
2. Motivation
3. Related works
4. Sparse representations of signals
5. Proposal
   - Discriminative methods for signal classification
   - Measuring complexity in sparse representations
   - Multi-class discriminative dictionary learning
6. Conclusions

Related works

- E. Chiner *et. al.*, Nocturnal oximetry for the diagnosis of the sleep apnoea hypopnoea syndrome: a method to reduce the number of polysomnographies?, (1999).
- J. Vázquez *et. al.*, Automated analysis of digital oximetry in the diagnosis of obstructive sleep apnoea, (2000).
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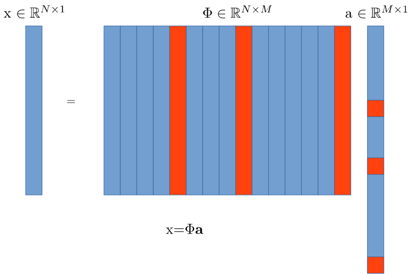
Sparse representations



Sparse

Description of a signal in terms of a few significant characteristics.

Sparse code

Represents the information in terms of a few number of descriptors taken from a large set.

Why sparse?

Sparse representations

Problem statement

Let $X \doteq [\mathbf{x}_1 \ \mathbf{x}_2 \ \cdots \ \mathbf{x}_n] \in \mathbb{R}^{N\times n}$ a matrix composed by "n" N-dimensional signals, let $\Phi \doteq [\phi_1 \ \phi_2 \ \cdots \phi_M] \in \mathbb{R}^{N\times M}(M \gg N)$ a matrix (dictionary) whose columns (atoms) normalized via l_2-norm. The problem can be written as $\mathbf{x} = \Phi\mathbf{a}$; where

$$(P_0) \qquad \mathbf{a} = \underset{\mathbf{a}}{\operatorname{argmin}} \, ||\mathbf{a}||_0 \ \text{ subject to } \ \mathbf{x} = \Phi\mathbf{a}, \tag{1}$$

where $||\mathbf{a}||_0$ denotes the l_0 pseudo-norm of $\mathbf{a}$.

Convex relaxation

$$(P_1) \qquad \mathbf{a} = \underset{\mathbf{a}}{\operatorname{argmin}} \, ||\mathbf{a}||_1 \ \text{ subject to } \ \mathbf{x} = \Phi\mathbf{a}, \tag{2}$$

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- Many others...

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Sparse representations

Noise degree in the representation

$$(P_2) \qquad \mathbf{a} \doteq \underset{\mathbf{a}}{\operatorname{argmin}} ||\mathbf{x} - \Phi\mathbf{a}||_2^2 \text{ subject to } ||\mathbf{a}||_1 \leq p_0. \tag{3}$$

Dictionary learning

$$< \Phi, \mathbf{a} >\doteq \underset{\Phi,\mathbf{a}}{\operatorname{argmin}} ||\mathbf{x} - \Phi\mathbf{a}||_2^2 + \lambda||\mathbf{a}||_1, \tag{4}$$

where λ is a regularization parameter.

- Method of optimal directions (MOD). Engan *et. al.* (1999).
- Noise overcomplete ICA (NOCICA). Lewiki *et. al.* (1999).
- K singular value decompositions (KSVD). Elad *et. al.* (2004).
- Others.

Organization

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Discriminative methods for signal classification

Problem

- Detection of apnea-hypopnea events (binary classification).
  - Class 1 (C_1): Segments of SaO_2 signals with apnea event.
  - Class 2 (C_2): Segments of SaO_2 signals without apnea event.
- Database with 995 complete studies [a].

[a] http://cci.case.edu/serc/

Polysomnography

- Airflow.
- Respiratory effort.
- Electrical activity of the brain along the scalp.
- Electrical activity of the heart using electrodes placed on the body's surface.
- Electrical activity produced by skeletal muscles.
- Blood oxygen saturation.
- Others.
- Annotations of sleep stages, arousals and apnea-hypopnea events.

