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Sparse molecular image representation ☆

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ABSTRACT

Sparsity-based models have proven to be very effective in most image processing applications. The notion of sparsity has recently been extended to structured sparsity models where not only the number of components but also their support is important. This paper goes one step further and proposes a new model where signals are composed of a small number of molecules, which are each linear combinations of a few elementary functions in a dictionary. Our model takes into account the energy on the signal components in addition to their support. We study our prior in detail and propose a novel algorithm for sparse coding that permits the appearance of signal dependent versions of the molecules. Our experiments prove the benefits of the new image model in various restoration tasks and confirm the effectiveness of priors that extend sparsity in flexible ways especially in case of inverse problems with low quality data.

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1. Introduction

Most tasks in signal processing and analysis are significantly simplified when the data is represented into its right form, especially for high-dimensional signals like images. The quest for the right signal representation has fostered the use of overcomplete dictionaries as tools for signal compression, denoising, enhancement and various other applications. Dictionaries have the advantage to have very few constraints in their construction, so that they can be finally adapted to the data processing task at hand. However, this flexibility has a price: the representation of a signal is unfortunately not unique in overcomplete dictionaries, and finding the best such representation is generally an ill-posed problem. As a result, well-chosen priors or models about the signal representation become necessary in order to develop effective signal processing algorithms with overcomplete representations.

The most common models in overcomplete signal representations are based on sparsity priors. This means that the signal is well represented by only a few components or atoms of the overcomplete dictionary. Sparsity is a pretty intuitive prior that is also biologically plausible, as shown in the pioneer work of Olshausen and Field [1] where it is suggested that sparsity could be a property employed by the mammalian visual system for achieving efficient representations of natural images. Vast research efforts have been deployed in the last decades in order to design algorithms that solve the hard problem of sparse decomposition of signals by effective approximation [2,3] or convex relaxation [4,5].

While sparsity is a simple and generic model, it is not always a sufficient prior to obtain good signal reconstruction, especially if the original data measurements are compressed or inaccurate. More effective signal models can therefore be built by considering the dependencies between the dictionary elements that appear in the signal representation instead of their number only. In that spirit, group sparsity has been introduced as a way to enforce a pre-specified structure in the decomposition. Specifically, the components of the dictionary are partitioned into groups and the elements of each group are encouraged to appear simultaneously in the signal decomposition [6]. Alternatively, the atoms can also obey a predefined hierarchical structure [7]. Other approaches have considered additional flexibility by constraining the signal decomposition to include elements from overlapping groups of atoms [8–10]. The group sparsity structure is however not always appropriate for modeling signal patterns as the groups are merely identified in terms of their support. It is however not suitable for differentiating patterns with the same support but different distributions, which could actually be very different signal patterns. Such a case is presented in Fig. 1 where we show how much the image of a face can change when varying the coefficients of its sparse code while keeping the same support. This ambiguity is unfortunately a serious drawback in various applications such as signal recovery and recognition, for example.

We propose here a new signal model to represent signal patterns and higher level structures. Our goal is to build richer priors

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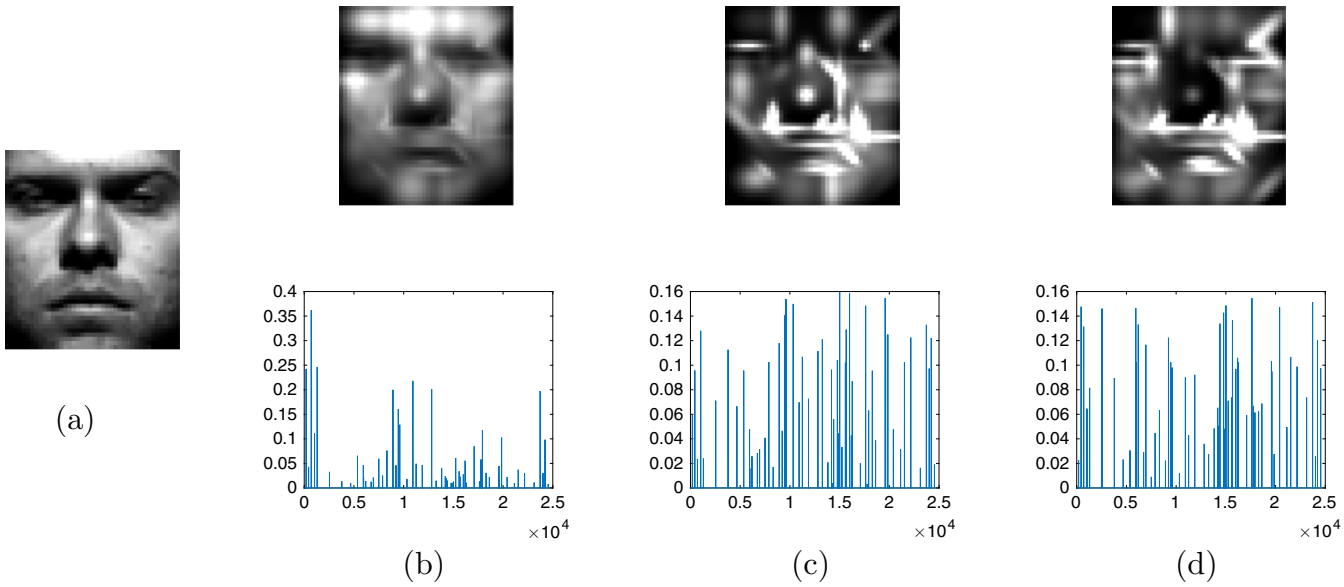

