

# An efficient supervised dictionary learning method for audio signal recognition

Imad Rida\*, Romain Hérault, Gilles Gasso

*Normandie Université, LITIS EA 4108, INSA Rouen Normandie, Avenue de l'Université,  
76800, Saint Etienne du Rouvray, France*

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## Abstract

Machine hearing or listening represents an emerging area. Conventional approaches rely on the design of handcrafted features specialized to a specific audio task and that can hardly be generalized to other audio fields. For example, Mel-Frequency Cepstral Coefficients (MFCCs) and its variants were successfully applied to computational auditory scene recognition while Chroma vectors are good at music chord recognition. Unfortunately, these predefined features may be of variable discrimination power while extended to other tasks or even within the same task due to different nature of clips. Motivated by this need of a principled framework across domain applications for machine listening, we propose a generic and data-driven representation learning approach. For this sake, a novel and efficient supervised dictionary learning method is presented. The method learns dissimilar dictionaries, one per each class, in order to extract heterogeneous information for classification. In other words, we are seeking to minimize the intra-class homogeneity and maximize class separability. This is made possible by promoting pairwise orthogonality between class specific dictionaries and controlling the sparsity structure of the audio clip's decomposition over these dictionaries. The resulting optimization problem is non-convex and solved using a proximal gradient descent method. Experiments are performed

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\*Corresponding author

*Email addresses:* `imad.rida@insa-rouen.fr` (Imad Rida),  
`romain.herault@insa-rouen.fr` (Romain Hérault), `gilles.gasso@insa-rouen.fr` (Gilles Gasso)

on both computational auditory scene (East Anglia and Rouen) and synthetic music chord recognition datasets. Obtained results show that our method is capable to reach state-of-the-art hand-crafted features for both applications.

*Keywords:* audio, scene recognition, music recognition, supervised dictionary learning, sparse coding

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## 1 Introduction

Humans have a very high perception capability through physical sensation, which can include sensory input from the eyes, ears, nose, tongue, or skin. A lot of efforts have been devoted to develop intelligent computer systems capable to interpret data in a similar manner to the way humans use their senses to relate to the world around them [49]. While most efforts have focused on vision perception which is the dominant sense in humans, machine listening (ability of a machine to fully understand an audio input) represents an emerging area [33]. One rising application domain we are interested in is the classification of environmental audio signals usually termed as Computational Auditory Scene Recognition (CASR). It refers to the task of associating a semantic label to an audio stream that identifies the environment in which it has been produced. Another application is music recognition especially chords recognition that represent the most fundamental structure and the back-bone of occidental music.

The usual trend to classify signals is first to extract discriminative feature representations from the signals, and then feed a classifier with them [55, 53, 50]. In this case, features are chosen so as to enforce similarities within a class and disparities between classes [52]. The more discriminative the features are, the better the classifier performs. Because of the specific peculiarities of audio clips in different application domains, specialized features have to be designed. For instance, **chroma vectors** represent the dominant representation in order to extract the harmonic contents from music signals [18, 60, 40, 25, 26]. In audio scene recognition, recorded signals can be potentially composed of a very large amount of sound events. To tackle this problem, features such as Mel-Frequency

Cepstral Coefficients (MFCCs) and its variants [11, 24, 72, 6, 31, 46] have been successfully combined with different classification techniques. These predefined features may be of variable discrimination power while extended to other tasks or different nature of clips. For this reason and due to the need to a machine hearing framework operating in various application domains, the suited feature representations should be automatically learned.

In recent years there has been a growing interest in the study of sparse representation learning. Using an overcomplete dictionary that contains prototype signal-atoms, signals are described as linear combinations of a few of these atoms. Audio representation learning techniques can be broadly divided into four main approaches [58]: wavelets [61, 68], Cohen distribution [12, 22], dictionary [38, 45] and filter banks [8, 58]. Choosing a pre-specified transform matrix is appealing because it is simpler. Also, in many cases it leads to simple and fast algorithms for the evaluation of the sparse representation. This is indeed the case for overcomplete wavelets, Cohen and filter banks. The success of such dictionaries in applications depends on how suitable they are to sparsely describe the signals in question.

Recently, a different route for designing dictionaries based on learning is considered. It seeks to find the dictionary  $\mathbf{D}$  that yields sparse representations for the training signals. Such dictionaries have the potential to outperform commonly used pre-determined dictionaries [1].

## 2 Motivations and Contributions

Conventional dictionary learning formulation minimizes the reconstruction error between a given signal and its (sparse) representation over the learned dictionary. Although this formulation is convenient for solving signal denoising [15, 37, 14], inpainting [16] and segmentation [17] problems, it may not suit classification tasks where the ultimate goal is to get discriminative decomposition of training signals over the learned dictionary [43, 2, 48]. Motivated by the limitation of the conventional dictionary learning techniques for classification,

supervised dictionary learning has known a wide emergence. Related techniques can be organized in six main groups [20] summarized in Table 1.

Table 1: Summary of supervised dictionary learning techniques for data classification [20].

Ref	Approach	Advantages & Limitations
[67] [45]	<b>A.</b> Dictionary per class	(+) ease dictionary computation (−) very large dictionary
[19] [65]	<b>B.</b> Prune large dictionaries	(+) ease dictionary computation (−) low performances
[38] [71]	<b>C.</b> Joint dictionary & classifier learning	(+) good performances (−) too many parameters
[70] [27]	<b>D.</b> Labels in dictionary	(+) good performances (−) complex optimization
[66]	<b>E.</b> Labels in coefficients	(+) good performances (−) complex
[63] [32]	<b>F.</b> Histograms of dictionary elements	(+) good performances (−) only based local constituents

- Learning one dictionary per class

Seeks to learn a dictionary per class [67, 62]. Although this approach can be potentially performing, learned dictionaries can capture similar properties for different classes leading to poor classification performance. To tackle this problem, [45] suggested to make the learned dictionaries as different as possible by enforcing their orthogonality to capture distinct information. A new test sample is assigned to class label of the dictionary providing the minimal residual reconstruction error.