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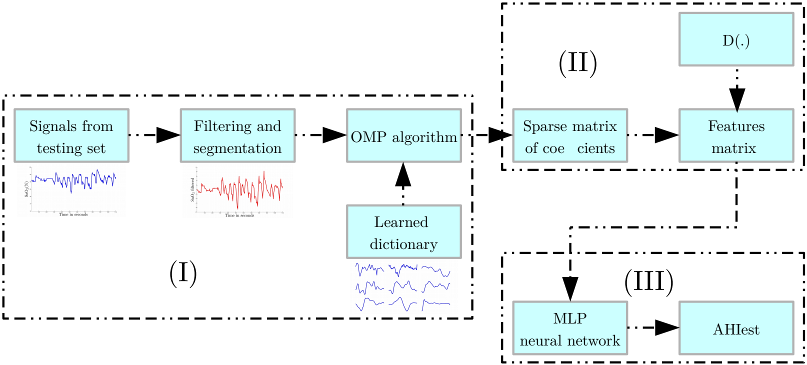
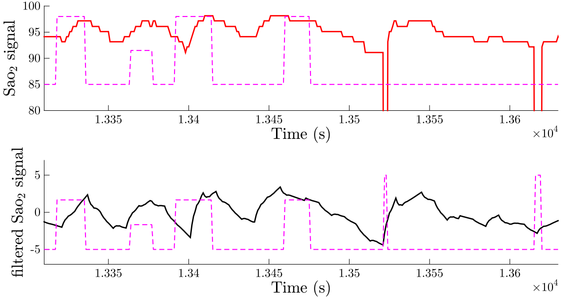
Discriminative methods for signal classification
Proposed system

Block diagram of the proposed system



Discriminative methods for signal classification
Filtering stage



Right! Wavelet Daubechies 2

(d) Scaling function ϕ. (e) Wavelet function ψ.

Main properties: asymmetric, orthogonal and biorthogonal.

Discriminative methods for signal classification
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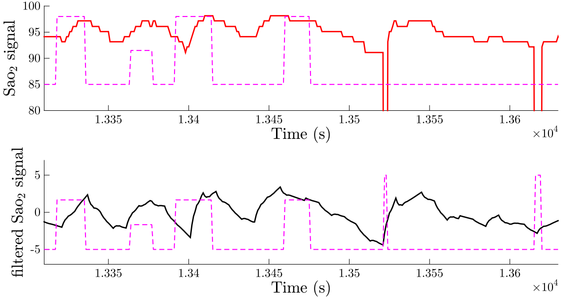

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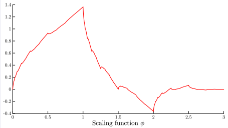
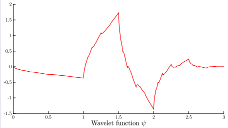


(f) Scaling function ϕ.



(g) Wavelet function ψ.

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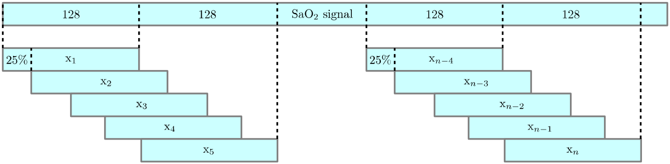
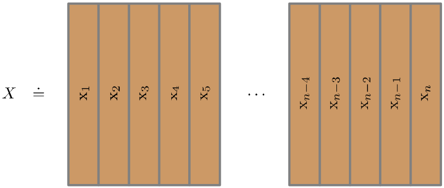
Discriminative methods for signal classification
Segmentation stage

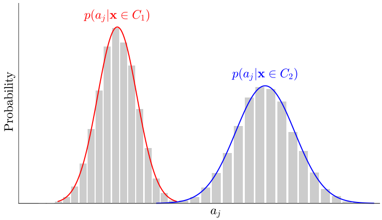


The signal matrix is defined as:

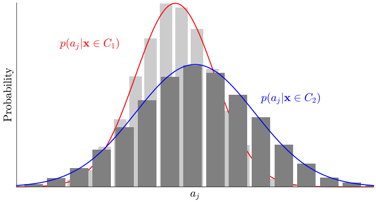
$$X \doteq [\mathbf{x}_1\ \mathbf{x}_2\ \mathbf{x}_3\ \mathbf{x}_4\ \mathbf{x}_5 \cdots \mathbf{x}_{n-4}\ \mathbf{x}_{n-3}\ \mathbf{x}_{n-2}\ \mathbf{x}_{n-1}\ \mathbf{x}_n]\,. \tag{5}$$



Discriminative methods for signal classification
Discriminative measure



(h) A discriminative atom ϕ_j.



