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A Review on Signal Decomposition Techniques

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Abstract: Analysis of audio and musical information signals deals with the decomposition into atoms. This subject is most interesting and useful for the researchers who want to invent the inherent properties of the signal under decomposition and to construct a new version of it. Many algorithms have been proposed for the decomposition of audio and musical content and methodologies have been demonstrated to visualizing the behavioral characteristics of such signals.This article outlines an overview of various decomposition algorithms such as high resolution matching pursuit, molecular matching pursuit, cyclic matching pursuit etc. and states the basis for that structural decomposition. Atomic decomposition of signal leads to represent the structure of audio or musical signal, allows to morph on sound into another by varying the parameter of an atom. This paper provides an overview of sound decomposition by Dictionary Based Methods (DBM). Audio signal can be decomposed into atoms by means of user-defined dictionary. This decomposition of signal using DBM can be achieved in different methods based on different parameters. DBM is useful to analyze the signal in multiple time scales such as music, environmental sound and biomedical signals.

Key words: Atoms · Matching Pursuit · Molecular Matching Pursuit · Cyclic Matching Pursuit · Signal Decomposition · Dictionary Based Methods

INTRODUCTION

Atoms are the particles which are decomposed from any audio signals and are referred as an acoustic quantum, grain, gaboret, short time segment, atom, wavelet etc and C. Roads has given 32 different names in his book [1]. Each atom is characterized by the set of parameters such as scale, time and frequency. To decompose a signal by different methods, the classification of decomposition techniques is depicted in Figure.1. Decomposition of the sound signal is represented by granular representation which carried out by Dictionary Based Methods [2] for multi resolution and Short Time Fourier Transform STFT for single time domain resolution.

Fourier analysis is an additive synthesis on other hand DBM can be seen as the analytical counterpart to a generalized granular synthesis [3]. In Fourier method, frequency resolution is influenced by the size of window which is nothing but the sample under consideration where as the DBM uses multi scale dictionary of atoms with frequency resolution and time-frequency resolution that are not related with the size of analysis sample. Another difference between Fourier and DBM is translation invariance. STFT is translation variance, which means changing the atomic parameter alters the entire characteristics of the sound. In DBM, alteration in the grain dose not affects the properties of the sound.

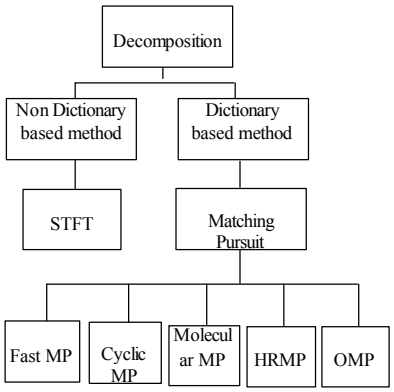

Fig. 1: Classification of Decomposition Techniques

Dictionary Based Methods (DBM): DBM otherwise referred as sparse approximation is implemented in audio, video and image signal decomposition that can be done by means of user-defined dictionary. A dictionary contains several short lengths of discrete time signals called atoms and each atom has a set of individual parameters. The parameterized

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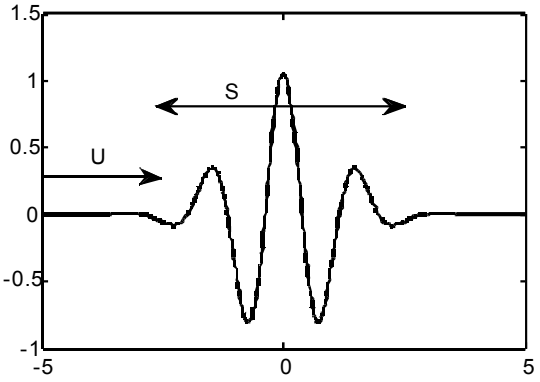


Fig. 2: An example of Gaussian atom with scale – s in ms and atom translation – u in ms

Table 1: Example Dictionary

f(n;s)	S	Δ_u	Δ_f (Hz)
Dirac	1	1	-
Rectangle	8	4	$\pi/2$
Gaussian	64	16	$\pi/4$
	128	32	$\pi/128$
Hann	1024	128	$\pi/2048$

waveforms have been interpreted against the index such as frequency, time-frequency and time-scale in the frequency dictionary or Fourier dictionary, time-frequency dictionary or Gabor dictionary and time-scale dictionary [4]. An atom can be expressed as,

$$k(n) = f(n-u;s)\cos(nw+\phi)$$

Based on the shape of the decomposed atom the function f(n;s) can be varied. Where s is the time scale, u is time translation, w is the modulation frequency. Figure 2 shows an example of a Gaussian atom with the time scale value and time translation. Table. 1 consists of several atoms with various shapes based on different parameters.