- Prune large dictionaries

In this approach, a very large dictionary is learned, then the dictionary atoms are merged based on a predefined criterion including Agglomerative

Information Bottleneck (AIB) [19] and Mutual Information (MI) [65].

- Joint dictionary and classifier learning

This approach seeks to jointly learn the classifier parameters and dictionary [38, 71].

- Embedding class labels into the learning of dictionary

In this approach, the data is first projected into a space where the intra and inter-class are minimized and maximized respectively, and subsequently learn the dictionary and the sparse representation in this new space [70, 27].

- Embedding class labels into the learning of sparse coefficients

This approach seeks to include class labels in the learning of coefficients. It is based on the minimization and the maximization of the within-class and the between-class covariance of the coefficients respectively [66].

- Learning a histogram of dictionary elements over signal constituents

In this approach a histogram of dictionary atoms learned on local constituents is computed. The resulting histograms are used to train a classifier and predict the class label of a new test signal [63] [32].

Based on the characteristics of these methods,, we introduce in the following a novel supervised dictionary method. Our proposed approach aims to exploit the strengths of the previous methods that is: i) learning one dictionary per class, and ii) embedding class labels to force sparsity pattern of the signal's representation. To this end, we encourage the dissimilarity between the dictionaries by penalizing the pairwise similarity between them. To reach superior discrimination power, we push towards zero the coefficients of a signal representation over other dictionaries than the one corresponding to its class label. The contributions of the paper are:

- a novel supervised dictionary learning formulation,

- a related optimization algorithm based on alternating a sparse coding step with the update step of the dictionaries,
- experimental evaluations on scene and chord recognition applications.

The remainder of this paper is organized as follows. Section 3 describes the proposed method. Section 4 reports the experimental results and discussions. Finally, Section 5 concludes the paper.

### 3 Proposed approach

Let consider  $\{(\mathbf{x}_n, y_n)\}_{n=1}^N$  where  $\mathbf{x}_n \in \mathbb{R}^M$  is a signal and  $y_n \in \{1, \dots, C\}$  its label. Our novel approach for supervised dictionary learning seeks to learn  $C$  incoherent dictionaries  $\mathbf{D}_c$ , each per class, by enforcing their pairwise orthogonality. Furthermore to render the representation of a signal  $\mathbf{x}$  with label  $y = c'$  specific to its class, the coefficients of its decomposition over dictionaries  $\mathbf{D}_c, c \neq c'$  are pushed towards zero. To illustrate the intuition behind the approach, let suppose a binary classification problem. Given a sample  $(\mathbf{x}, y = 1)$ , we aim to find a decomposition  $\mathbf{x} \approx \mathbf{D}_1 \mathbf{a}_1 + \mathbf{D}_2 \mathbf{a}_2$  such that the term  $\|\mathbf{D}_1^T \mathbf{D}_2\|_F^2$  reflecting the coherence between the dictionaries is small while enforcing the representation over  $\mathbf{D}_2$  to be negligible by pushing the term  $\|\mathbf{a}_2\|_2^2$  close to zero. The obtained representations of the signals are further used as features in a linear SVM [59].

Before delving into the detailed formulation of the proposed approach and the way the involved optimization problem is addressed, we introduce the conventional dictionary learning method and its limitations. The following notations will be adopted:  $\|\mathbf{z}\|_p = \sum_j |z_j|^p, p \geq 1$  stands for the  $\ell_p$ -norm of vector  $\mathbf{z}$  and  $\|\mathbf{M}\|_F = \sqrt{\sum_{i,j} M_{ij}^2}$  represents the Frobenius norm of matrix  $\mathbf{M}$ . Finally the indicator function  $\mathbb{1}_{y=c}$  is 1 if the inner condition is true, and 0 otherwise.

#### 3.1 Conventional dictionary learning

Dictionary learning was primary devised to find a linear decomposition of a signal using a few atoms of a learned overcomplete dictionary [15]. Let suppose a dictionary  $\mathbf{D} \in \mathbb{R}^{M \times K}$  composed of  $K$  atoms  $\{\mathbf{d}_k \in \mathbb{R}^M\}_{k=1}^K$ . The conventional approach seeks a sparse representation  $\mathbf{a}_n \in \mathbb{R}^K$  of a signal  $\mathbf{x}_n \in \mathbb{R}^M$  over  $\mathbf{D}$  such as  $\mathbf{x}_n \approx \sum_{k=1}^K a_{nk} \mathbf{d}_k \approx \mathbf{D} \mathbf{a}_n$ . Given a set of  $N$  signals  $\{\mathbf{x}_n\}_{n=1}^N$ , dictionary learning method intends to find simultaneously the dictionary  $\mathbf{D}$  and the sparse codes  $\mathbf{a}_n$  by solving the following optimization problem

$$\begin{cases} \min_{\mathbf{D}, \{\mathbf{a}_n\}_{n=1}^N} \sum_{n=1}^N \|\mathbf{x}_n - \mathbf{D} \mathbf{a}_n\|_2^2 + \lambda \|\mathbf{a}_n\|_1 \\ \text{s.t.} \quad \|\mathbf{d}_k\|_2^2 \leq 1 \quad \forall k = 1, \dots, K \end{cases} \quad (1)$$

Formulation (1) is not suitable for classification since it solely seeks to minimize the reconstruction error between the input signal and its representation over the dictionary [56, 51, 47]. In the following we extend this formulation to take into account the label information. Instead of determining a single global dictionary we focus in learning class specific dictionaries as presented in the next subsection.