(i) A non-discriminative atom ϕ_j.

Let $\eta_1^j \doteq p(a_j \neq 0|\mathbf{x} \in C_1)$ and $\eta_2^j \doteq p(a_j \neq 0|\mathbf{x} \in C_2)$ being the probabilities of activation of the j^{th}-atom for data belonging to the classes $k = 1$ and $k = 2$, respectively. The discriminative measure for atoms selection is as follow:

$$D\{\eta_1^j, \eta_2^j\} \doteq |\eta_1^j - \eta_2^j|. \tag{6}$$

Discriminative methods for signal classification

Simplified algorithm

Simplified steps of the proposed system

Given X and p_0:

- Learn Φ by using NOCICA method.
- Obtain sparse codes $\mathbf{a}_i$ by applying OMP algorithm.
- Apply Eq. (6) for detecting the most discriminative atoms (ϕ_d) of Φ.
- Construct a sub-dictionary $\hat{\Phi}$ by using ϕ_d.
- Obtain the new sparse codes $\mathbf{a}_i$ by applying OMP algorithm.
- Train a MLP neural network for data classification.
- Test the performance of the system using the testing database.

Return AHIest

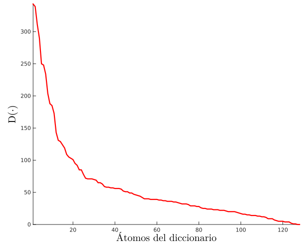
Discriminative methods for signal classification
Experiments

Experimental setup

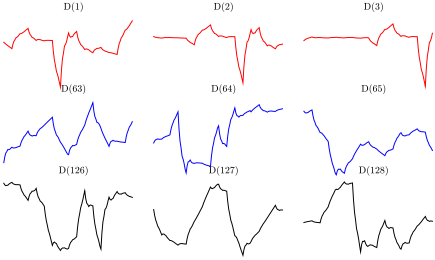
- The complete dataset contains 995 studies, 41 of which were discarded due to incomplete information.
- Among the remaining 954 studies, a subset of 667 (70 %) studies were randomly selected and fixed for training.
- The final test was made using the remaining 287 (30 %) studies of the database.
- The NOCICA method was used for the dictionary learning stage.
- Sparsity level $p_0 = 16$ was chosen.
- The representation coefficients $\mathbf{a}$ were obtained by applying the OMP algorithm.
- A variation of the back-propagation algorithm, called mini-batch training procedure, was used to train the MLP neural network.

Discriminative methods for signal classification
Results

Most discriminative atoms of the dictionary



(j) $D \doteq |\eta_1^j - \eta_2^j|$ ordered in decreasing order of magnitude.



(k) Waveforms of the atoms corresponding to three different regions of D.

Discriminative methods for signal classification
Results

Performance measures

- Sensitivity:
$$SE = \frac{VP}{VP + FN}. \tag{7}$$
- Specificity:
$$SP = \frac{VN}{VN + FP}. \tag{8}$$
- Accuracy:
$$ACC = \frac{VP + VN}{P + N}. \tag{9}$$
- Area under de ROC curve.

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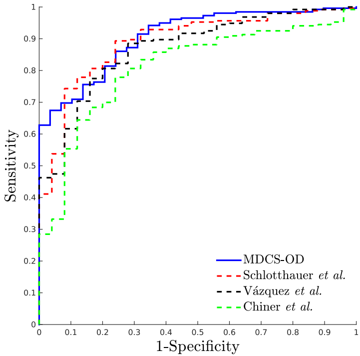
Discriminative methods for signal classification
Results

A comparison of the performance measures obtained for the detection of OSAHS using different methods

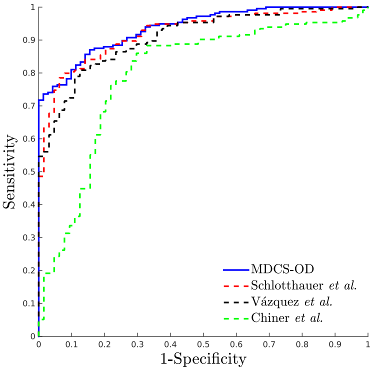
Method	AHI_{thr}	AUC	SE(%)	SP(%)	ACC(%)
Proposed	10	**0.906**	**81.40**	79.31	80.35
	15	**0.937**	**85.65**	85.92	**85.78**
Chiner *et al.*	10	0.810	77.87	76.00	76.93
	15	0.795	76.17	78.12	77.15
Vázquez *et al.*	10	0.870	77.47	**84.00**	80.74
	15	0.909	80.84	**87.50**	84.17
Schlotthauer *et al.*	10	0.890	80.63	**84.00**	**82.32**
	15	0.922	84.11	85.94	85.02