Fig. 1. An example of the ambiguity related to the support of the sparse codes. In (a) we show the image of a face and in (b) its sparse approximation with 60 atoms on a dictionary of Gaussian atoms. The next two columns are produced by randomly choosing the values of the coefficients on the same support. The final signal is then normalized. The resulting images are quite different than the original face proving the importance of the coefficients along with the support of the sparse code.

than classical structured sparsity models that merely focus on the support of the signal representation and not on the actual energy distribution. Our model builds on our previous work on structured sparsity [11] and represents signals as sparse sets of molecules, which are linear combinations of atoms from a redundant dictionary of elementary functions. To enhance the flexibility of our model, in this work we go one step further and instead of allowing only small variations in the coefficients of the molecules, we allow molecule realizations to appear in various forms that can have small deviations on both their coefficients and their support. To this end, we form pools of similar atoms in the dictionary, and assume that all atoms in a pool carry similar information. The molecule realizations are then defined as slightly deformed versions of the molecule prototypes, where atoms could be replaced by similar atoms from their respective pools. As a result, a given molecule prototype represents a group of structurally similar patterns whose exact form in signals is controlled by the construction of the atom pools. This provides flexibility in the representation of signals with molecules, while preserving the main structural information in the sparse signal approximation.

We study in details our new structured sparsity model and analyze the recovery performance of molecule representations. We formally show that our choice of the synthesis dictionary based on molecules realizations provides a good compromise between structure and flexibility. Then we propose a novel constructive sparse coding algorithm of signals with our new structured sparsity model. We exploit the characteristics of atoms pools to design effective similarity measures for detecting molecule realizations in signals. Finally, we show the use of our new framework with illustrative experiments in various applications such as compressed sensing, inpainting and denoising. Our results show that the new structured sparsity prior leads to better reconstruction performance than classical sparsity priors due to its flexible molecule-based representation.

Our efficient structured sparsity model represents a quite unique framework in the literature. In particular, the consideration of the coefficient distribution and the atom pools, as well as the definition of both molecule prototypes and realizations, are important characteristics of our new signal representation model. The coefficients permit to differentiate structures with distinct energy distributions on the same support and thus to facilitate the proper recovery of image information in case of incomplete or inaccurate observations. Another definition of molecule has been previously proposed in [12] to describe a set of coherent atoms in a dictionary, but it is more related to the notion of a group or a pool of atoms than to our original definition of a molecule. Multi-level structures are also related to the concept of double sparsity introduced in [13] where the authors learn structures on top of a set of predefined set of atoms. It is however less flexible than our model, where we include the notion of pools and molecules realizations that enable the proper handling of minor structure deformation in the signals. Less close to our model, some recent works describe the statistical dependencies between the atoms in a dictionary with graphical models. For example, Markov Random Fields (MRFs) are employed for modeling these dependencies in [14–16]. The resulting structure model is a probability distribution function that compares the different possible supports of atoms in the signal representation. These models are quite powerful but unfortunately quite complicated and highly parametric, such that they are difficult to deploy and adapt to various applications. Next, the idea of pooling that is used for defining molecules realizations is quite often used under different forms to provide local invariance [17,18] in the signal representation. In our case however, it provides local invariance to small deformations of a set of atoms with higher resilience to sparse code variability in the identification of typical patterns in images. Finally, the differentiation between the molecule prototypes and molecule realizations in our new model leads to realizations of structures that are signal dependent, like in [19,20]. Hence, the signal representation is flexible but nevertheless follows a pre-defined structure. The specific characteristics of our scheme make it very suitable for various signal processing tasks and especially signal denoising and inpainting.

The structured sparsity model proposed in this paper is essentially a two-layer architecture with the first layer consisting of the dictionary atoms and the second of the molecules. The benefits of such architectures over the flat ones has been a subject of research for a long time in the feature extraction and machine learning community. It has been validated experimentally in the case of signal recognition in [21] while the mere existence of the field of deep learning can argue in benefit of multistage architectures. The deep learning systems consist of a hierarchy of features along with some pooling and contrast normalization operators that

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