### 3.2 Formulation of the supervised dictionary learning problem

We consider a dictionary  $\mathbf{D}_c \in \mathbb{R}^{M \times K'}$  associated to each class  $c$ . The global dictionary  $\mathbf{D} = [\mathbf{D}_1 \cdots \mathbf{D}_C] \in \mathbb{R}^{M \times K}$  represents the concatenation of the class based dictionaries  $\{\mathbf{D}_c\}_{c=1}^C$ . Each dictionary  $\mathbf{D}_c$  is composed of  $K'$  atoms  $\{\mathbf{d}_k \in \mathbb{R}^M\}_{k=1}^{K'}$ . For simplicity sake and without loss of generality we consider  $K'$  is the same for all  $\{\mathbf{D}_c\}_{c=1}^C$ . We assume the decomposition of  $\mathbf{x}_n$  over the global dictionary  $\mathbf{D}$  is given by  $\mathbf{x}_n \approx \mathbf{D} \mathbf{a}_n \approx \sum_{c=1}^C \mathbf{D}_c \mathbf{a}_{nc}$  where the vector  $\mathbf{a}_n^T = [\mathbf{a}_{n1}^T \cdots \mathbf{a}_{nc}^T \cdots \mathbf{a}_{nC}^T]$  represents the overall sparse code of  $\mathbf{x}_n$  and  $\mathbf{a}_{nc} \in \mathbb{R}^{K'}$  represents its sparse representation over the class specific dictionary  $\mathbf{D}_c$ . The supervised dictionary learning problem we intend to address seeks to:

- capture as much as possible information in the signal by minimizing the global reconstruction error over  $\mathbf{D}$ ;

- specialize the extracted information per class by minimizing the class specific reconstruction error similar to the minimization of intra-class homogeneity;
- render dissimilar the extracted class specific information by promoting pairwise orthogonality between dictionaries and "zeroing" coefficients not specific to the signal label. In other words, we attempt to maximize class separability; and
- promote the sparsity of signal representations over the dictionaries to preserve generalization ability of the linear SVM built upon the sparse codes.

Let assume the coefficients related to the training signals  $\{\mathbf{x}_n\}_{n=1}^N$  are gathered in  $\mathbf{A} = [\mathbf{a}_1 \cdots \mathbf{a}_n]$ . The dictionaries  $\{\mathbf{D}_c\}_{c=1}^C$  and the codes  $\mathbf{A}$  are obtained by solving the optimization problem

$$\left\{ \begin{array}{l} \min_{\{\mathbf{D}_c\}_{c=1}^C, \{\mathbf{a}_n\}_{n=1}^N} J(\mathbf{A}, \mathbf{D}) = J_1(\mathbf{D}, \mathbf{A}) + \mu J_2(\mathbf{D}, \mathbf{A}) + \lambda J_3(\mathbf{A}) + \gamma_1 J_4(\mathbf{A}) + \gamma_2 J_5(\mathbf{D}) \\ s.t. \quad \|\mathbf{d}_{ck}\|_2^2 \leq 1 \quad \forall c = 1, \dots, C \quad \text{and} \quad \forall k = 1, \dots, K \end{array} \right. \quad (2)$$

The terms included in problem (2) are defined as follows:

$$J_1(\mathbf{D}, \mathbf{A}) = \sum_{n=1}^N \|\mathbf{x}_n - \mathbf{D}\mathbf{a}_n\|_2^2$$

measures the global reconstruction error of all training signals over the global dictionary  $\mathbf{D}$ . It is intended to capture the common patterns of the signals shared across different classes. The term

$$J_2(\mathbf{D}, \mathbf{A}) = \sum_{n=1}^N \sum_{c=1}^C \mathbb{1}_{y_n=c} \|\mathbf{x}_n - \mathbf{D}_c \mathbf{a}_{nc}\|_2^2$$

stands for the class specific reconstruction error over the dictionary  $\mathbf{D}_c$ . In other words  $J_2$  measures the quality of reconstructing a sample  $(\mathbf{x}_n, \mathbf{y}_n = c)$  over the sole dictionary  $\mathbf{D}_c$ . It aims to minimize intra-class homogeneity.



Beyond these fitting errors, our learning scheme involves some regularization terms. The first one

$$J_3(\mathbf{A}) = \sum_{n=1}^N \|\mathbf{a}_n\|_1$$

is the classical sparsity regularization in overcomplete dictionary learning while

$$J_4(\mathbf{A}) = \sum_{n=1}^N \sum_{c=1}^C \mathbb{1}_{y_n \neq c} \|\mathbf{a}_{nc}\|_2^2$$

aims to push towards zero the coefficients  $\mathbf{a}_{nc}$  of the signal  $\mathbf{x}_n$  representation over non-class specific dictionary  $\mathbf{D}_j$ ,  $j \neq y_n$ . Finally

$$J_5(\mathbf{D}) = \sum_{c=1}^C \sum_{\substack{c'=1 \\ c' \neq c}}^C \|\mathbf{D}_c^T \mathbf{D}_{c'}\|_F^2$$

encourages the pairwise orthogonality between different dictionaries. The last two regularization terms are deemed to promote large class separability of the learned coefficients.

$\mu, \lambda, \gamma_1$  and  $\gamma_2$  are regularization parameters controlling respectively the class specific fitting error, the sparsity level of each signal, the sparsity structure of the codes and pairwise orthogonality of learned dictionaries. From this formulation we derive an optimization framework presented hereafter.