Discriminative methods for signal classification
Results

ROC curve analysis



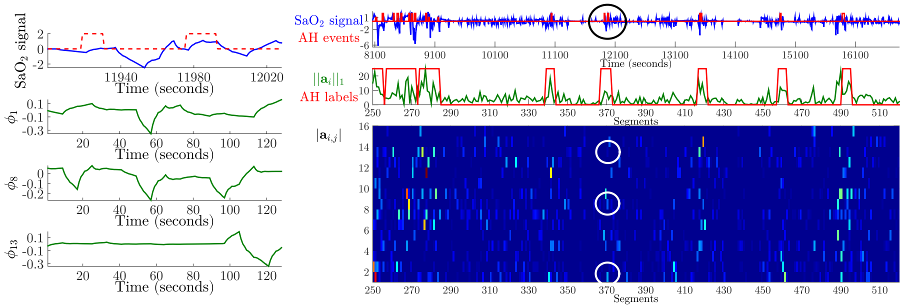
(l) Detection threshold of 10.



(m) Detection threshold of 15.

Discriminative methods for signal classification
Results

Final feature vectors to apnea-hypopnea events correlation[1]



Are the hypotheses verified?

[1] R. Rolón, L. Larrateguy, L. Di Persia, R. Spies and L. Rufiner, Discriminative methods based on sparse representations of pulse oximetry signals for sleep apnea-hypopnea detection. *Biomedical Signal Processing and Control (BSPC)*, Vol. 33, (2017), pp. 358-367.

Discriminative methods for signal classification

Results

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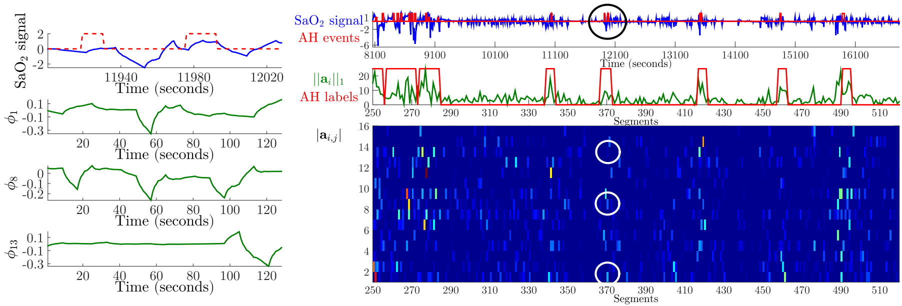

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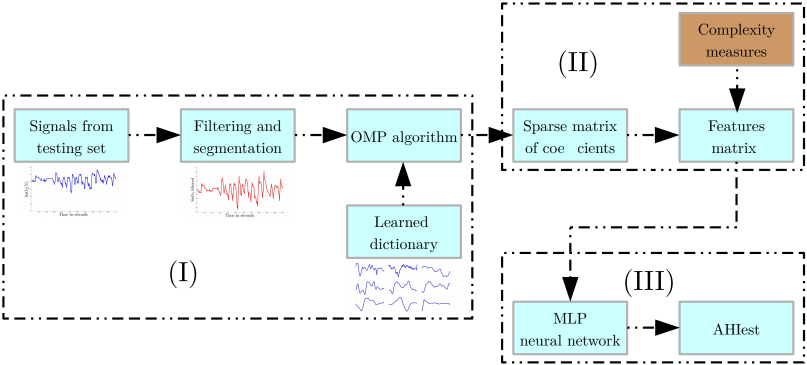
Discriminative methods for signal classification
Publications