Matching Pursuit Algorithm: Normally a sound signal consists of transient and sustained parts. STFT and other transformations decomposed the signal by means of fixed basis with the transient parts of the signal represented by short waveforms and sustained parts are decomposed by long waveforms with short frequency [5]. So fixed basis decomposed methods are not enough to efficiently represent all components. An adaptive method is used to decompose the signal with efficient manner.

Matching Pursuit algorithm uses this adaptive technique to decompose the signal. This algorithm follows dictionary based methods and decomposition vectors are selected based on well localized time and frequency.

Algorithm:

Step 1: Receive the signal x(t) and set the dictionary D

Step 2: Initialization:

$Rx_1 \leftarrow x(t)$
$n \leftarrow 1$

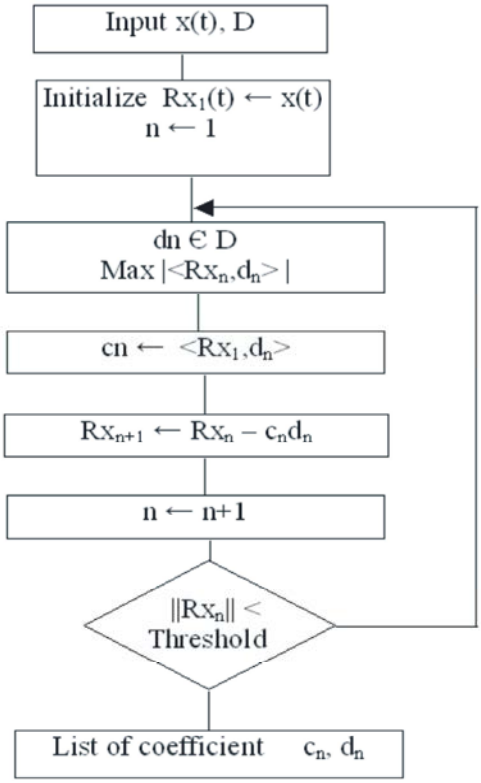
Step 3:

find d_n with maximum inner product $<Rx_n,d_n>$
$c_n \leftarrow <Rx_n,d_n>$
$Rx_{n+1} \leftarrow Rx_n - c_nd_n$
$n \leftarrow n+1$

Step 4: Repeat step 3 until ||Rxn|| < threshold

Step 5: Find the coefficients C_n, d_n

Flow Chart:



The computation time characterizes matching pursuit algorithm depends on the complexity of the data, initialization parameters and breadth of the dictionary [6]. Reducing the computational time complexities by the factor of 1.9 and 44 of accuracy & performance carried out in terms of correlation threshold (CT) that decreases the time and the dictionary size. Multiple atom extraction also reduces the time by bringing down the number of iterations. And coarse-fine grid technique enables atoms with numerous variable parameters to effectively represent the dictionary.

For effective decomposition, complete dictionary is required but majority of the atoms are not used in dictionary during the decomposition. Removal of unused atoms from the dictionary reduces the dictionary size and improves the performance without affecting the accuracy. This can be achieved by correlation threshold that is the ratio of maximum correlation value to the largest correlation of all atoms in the dictionary. This CT is calculated for all atoms during the decomposition process, based on this a reduced dictionary is formulated. When the accuracy is mandatory, more number of CT values are chosen otherwise for maximum performance gain lesser number of threshold is enough. After getting a reduced dictionary, an atom with maximum correlation is chosen but it is not immediately subtracted. Instead a fine gird around the selected atom is found from that grid, the best matched atom is estimated then this value can be subtracted from the signal.

The main limitation in the standard matching pursuit (MP) algorithm is the computational expensive which means this algorithm find the maximum inner product in lengthy manner if the dictionary is large. Hence fast and efficient schemes are used to minimize the computational complexity. Based on that the standard MP is implemented in different flavors such as fast MP, high resolution MP, cyclic MP, molecular MP and orthogonal MP.

Fast Matching Pursuit: Fast matching pursuit can be implemented by the modified MP algorithm called Fast Ridge Pursuit, which means it approximates M terms of Gaussian chirps from an N number of acoustic signals using Gaussian chirp dictionary [7]. Gribonval suggested to use fast ridge pursuit algorithm that reduce the cost of the computation complexities to O(MN) from the standard matching pursuit complexity $O(MN\log_2 N)$. Fast ridge pursuit is obtained from ridge pursuit algorithm that depends on the chirp dictionary. Standard MP Dictionary D have a set of inner products $<Rx_n,d_n>$ contains all information about Rx_n. From the theorem, [8] the behavior of $<Rx_n,d_n>$ in the neighborhood of the best atom contain enough information to select a chirp atom.

Outline steps for the ridge pursuit algorithm is given below:

- Select the best Gabor atom like standard matching pursuit algorithm
- Select a "locally optimal" chirp atom from the Gabor atom
- Compute new residual using the chirp atom

From this ridge pursuit use a sub-dictionary of local maxima of the Gabor dictionary.