### 3.3 Optimization scheme

The optimization problem (2) may seem complicated but it can be solved based on an alternating optimization scheme which involves a sparse coding step and dictionary optimization step. Indeed, problem (2) is convex in  $\mathbf{D}_c$  for the coefficients  $\mathbf{a}_{nc}$  fixed and is so the reverse way when the  $\mathbf{D}_c$  are fixed.

#### 3.3.1 Sparse coding step

Assume the dictionaries  $\{\mathbf{D}_c\}_{c=1}^C$  are fixed; we estimate the sparse codes  $\{\mathbf{a}_n\}_{n=1}^N$  using a Lasso-type algorithm [28]. Minimizing  $J(\mathbf{D}, \mathbf{A})$  with relation to  $\mathbf{A}$  amounts to minimize  $J_1(\mathbf{D}, \mathbf{A}) + \mu J_2(\mathbf{D}, \mathbf{A}) + \lambda J_3(\mathbf{A}) + \gamma_1 J_4(\mathbf{A})$  over  $\mathbf{A}$

as the other terms in  $J$  are independent of  $\mathbf{A}$ . Moreover for each signal  $\mathbf{x}_n$  of class  $y_n$ , the related vector  $\mathbf{a}_n$  is decoupled in the optimization problem. Let  $y_n = c'$ ; by putting apart all terms that do not involve  $\mathbf{a}_n$ , we are to solve the following optimization problem to estimate  $\mathbf{a}_n$ :

$$\min_{\mathbf{a}_n} \|\mathbf{x}_n - \mathbf{D}\mathbf{a}_n\|_2^2 + \mu \|\mathbf{x}_n - \mathbf{D}_{c'}\mathbf{a}_{nc'}\|_2^2 + \gamma_1(\|\mathbf{a}_n\|_2^2 - \|\mathbf{a}_{nc'}\|_2^2) + \lambda \|\mathbf{a}_n\|_1 \quad (3)$$

$$\text{where } \|\mathbf{a}_n\|_2^2 = \sum_{c=1}^C \|\mathbf{a}_{nc}\|_2^2 \text{ and } \sum_{c=1}^C \mathbb{1}_{c \neq c'} \|\mathbf{a}_{nc}\|_2^2 = \|\mathbf{a}_n\|_2^2 - \|\mathbf{a}_{nc'}\|_2^2$$

It can be seen that (3) consists of quadratic error terms and elastic-net type penalization ( $\ell_1 - \ell_2$  norm penalty). Thus this problem is amenable to a Lasso problem which can be solved by a classical Lasso solver [28].

### 3.3.2 Dictionary optimization step

Here we illustrate the estimation of  $\{\mathbf{D}_p\}_{p=1}^C$  while fixing  $\{\mathbf{a}_n\}_{n=1}^N$ . Optimizing  $J$  w.r.t the dictionaries  $\mathbf{D}_p$  is equivalent to solve  $\min_{\{\mathbf{D}_p\}_{p=1}^C} J_1(\mathbf{D}, \mathbf{A}) + \mu J_2(\mathbf{D}, \mathbf{A}) + \gamma_2 J_5(\mathbf{D})$  under the constraints  $\|\mathbf{d}_{pk}\|_2^2 \leq 1, \forall p, k$ . As the objective functions  $J_1$ ,  $J_2$  and  $J_5$  are all quadratic with respect to the  $\mathbf{D}_p$  and the constraints are simple, we adopt a gradient projection approach [7]. it consists to update iteratively the dictionaries by  $\mathbf{D}^t = \text{Prox}(\mathbf{D}^{t-1} - \eta_t \nabla J(\mathbf{D}^{t-1}, \mathbf{A}^t))$  that is taking a gradient step followed by a projection onto the constraints via the proximal projection operator  $\text{Prox}$  (see Algorithm 1). This requires the computation of the gradient of the objective function with respect to  $\mathbf{D}_p$  which is defined as follows:

$$\nabla_{\mathbf{D}_p} J(\mathbf{D}, \mathbf{A}) = \nabla_{\mathbf{D}_p} J_1(\mathbf{D}, \mathbf{A}) + \mu \nabla_{\mathbf{D}_p} J_2(\mathbf{D}, \mathbf{A}) + \gamma_2 \nabla_{\mathbf{D}_p} J_5(\mathbf{D}) \quad (4)$$

The involved terms are obtained below using the matrix derivation formula [42].

Notice that  $J_1(\mathbf{D}, \mathbf{A}) = \sum_{n=1}^N \|\mathbf{x}_n - \mathbf{D}\mathbf{a}_n\|_2^2$  can also take the form  $J_1(\mathbf{D}, \mathbf{A}) =$

$\sum_{n=1}^N \|\tilde{\mathbf{x}}_n - \mathbf{D}_p \mathbf{a}_{np}\|_2^2$  where  $\tilde{\mathbf{x}}_n = \mathbf{x}_n - \sum_{\substack{c=1 \\ c \neq p}}^C \mathbf{D}_c \mathbf{a}_{nc}$ . Hence the derivative is

$$\nabla_{\mathbf{D}_p} J_1(\mathbf{D}, \mathbf{A}) = \sum_{n=1}^N -2\tilde{\mathbf{x}}_n \mathbf{a}_{np}^T + 2\mathbf{D}_p \mathbf{a}_{np} \mathbf{a}_{np}^T \quad (5)$$

Similarly we can express the term  $J_2$  as  $J_2(\mathbf{D}, \mathbf{A}) = \sum_{n=1}^N \mathbb{I}_{y_n=p} \|\mathbf{x}_n - \mathbf{D}_p \mathbf{a}_{np}\|_2^2 + \sum_{n=1}^N \sum_{c \neq p} \mathbb{I}_{y_n=c} \|\mathbf{x}_n - \mathbf{D}_c \mathbf{a}_{nc}\|_2^2$ . Hence the second term of the gradient writes

$$\nabla_{\mathbf{D}_p} J_2 = \sum_{n=1}^N \mathbb{I}_{y_n=p} - 2\mathbf{x}_n \mathbf{a}_{np}^T + 2\mathbf{D}_p \mathbf{a}_{np} \mathbf{a}_{np}^T \quad (6)$$