- R. Rolón, L. Di Persia, L. Rufiner and R. Spies, *Most discriminative atom selection for apnea-hypopnea events detection*, VI Latin American Congress on Biomedical Engineering (CLAIB), (2014), pp. 572-575.
- L. Larrateguy, R. Rolón, L. Di Persia, R. Spies and L. Rufiner, *Método de screening para la detección de SAHOS utilizando selección de funciones discriminativas*, Revista Americana de Medicina Respiratoria (RAMR), (2014).
- R. Rolón, L. Di Persia, L. Rufiner and R. Spies, *A method for atoms selection applied to screening for sleep disorders*, 1st Pan-American Congress on Computational Mechanics (PANACM), (2015), pp. 1155-1166.
- R. Rolón, L. Di Persia, L. Rufiner and R. Spies, *Two alternatives for atoms selection applied to screening for sleep disorders*, V Congreso de Matemática Aplicada, Computacional e Industrial (MACI), (2015), pp. 437-440.
- R. Rolón, L. Larrateguy, L. Di Persia, R. Spies and L. Rufiner, Discriminative methods based on sparse representations of pulse oximetry signals for sleep apnea-hypopnea detection. *Biomedical Signal Processing and Control (BSPC)*, Vol. 33, (2017), pp. 358-367.

Measuring complexity in sparse representations

Proposed system

Block diagram of the proposed system



Measuring complexity in sparse representations

Complexity measures

Absolute difference of frequency activation

$$d_R\{\eta_1^j, \eta_2^j\} \doteq |\eta_1^j - \eta_2^j|. \tag{10}$$

Kullback-Leibler (KL) divergence

$$d_{KL}\{\eta_1 || \eta_2\} \doteq \sum_{j \in M} \eta_1^j \log \left(\frac{\eta_1^j}{\eta_2^j} \right), \tag{11}$$

under the assumption that $0 \log(0) \doteq 0$.

J-divergence

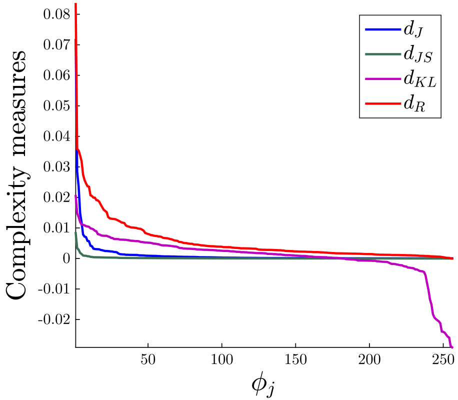
$$d_J\{\eta_1, \eta_2\} \doteq d_{KL}\{\eta_1 || \eta_2\} + d_{KL}\{\eta_2 || \eta_1\}. \tag{12}$$

Jensen-Shannon divergence

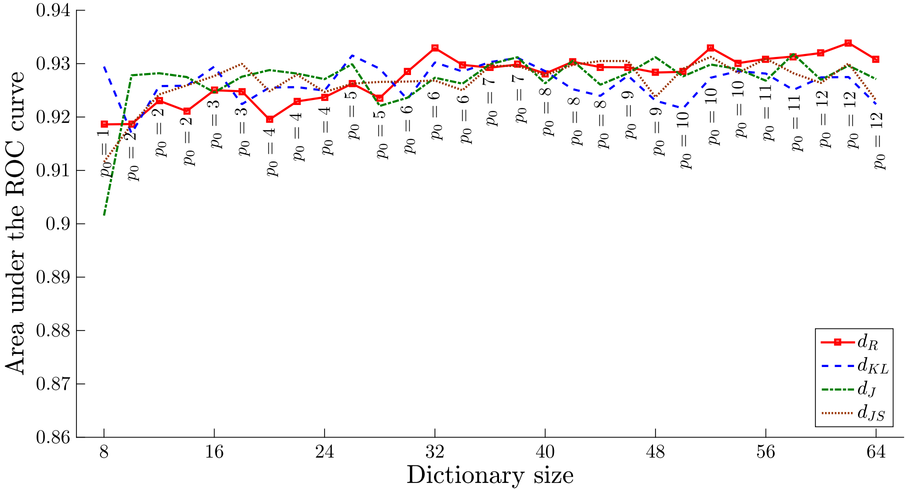
$$d_{JS}\{\eta_1, \eta_2\} \doteq \frac{1}{2} d_{KL}\{\eta_1 || \eta_3\} + \frac{1}{2} d_{KL}\{\eta_2 || \eta_3\}, \tag{13}$$

where $\eta_3 = \frac{\eta_1 + \eta_2}{2}$.

