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Adaptive chirp mode pursuit: Algorithm and applications

Shiqian Chen [a], Yang Yang [b], Zhike Peng [a,*], Xingjian Dong [a], Wenming Zhang [a], Guang Meng [a]

[a] State Key Laboratory of Mechanical System and Vibration, Shanghai Jiao Tong University, Shanghai 200240, China
[b] Science and Technology on vehicle transmission laboratory, China North Vehicle Institute, Beijing 100072, China

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A B S T R A C T

Signal decomposition has drawn growing interest in various applications these days. Some recent decomposition methods, like the variational mode decomposition (VMD) and the variational nonlinear chirp mode decomposition (VNCMD), employ a joint-optimization scheme to accurately estimate all the signal modes underlying a signal. Some existing issues for these methods are: requiring prior knowledge of the number of the signal modes, empirically setting the bandwidth parameter to a fixed value, and lacking of an effective initialization scheme for the optimization algorithm. To address these issues, this paper presents a new decomposition approach called adaptive chirp mode pursuit (ACMP). Similar to the matching pursuit method, the ACMP captures signal modes one by one in a recursive framework. In addition, an adaptive bandwidth parameter updating rule and an instantaneous frequency initialization method based on Hilbert transform are incorporated into the ACMP. Several examples including simulated signals as well as real-life applications are provided to show the effectiveness and advantages of the ACMP.

1. Introduction

Signal or data processing has drawn increasingly attention in various fields. Signals generated by real-life physical systems usually consist of multiple superimposed oscillations which are also called signal modes [1]. These signal modes contain valuable information of the system. Therefore, extracting the constituent modes underlying the signal becomes very important to study a physical system. In some applications such as fault diagnosis of varying-speed rotating machineries [2–5], the systems will generate non-stationary signals, i.e., signals whose frequency contents change with time, also known as chirp signals [6,7]. Decomposing a chirp signal or finding its modes (referred to as chirp modes) is quite challenging for existing methods [8].

During the past decades, researchers have proposed many adaptive signal decomposition methods among which the empirical mode decomposition (EMD) method is the most popular one [9,10]. The EMD employs a recursive sifting algorithm to find each signal mode. The problem is that the sifting algorithm is empirical and therefore it is difficult to model the algorithm with mathematical theory. In addition, the sifting procedure involves detecting and interpolating local extreme points of the signal, which is sensitive to noise and suffers from end effects. Despite these limitations, the EMD is still widely used in various applications such as speech processing [11] and condition monitoring of mechanical systems [12]. Although some

* Corresponding author.
E-mail addresses: chenshiqian@sjtu.edu.cn (S. Chen), yangyang913@163.com (Y. Yang), z.peng@sjtu.edu.cn (Z. Peng), donxij@sjtu.edu.cn (X. Dong), wenmingz@sjtu.edu.cn (W. Zhang), gmeng@sjtu.edu.cn (G. Meng).

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improved versions of EMD such as ensemble EMD (EEMD) [13] and the recent time-varying filter based EMD (TVF-EMD) [14] were developed, these methods still cannot achieve desired performance.

To overcome the limitations of the EMD, many advanced alternative methods have been used. For example, some methods retrieve each signal mode from proper time-frequency (TF) distributions because TF analysis methods can better represent the time-varying frequency contents of non-stationary signals [1,15]. Decomposition methods of this type usually use a post-processing procedure to find TF coefficients (obtained by certain TF transforms) associated with each mode and then reconstruct the modes using inverse TF transforms. The synchrosqueezing transform (SST) [16] is one of the most popular methods belonging to this type because it can significantly improve the readability and the resolution of the TF distribution (TFD) by using a TF reassignment technique. Researchers also developed some improved versions of the SST such as the high-order SST [17] or the matching SST [18] for signals with fast varying frequencies, and the synchroextracting transform [19] allowing for greatly enhancing the energy concentration of the TFD. Some different methods use advanced filtering techniques to extract signal modes. For example, the variational mode decomposition (VMD) method employs the Wiener filter bank [20,21], the empirical wavelet transform (EWT) [22,23] makes use of the wavelet filter bank, and the method in [24] utilizes the adaptive local iterative filtering technique. Other authors use a different way for signal decomposition by Hilbert transform [25,26]. The basic idea of the methods of this class is that the Hilbert transform can obtain the information of signal frequencies and amplitudes which can be further used for signal reconstruction. Other more widely used schemes decompose signals by optimization. For example, the operator based methods [21,27,28] and the sparse TF methods [29–31] explicitly model each signal mode as a local narrow-band signal or an AM-FM signal, and then find the modes by optimizing a function which incorporates the regularity assumptions about the defined model. The convergence of the resulting optimization algorithms usually depends on the initialization. Therefore, how to obtain a good initialization becomes quite important for this class of methods. Other recent work reports that the subspace decomposition algorithm based on SVD can also be used to extract desired signal modes [32,33].

