Dictionary-based Methods for Building Efficient and Meaningful Signal Models

[Extended Abstract]

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ABSTRACT

This poster will outline some of our recent contributions to using dictionary-based methods (also called sparse approximation) for building efficient and meaningful models of signals.

1. INTRODUCTION

A sparse and efficient model of a signal, or more generally, any data, can be found heuristically by iteratively decomposing it over a redundant and overcomplete set (dictionary) of functions (atoms). Sparse approximation algorithms, called "pursuits," have been developed to find signal models that are constrained by, for instance, minimizing the number of atoms selected at a given distortion, or meeting a distortion criterion within a given number of terms [1, 8]. More generally, we call such methods "dictionary-based" since they decompose a signal in terms of elements of a user-defined dictionary [15].

Such approaches have been motivated in part by fundamental problems inherent to efficiently and meaningfully modeling signals rich with structure using an orthogonal basis [2,3,7]. Using a dictionary that may be a union of two or more orthogonal bases, a pursuit adapts a basis in a manner that preserves the significant characteristics of the signal. Sparse approximation has found use in, among other things, data analysis [4, 23], signal compression and coding [2, 6, 10], and signal transformation [5, 13, 22].

Our work in this field addresses the issue of maintaining an informative and useful correspondence between the content of a signal and the elements of its model, which we broadly call "meaningfulness" [12, 16–22]. For instance, in the application of audio analysis and transformation, we want a direct correspondence between the parameters of time-frequency atoms selected by a pursuit for the signal model, and the characteristics of the signal. Such a model will provide an unambiguous interpretation of the signal in terms of those atoms. This is not a trivial task with pursuits that are built on the principle of greedy iterative descent using redundant dictionaries [12].

Another aspect of our work is in the productive use of sparse approximation for the analysis, visualization, and transformation of audio signals [13, 14]. In this realm we are less interested in the sparsity and more interested in the malleability of a signal model. Dictionary-based methods are essentially the analytical counterpart to a granular synthesis; they answer the question of how to build a given sound using the grains in the user-defined dictionary. Through the resulting atomic decompositions, one can obtain novel ways for analyzing, visualizing, and parametrically manipulating audio signals.

In our poster presentation, we will discuss sparse approximation and dictionary-based methods, and present several examples. Then we discuss our work [16, 17, 20] in increasing the meaningfulness, and consequently increasing the efficiency, of signal models produced by greedy iterative descent pursuits , such as orthogonal matching pursuit (OMP) [9,11]. We present results of finding and creating higher-level structures through the agglomerative clustering of atoms into molecules [21, 22] — which is another means of finding a meaningful signal representation.

2. REFERENCES

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