Finally expressing  $J_5(\mathbf{D}) = \sum_{c \neq p} 2 \|\mathbf{D}_p^T \mathbf{D}_c\|_F^2 + \sum_{c \neq p} \sum_{\substack{c' \neq c \\ c' \neq p}} \|\mathbf{D}_c^T \mathbf{D}_{c'}\|_F^2$  we get the

last term of the gradient as

$$\nabla_{\mathbf{D}_p} J_5(\mathbf{D}) = \sum_{c \neq p} 4(\mathbf{D}_c \mathbf{D}_c^T) \mathbf{D}_p \quad (7)$$

Algorithm 1 summarizes the different steps of our alternating optimization scheme: the first step consists of a signal sparse coding based on the Lasso algorithm. The second step is dictionary optimization based on proximal gradient descent approach. The proximal procedure allows to handle the atom normalization constraint  $\|\mathbf{d}_{ck}\|_2^2 \leq 1$  in the problem (2).

### 3.4 Classification

Our overall signal classification scheme consists of the following steps:

- (i) the class specific dictionaries  $\{\mathbf{D}_c\}_{c=1}^C$  are estimated in a supervised way using Algorithm 1 as shown in figure 1;
- (ii) the dictionaries are then used to encode the training signals (based on Lasso), leading to the sparse codes  $\{\mathbf{a}_n\}_{n=1}^N$  which serve as features to learn an SVM function  $h$ . This is summarized by the processing flow in figure 2; and

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**Algorithm 1** The optimization algorithm

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- 1: **Initialization:**  $\mathbf{D}^0$ ,  $t \leftarrow 1$ , initialize  $\eta_0$  and  $\alpha \in (0, 1)$
  - 2: **while**  $t \leq T$  **do**
  - 3:   Solve for  $\mathbf{A}^t \leftarrow \underset{\mathbf{A}}{\operatorname{argmin}} J(\mathbf{D}^{t-1}, \mathbf{A})$  using Lasso algorithm applied to (3)
  - 4:   Compute the gradient  $\mathbf{G}^t = \nabla_{\mathbf{D}} J(\mathbf{D}^{t-1}, \mathbf{A}^t)$  based on eq. (4) to (7)
  - 5:    $\eta \leftarrow \eta_0$
  - 6:   **repeat**
  - 7:      $\mathbf{D}^{\frac{t}{2}} \leftarrow \mathbf{D}^{t-1} - \eta \mathbf{G}^t$
  - 8:      $\mathbf{D}^t \leftarrow \operatorname{Prox}(\mathbf{D}^{\frac{t}{2}})$
  - 9:      $\eta \leftarrow \eta \times \alpha$
  - 10:   **until**  $J(\mathbf{D}^t, \mathbf{A}^t) < J(\mathbf{D}^{t-1}, \mathbf{A}^{t-1})$
  - 11:    $t \leftarrow t + 1$
  - 12: **end while**
- 

$$\text{with} \quad \operatorname{Prox}(\mathbf{D}^{\frac{t}{2}}) : \{\mathbf{d}_k\}_{k=1}^K = \begin{cases} \mathbf{d}_k & \text{if } \|\mathbf{d}_k\|_2 \leq 1 \\ \frac{\mathbf{d}_k}{\|\mathbf{d}_k\|_2} & \text{otherwise} \end{cases}$$

- (iii) any testing signal is classified by computing its sparse representation which is fed to the classifier  $h$  to predict the corresponding label (see figure 3).

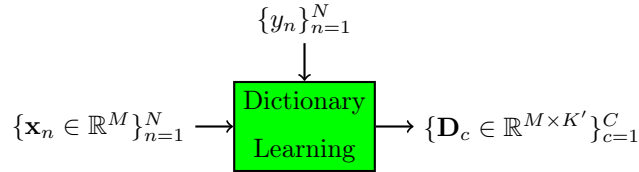


Figure 1: Processing flow of dictionary learning on the training set.

To solve our  $C$ -class audio classification problem we employ one-against-all strategy [59]. Note that in our case we have used a simple linear kernel as the non-linear aspect of the problem is taken into account in the dictionary learning. This is customary in supervised dictionary classification [38, 36].

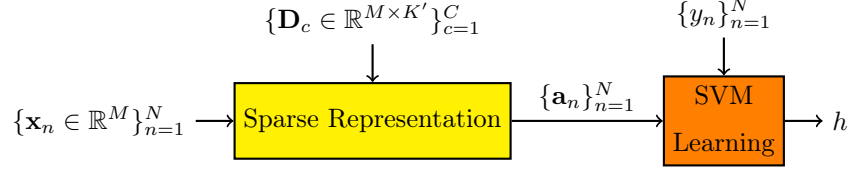


Figure 2: Processing flow of SVM training over the learned dictionary and training set.

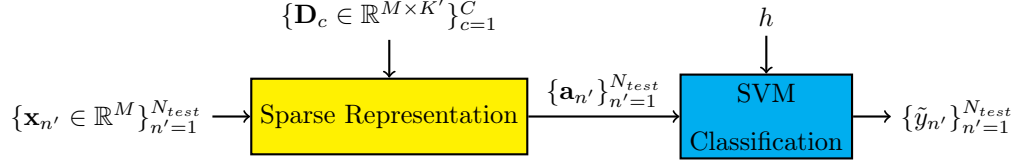


Figure 3: Processing flow of classification over testing set.