Outline steps for the fast ridge pursuit algorithm is given below:

- Build a sub Dictionary D_k of L local maxima of the Gabor dictionary D.
- For each atom in D_k, use the fast local estimation procedure to get chirp atom sub dictionary.
- Run normal pursuit in D_k until it reaches to empty.

Cyclic Matching Pursuit (CMP): This approach provides lower approximation error than standard MP by means of modifying the parameters of atoms in cyclic manner. After the selection of atoms using standard MP for n-order representation

$$SD_{MP,n} = \{ H(n),d(n),c(n) \}$$
$$x(n) = H(n)d(n) + c(n)$$

Augment this representation by the rule introduced by L.Sturm in [8].

$$H(n+1) = [H(n)|h(n)]$$
$$D(n+1) = [dT(n),<c(n),h(n)>]T$$
$$C(n+1) = x - H(n+1)d(n+1)$$

and finally refined ith atoms from n atoms by means of

$Rx_{n/i} = Rx_{n/i-1} + d_n(0)c_n(0)$. Parameters $d_n(0)$ and $c_n(0)$ are the zeroth set of refined parameters. For each iteration this refinement can be implemented and to get less error during the decomposition of a signal. This approach gives the better error control but the drawback of this method is the highest computational cost.

Molecular Matching Pursuit (MMP): L.Daudet define that the audio or musical signals have a structured data such as tonal part, transient part and residual [9]. This structural information is used to group the atoms of the same class and that groups of atoms are called as molecules. Based on these molecules a molecular matching pursuit algorithm is proposed [9]. To design a molecule MP by estimating m_i atoms from Mi group and subtract from the residual. In order to decompose the signal, form two different dictionary such as discrete cosine transform and wavelet transform. Decompose the signal based on grouping the tonal molecules (group of discrete cosine transform atoms) and grouping transient molecules (group of discrete wavelet transform atoms). Decomposes the signal based on this dictionary, the MMP algorithm for signal decomposition is given below:

Step 1: Initialization: Compute tonal atoms and transient atoms of the signal x.

Step 2: Find modulus of regularity L and local tonality index T by L = max Ł and T = max T.

Step 3: Identify the most significant structure that is if L > T, the structure type is "transient molecule" otherwise if T > L, then the structure type is "tonal molecule".

Step 4: Identify the atom and redefine the residual and correlation values.

Step 5: If max (T,L) < ε_{stop} then stop, otherwise increment the i value to one and repeat step 2.

High Resolution Matching Pursuit (HRMP): Like standard matching pursuit, HRMP also used the time-frequency dictionaries in advanced manner. By using different correlation function, each step in algorithm finds the best match between the selected atoms. In standard MP, the atom selection is based on the inner product between the time-frequency atoms but a new correlation function [10] maximizes the signal energy, based on that the algorithm can select the atom in efficient manner. HRMP avoids to create an energy at time-frequency location where there was nothing. Since it creates energy at the beginning of the signal and avoids the pre-echo effects.

Algorithm of HRMP is given in the following steps:

Step 1: Initialize Rx from x(t)

Step 2: Find the atom based on the energy of the Rx located on the time-frequency dictionary d_n. This is small value compared with correlation between Rx and d_n in Standard MP

Step 3: Find the residue Rx_{n+1}

Step 4: Check the residue whether it reaches the below threshold value or not.

Step 5: If not, repeat step2 until the value should below the threshold value.

Orthogonal Matching Pursuit (OMP): OMP is somewhat similar to standard MP but the difference is, after finding the residual an orthogonality between the selected atoms calculated. This is used to avoid the redundancy of atoms chosen during the iteration process [11]. The step for an OMP is given below:

Step 1: Initialize the signal x(t) and Rx = x(t)

Step 2: Select the atom based on maximum inner product of Rxn with dn.

Step 3: Form a matrix based on the previously selected atoms as the columns. Find the orthogonal projection operator onto the span of column.

Step 4: Apply the orthogonal projection to the residue.

Step 5: Update the residue through an identity matrix.

OMP gives faster convergence for non-orthogonal dictionaries. By using full backward orthogonality of error it gives optimal approximation with respect to the selected subset of the dictionary [12]. OMP guarantees converge of the signal decomposition in efficient manner by means of limited number of steps.

CONCLUSION

While surveying the decomposition methods of musical and audio signal, it is concluded that dictionary based method with different flavors has flexibility in design procedure when compared with STFT and orthogonal transformations. This paper gives a snapshot for the beginners of the musical information technology and an eye opener manuscript for those who want to work on audio signal decomposition technology. Appropriate signal representation can be

figured out based on the decomposition analysis for various applications like musical signal processing and audio morphing, digital image processing bio-signal processing etc.

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