It is worth noting that some decomposition methods (e.g., the VMD and EWT above) work in the frequency domain and thus cannot deal with chirp modes whose frequency ranges overlap. To address this issue, McNeill proposed the short-time narrow-banded mode decomposition (STNBMD) method [34] which extracts signal modes by optimizing an object function imposing constraints on the mode reconstruction error and the smooth degrees of the mode amplitudes and frequencies. The STNBMD is a successful and systematic extension of the VMD to signals with time-varying frequencies. Then, more recently, Chen introduced the variational nonlinear chirp mode decomposition (VNCMD) method [35] which exploits a complete variational framework to generalize the VMD. The VNCMD can decompose chirp signals with very close or even crossed modes. However, several issues still remain to be addressed for both VMD and VNCMD. Firstly, the two methods (as well as the STNBMD) find all the signal modes concurrently via a joint-optimization technique and therefore the number of the signal modes should be specified in advance. In fact, it is difficult to know the exactly number of the modes for real-life data. Secondly, the bandwidth parameter for both methods is fixed during the optimization. Nevertheless, to facilitate the convergence of the algorithm, it is desired to adjust the bandwidth parameter according to different stages of the optimization. Last but not least, how to obtain good initializations for the frequencies of the modes is unsolved for these methods.

In this paper, a signal decomposition method called adaptive chirp mode pursuit (ACMP) is proposed to address the issues listed above. Inspired by the matching pursuit method [30,36], the ACMP adopts a recursive decomposition scheme to extract the signal modes one by one. The algorithm no longer requires the input of the number of the modes. We also show that the bandwidth parameter can be adaptively updated with the iterations of the algorithm. In addition, we show the initial frequencies for the iterative algorithm of ACMP can be obtained by using Hilbert transform.

The rest of the paper is organized as follows. In Section 2, we introduce the model of the chirp mode and review the VNCMD method. The proposed ACMP method is introduced in Section 3 where a simulated example is also considered to demonstrate our method. In Section 4, various examples including simulated and real-life applications are presented to test the performance of the ACMP. The conclusion is summarized in Section 5.

2. Theoretical background

2.1. Signal model

In reality, non-stationary signals often contain several sub-signals which are termed as chirp modes in this paper. Each chirp mode can be modeled as an AM-FM signal. More precisely, the signal model is expressed as

$$x(t) = \sum_{m=1}^{M} x_m(t) = \sum_{m=1}^{M} a_m(t)\cos(2\pi\int_0^t f_m(s)\mathrm{d}s + \varphi_m) \tag{1}$$

where the signal $x(t)$ is a superposition of M chirp modes $x_m(t)$ for $m = 1, \ldots, M$; $a_m(t) > 0$ is the non-negative envelope (or amplitude) of the m-th mode, $f_m(t) > 0$ is the instantaneous frequency (IF), and φ_m denotes the initial phase. Generally, the envelope and the IF are slowly varying functions compared to the phase function, i.e., $|a'_m(t)|, |f'_m(t)| \ll |f_m(t)|$. In this paper, we assume that these signal modes are well separated in the TF domain as the SST does. Namely, the IFs of the signal modes should satisfy the separation condition [16]: $f_m(t) > f_{m-1}(t)$ and $|f_m(t) - f_{m-1}(t)| \geqslant \gamma |f_m(t) + f_{m-1}(t)|$ with the separation