## 4 Experiments

We conduct our experiments on two different audio signal classification problems, Computational Auditory Scene Recognition (CASR) and music chord recognition. For each problem, our dictionary learning based on a initial time-frequency representation is compared to conventional predefined features.

### 4.1 Computational auditory scene recognition (CASR)

In this section we briefly review different approaches to tackle CASR problem as well as the evaluation of our proposed dictionary learning technique compared with predefined features based approaches on two datasets: East Anglia (EA) and LITIS Rouen.

Several categories of audio features have been employed in CASR systems [4]. A considerable amount of works have applied MFCCs for CASR. Aucouturier *et al.* [3] used Gaussian Mixture Model (GMM) to estimate the distribution of MFCC coefficients. Ma *et al.* [34] combined MFCCs with Hidden Markov Models (HMM). Cauchi [9] exploited Non-Negative Matrix Factorization (NMF) with MFCC features. Hu *et al.* [23] employed MFCC features in a two-stage framework based on GMM and SVM. Lee *et al.* [30] used sparse restricted Boltzmann machine to capture relevant MFCC coefficients. Geiger *et al.* [21]

extracted a large set of features including MFCCs using a short sliding window approach. SVM is used to classify these short segments, and a majority voting scheme is employed for the whole sequence decision. Roma *et al.* [57] applied Recurrence Quantification Analysis (RQA) on the MFCCs for supplying some additional information on temporal dynamics of the signal.

Another trend is to extract discriminative features from time-frequency representations. Cotton and Ellis [10] applied NMF to extract time-frequency patches. Benetos *et al.* [5] used temporally-constrained Shift-Invariant Probabilistic Latent Component Analysis (SIPLCA) instead of NMF in order to extract time-frequency patches from spectrogram. Yu and Slotine [69] proposed a method based on treating time-frequency representations of audio signals as image texture. In the same context, Dennis *et al.* [13] introduced novel sound event image representation called Subband Power Distribution (SPD). The SPD captures the distribution of the sound’s log-spectral power over time in each subband. Rakotomamonjy and Gasso [44] proposed to use Histogram of Oriented Gradient to extract information from time-frequency representations.

#### 4.1.1 Datasets

We rely our experiments on two representative datasets described hereafter.

- East Anglia (EA): this dataset <sup>1</sup> provides environmental sounds [35] coming from 10 different locations: *bar, beach, bus, car, football match, laundrette, lecture, office, rail station, street*. In each location a recording of 4-minutes at a frequency of 22.1 kHz has been collected. The 4-minutes recordings are splitted into 8 recordings of 30-seconds so that in total we have 10 locations (classes) and each class has 8 examples of 30-seconds.
- Litis Rouen: this dataset <sup>2</sup> provides environmental sounds [44] recorded in 19 locations. Each location has different number of 30-seconds examples downsampled at 22.5 kHz. Table 2 summarizes the content of the dataset.

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<sup>1</sup>[http://lemur.cmp.uea.ac.uk/Research/noise\\_db/](http://lemur.cmp.uea.ac.uk/Research/noise_db/)

<sup>2</sup><https://sites.google.com/site/alainrakotomamonjy/home/audio-scene>

Table 2: Summary of Litis Rouen audio scene dataset.

Classes	# examples
plane	23
busy street	143
bus	192
cafe	120
car	243
train station hall	269
kid game hall	145
market	276
metro-paris	139
metro-rouen	249
billiard pool hall	155
quite-street	90
student hall	88
restaurant	133
pedestrian street	122
shop	203
train	164
high-speed train	147
tube station	125

#### 4.1.2 Competing features and protocols

In the following we introduce the different features used in our experiments as well as the data partition and protocols.

##### *Features*

Based on an initial time-frequency representation (spectrogram) computed on sliding windows of size 4096 samples and hops of 32 samples, we apply our dictionary learning method. In order to evaluate the efficiency of our proposed method, we compare its performance to the following conventional features:

- Bag of MFCC: consists in calculating the MFCC features on windows of size 25 ms with hops of 10 ms. For each window, 13 cepstra over 40 bands are computed (lower and upper band are set to 1 and 10 kHz). The final feature vector is obtained by concatenating the average and standard deviation of the batch of 40 windows with overlap of 20 windows.

- Bag of MFCC-D-DD: in addition to the average and standard deviation, the first-order and second-order differences of the MFCC over the windows are concatenated to the feature vector.
- Texture-based time-frequency representation: it consists on extracting features from time-frequency texture [69].
- Recurrent Quantification Analysis (RQA): aims to extract from MFCCs some additional information on temporal dynamics. For all MFCCs obtained over 40 windows with overlap of 20, 11 RQA features have been computed [57]. Afterwards, MFCC features and RQA features are all averaged over time and MFCC averages, standard deviations as well as the RQA averages are concatenated to form the final feature vector.
- HOG of time-frequency representation: applies HOG to time-frequency representations transformed to images. The time-frequency representations are calculated based on Constant-Q Transform (CQT). HOG is able to provide information about the occurrence of gradient orientations in the resulting images [44].

More details about these features can be found in [44]. Note that for classification, linear Support Vector Machine (SVM) is applied.

#### *Protocols and parameters tuning*

For sake of comparison we have performed the same experiments using the same repartitions and protocols in [44]. We have averaged the performances from 20 different splits of the initial data into training and test. The training set represents 80 % of data while the rest represents the test set.