Measuring complexity in sparse representations
Preliminary results



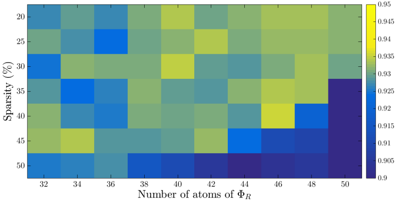
Measuring complexity in sparse representations
Preliminary results



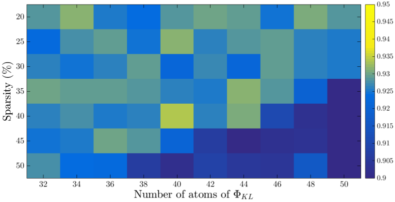
Measuring complexity in sparse representations

Preliminary results

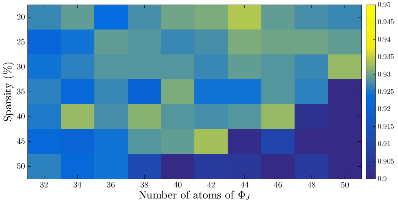
Images representing performance measures obtained by different percentages of sparsity and different dictionary sizes



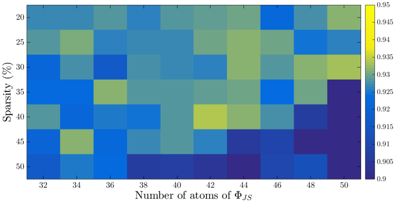
(n) Φ_R.



(ñ) Φ_{KL}.

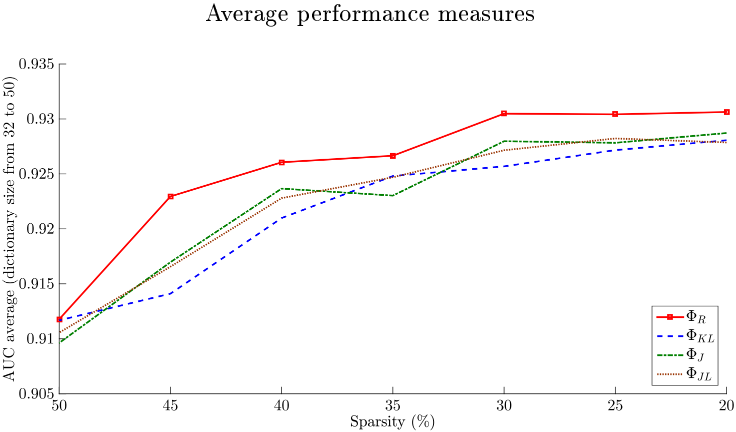


(o) Φ_J.

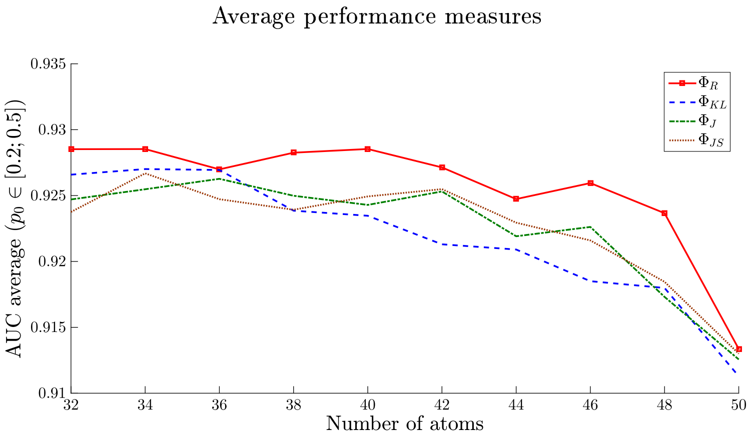


(p) Φ_{JS}.

Measuring complexity in sparse representations
Preliminary results



Measuring complexity in sparse representations
Preliminary results



Multi-class discriminative dictionary learning

Proposal

Development of a discriminative dictionary learning algorithm for multi-class signal classification using a generalized version of the absolute difference of frequency activation measure.