Our proposed dictionary learning technique requires the tuning of some hyper-parameters:  $K'$  the size of each dictionary  $\mathbf{D}_c$ ,  $\lambda$ ,  $\gamma_1$ ,  $\gamma_2$  controlling respectively, the sparsity, the structure of sparse coefficients and the pairwise orthogonality of learned dictionaries and  $\mu$  the weight affected to the class



specific reconstruction error  $J_2$ . To avoid a tedious hyper-parameters' selection step and guided by empirical findings, we fix  $\mu = 1$ . Hence the remaining parameters are determined as follows:

- $\lambda$ ,  $\gamma_1$  and  $\gamma_2$  are selected among  $\{0.1, 0.2, 0.3\}$ .
- the size  $K'$  of each dictionary is explored among  $\{10, 20, 30\}$ .

Beyond that we use a linear SVM classifier which regularization parameter  $C_{svm}$  is selected among 10 values logarithmically scaled between 0.001 and 100. All these parameters are tuned according to a cross-validation scheme. Model selection is performed by resampling 5 times the training set into learning and validation sets of equal size. The best parameters are considered as those maximizing the averaged performances on the validation sets. Note that K-SVD [1] has been used to initialize the class based dictionaries and the parameters  $T = 200$ ,  $\alpha = 0.5$  and  $\eta = 10^{-3}$  were applied for the optimization scheme (see Section 3.3).

#### 4.1.3 Results and analysis

Table 3 represents the performance (classification accuracy) comparison between different conventional features as reported in [44] and our class based dictionary method on Rouen and EA datasets. Texture denotes the work of [69] while MFCC-D-DD denotes the MFCC with derivatives features. MFCC, MFCC-RQA, MFCC-900 and MFCC-RQA-900 respectively denote, MFCC features, the MFCC with RQA with cut-off frequency of 10 kHz, the MFCC and the MFCC combined RQA with upper frequency set at 900 Hz respectively. HOG-full and HOG-marginalized represent the concatenation of histogram obtained from different cells resulting in a very-high dimensionality feature vector and the concatenation of the averaged histograms over time and frequency respectively.

It can be seen in Table 3 that HOG-marginalized outperforms all competing features in Rouen dataset. Note also that MFCC+RQA features are performing better than other MFCC based features, however the cut-off-frequency of 900 Hz leads to a large loss in performance. We can also notice that our proposed

Table 3: Comparison of performances related to different feature representations on Rouen, EA audio scene classification datasets. Bold values stand for best values on each dataset.

Features	Rouen	EA
Texture	-	$0.57 \pm 0.13$
MFCC-D-DD	$0.66 \pm 0.02$	$0.98 \pm 0.04$
MFCC	$0.67 \pm 0.01$	<b><math>1.00 \pm 0.01</math></b>
MFCC-900	$0.60 \pm 0.02$	$0.91 \pm 0.07$
MFCC+RQA	$0.78 \pm 0.01$	$0.95 \pm 0.08$
MFCC+RQA-900	$0.72 \pm 0.02$	$0.93 \pm 0.06$
HOG-full	$0.84 \pm 0.01$	$0.99 \pm 0.02$
HOG-marginalized	<b><math>0.86 \pm 0.01</math></b>	$0.97 \pm 0.06$
Dictionary learning	$0.71 \pm 0.01$	$0.97 \pm 0.04$

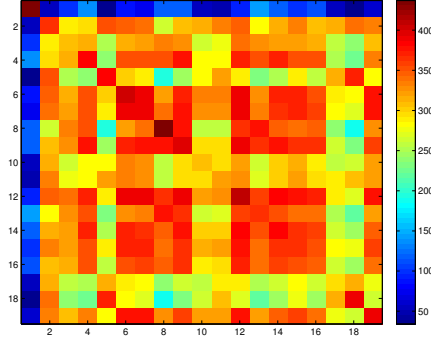


Figure 4: Similarity between different learned dictionaries on Rouen dataset. X-axis and Y-axis stand for the class numbers organized in the same order in Table 2.

dictionary learning is giving very promising results and is outperforming texture and conventional speech recognition feature, MFCC and MFCC-D-DD features which have been widely used in the literature and have showed their ability to tackle the problems of audio scene recognition. Finally, in the East Anglia dataset, all features including our proposed dictionary learning perform well except texture, however we should note a slight advantage of MFCC.

Figure 4 shows the pairwise similarity of the learned dictionaries per class

on Rouen dataset. The idea behind estimating the similarity between different learned dictionaries is to verify the initial goal to learn dissimilar dictionaries able to extract diverse information from classes for discrimination purpose. It can be seen that there is some similarity between some learned dictionaries which could influence the classification accuracy since these dictionaries tend to provide similar information for different classes. This may be related to the increasing number of classes that makes enforcing the pairwise dictionaries dissimilarity hardly feasible.

#### 4.2 Music chord recognition

The simplest definition of a chord is few musical notes played at the same time. In western music, each chord can be characterized by the:

- *root or fundamental*: the fundamental note on which the chord is built
- *number of notes*
- *type*: gives the interval scheme between notes

A music signal can be deemed composed of sequences of these different chords. Commonly, the duration of the chords in the sequence varies over time rendering their recognition difficult. Given a raw audio signal, chord recognition system attempts to automatically determine the sequence of chords describing the harmonic information. To recognize chords most approaches rely on features crafted based on time-frequency representation of the raw signals, the most common and dominant features being chroma [39]. Pitch Class Profiles (PCP) or chroma vectors was introduced by Fujishima [18]. It is a 12-dimensional vectors representing the energy within an equal-tempered chromatic scale  $\{C, C^\#, D, \dots, B\}$ . The chroma has several variations, among them we can cite Harmonic Pitch Class Profiles (HPCPs) which is an extension of the Pitch Class Profiles (PCPs) by estimating the harmonics [41] and Enhanced Pitch Class Profile (EPCP) which is calculated using the harmonic product spectrum [29]. Chroma vectors were combined with different machine learning techniques [60, 64].

#### 4.2.1 Dataset

We will focus on third, triad and seventh chords which are respectively composed of 2, 3 and 4 notes. When a note B has twice the frequency of a note A, the interval  $[A\ B]$  forms an octave. In tempered occidental music, the smallest subdivision of an octave is a semitone which corresponds to one twelfth of an octave, that is a multiplication by  $\sqrt[12]{2}$  in term of frequency. To be tertian, i.e a standard harmony, each interval between notes in a chord must be composed of 3 or 4 semitones. These intervals are respectively called *minor* and *Major*. Thus, for a given root, there is 2 possible thirds, 4 possible triads, and 8 possible sevenths. Table 4 sum-up all the possible tertian third, triad and seventh chords. The pursued goal in this work is to guess the type and not the fundamental of a chord leading to 14 possible labels ( $= 2 + 4 + 8$ ). For this purpose, we have created a dataset which contains 2156 music chord samples of duration 2-seconds at frequency 44100 Hz with the 14 different classes. Each class contains 154 samples from 11 different instruments at different fundamentals.

Table 4: Different kind of tertian chords, intervals are in semitones

# of notes	Common name or type	1st interval	2nd int.	3rd int.
2	Minor third	3	-	-
2	Major third	4	-	-
3	Diminished triad	3	3	-
3	Minor triad	3	4	-
3	Major triad	4	3	-
3	Augmented triad	4	4	-
4	Diminished seventh	3	3	3
4	Half-diminished seventh	3	3	4
4	Minor seventh	3	4	3
4	Minor major seventh	3	4	4
4	Dominant seventh	4	3	3
4	Major seventh	4	3	4
4	Augmented major seventh	4	4	3
4	Augmented augmented seventh	4	4	4

#### *4.2.2 Competing features and protocols*

In the following we introduce the different features used in our experiments as well as the data partition and protocols.

##### *Features*

Similar to the previous application we compute an initial time-frequency representation (spectrogram) on sliding windows of size 4096 samples and hops of 32 samples. Then we apply our dictionary learning method. The resulting sparse representations are used as inputs of an SVM. The following conventional features serve as competitors to our approach.

- Spectrogram pooling: represents the temporal pooling of the spectrogram.
- Interpolated power spectral density: music notes follow an exponential scale, however Power Spectral Density (PSD) is based on Fourier transform which follows a linear scale. To address this problem PSD (which lies on a linear scale) is sampled at specific frequencies corresponding to 96 notes leading to an exponential representation more suitable for chord recognition [54].
- Chroma: it represents a 12-dimensional vector, every component represents the spectral energy of a semi-tone within the chromatic scale. Chroma vector entries are calculated by summing the spectral density corresponding to frequencies belonging to the same chroma [39].

##### *Protocols and parameters tuning*

We have averaged the performances from different 10 splits of the initial data into training and test. The training set represents 2/3 of data. Model selection is performed by resampling 2 times the training set into learning and validation set of equal size. The best parameters are considered as those maximizing the averaged performances on the validation sets. Note that the parameters are chosen from the same intervals used above in the computational auditory scene recognition problem.

#### 4.2.3 Results and analysis

Table 5 reports the performance (classification accuracy) comparison of evaluated features on music chord dataset. It can be seen that our dictionary learning method outperforms all other approaches.

Table 5: Comparison of performances related to different feature representations on music chord dataset based on linear SVM. Bold value stands for best performance.

Features	Music chord
Chroma	$0.19 \pm 0.01$
Interpolated PSD	$0.15 \pm 0.02$
Spectrogram pooling	$0.14 \pm 0.01$
Dictionary learning	<b><math>0.66 \pm 0.01</math></b>

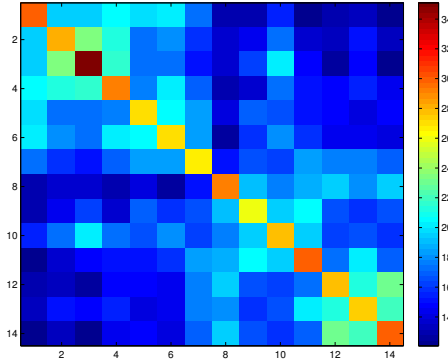


Figure 5: Similarity between different learned dictionaries on music chord dataset. X-axis and Y-axis stand for the class numbers.

Figure 5 shows the pairwise similarity between the learned dictionaries. Contrary to CASR Rouen dataset, it can be seen that the highest similarity between learned dictionaries is on the diagonal. This means that the resulting dictionaries are different between them leading to extract diverse information per class. While chroma, interpolated PSD and spectrogram failed totally to reach good performances based on a linear SVM, our dictionary learning method could achieve very promising results. As a conclusion, the sparse coding of the signals

over the learned dictionaries can be seen as a nonlinear feature mapping which is able to disentangle the factors of variation within the audio samples of different labels.

## 5 Conclusion

We have proposed a novel supervised dictionary learning method for audio signal recognition. The proposed method seeks to minimize the intra-class homogeneity, maximize the class separability and promote the sparsity to control the complexity of the signal decomposition over the dictionary. This is done by learning a dictionary per class, minimizing the class based reconstruction error and promoting the pairwise orthogonality of the dictionaries. The learned dictionaries are supposed to provide different information per class. The resulting problem is non-convex and solved using a proximal gradient descent method.

Our proposed method was extensively tested on two different audio recognition applications: computational auditory scene recognition and music chord recognition. The obtained results were compared to different conventional pre-defined features. While there is no universal pre-specified feature representation able to successfully tackle different audio recognition problems, our proposed dictionary learning method combined with a simple linear classifier showed very promising results while dealing with two different audio recognition tasks.

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