Discriminative coupled dictionary

The dictionary $\Phi \in \mathbb{R}^{M \times \kappa}$ is composed by a collection of sub-dictionaries $(\Phi_{c\kappa})$ as follows:

$$\Phi = [\Phi_{c1}\ \Phi_{c2}\ \cdots\ \Phi_{c\kappa}], \text{ (para } \kappa \text{ clases)} \tag{14}$$

where $\Phi_{c\kappa} = [\phi^1_{c\kappa}\ \phi^2_{c\kappa}\ \cdots\ \phi^I_{c\kappa}]$, ($I$ dicriminative atoms for each class)

Discriminative measure

$$D(j,k) = \eta^j_k - \max_{\kappa \neq k}\left(\eta^j_\kappa\right). \tag{15}$$

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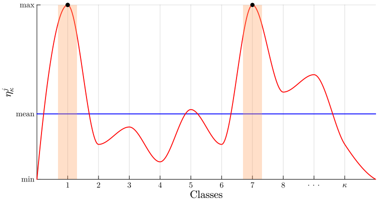
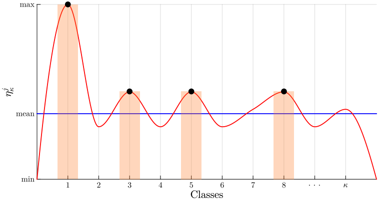
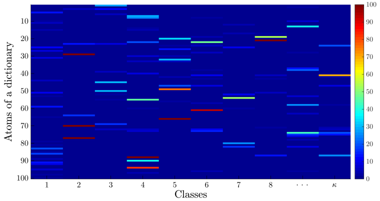
Multi-class discriminative dictionary learning



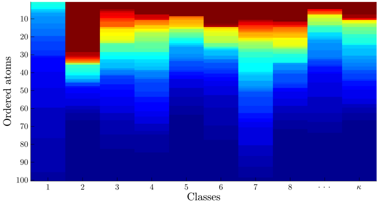
(q) A non-discriminative atom.



(r) A discriminative atom



(s) Matrix D.



(t) Matrix D whose columns were ordered in decreasing order of magnitude.

Multi-class discriminative dictionary learning

Proposed algorithm

Algorithm 1 DKSVD

procedure DKSVD(X, p_0, r, I, κ)
  $inc = 1$
  for $i \leftarrow 1, I$ **do**
    $\Phi_{init} \leftarrow$ KSVD(X, p_0)
    Get sparse matrix $A = [A_1\ A_2\ A_3\ \cdots\ A_\kappa]$ that accomplish $X = \Phi A$
    Get D according to Ec. (4)
    Get Φ_d and Rem
    if $Rem = \emptyset$ **then**
      $inc = 0$
    end if
    while $inc = 1$ **do**
      Get $\hat{X}$ by removing the input signals corresponding to the discriminative atoms
      $\Phi \leftarrow$ KSVD$(\hat{X}, p_0)$
      Get sparse matrix A that accomplish $\hat{X} = \Phi A$
      Get D according to Ec. (15)
      Get Φ_d and Rem
      if $Rem = \emptyset$ **then**
        $inc = 0$
      end if
    end while
    $\Phi_D \leftarrow [\Phi_D\ \Phi_d]$
    Remove signals.
  end for
  $\Phi_D \leftarrow [\Phi_{c1}\ \Phi_{c2}\ \cdots\ \Phi_{c\kappa}]$ where $\Phi_{c\kappa} = [\phi^1_{c1}\ \phi^2_{c2}\ \cdots\ \phi^I_{c\kappa}]$
  return Φ_D
end procedure

Multi-class discriminative dictionary learning
Preliminary results (MNIST database)

Some atoms in a redundant dictionary learned using KSVD method

First six atoms for three of the classes captured by the proposed discriminative dictionary learning algorithm

(u) Class 3.

(v) Class 6

(w) Class 8.

Publications

- R. Rolón, L. Di Persia, L. Rufiner and R. Spies, *A method for discriminative dictionary learning with application to pattern recognition*, VI Congreso de Matemática Aplicada, Computacional e Industrial (MACI), (2017).

Organization

Conclusions

Conclusions

- The sparse representations of pulse oximetry signals is undoubtedly a promising technique for the design of new methods for OSAHS detection.
- New discriminative methods based on sparse representations for signal classification were successfully applied for the detection of apnea-hypopnea events.
- It is possible to include discriminative information in the representation for improving the performance of the classifier.
- A quite good performance in the detection of OSAHS was obtained.

sinc(i)

Thanks!

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