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A local and online sifting process for the empirical mode decomposition and its application in aircraft damage detection

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ABSTRACT

This paper introduces the Variable-Span Smoothing Sifting (VSSS) for the Empirical Mode Decomposition (EMD), as a substitute for the traditional sifting process. In this method, the local mean of the signal at each point is extracted by applying some smoothing filters to its adjacent data points, within a variable span sliding window. The VSSS is direct, local and online; hence, it may improve the EMD performance, and overcome many drawbacks of the classical algorithm. The performance of the VSSS is verified through some numerical studies, in which, results of the new and traditional sifting processes are compared for some benchmark signals. Finally, the VSSS is applied to the aircraft damage detection problem.

1. Introduction

In order to improve the survivability of a damaged aircraft, researches in the field of Fault Tolerant Control Systems (FTCS) have been dramatically developed in recent decades. For this purpose, several studies have been conducted to provide control systems which are capable of maintaining the stability and performance of the aircraft in acceptable ranges, in case of any damage [1–5]. Damage detection has a crucial role in designing the FTCS; because it is necessary for the controller adaption to identify the type, amount and location of the damages, in an online manner. In signal-based damage detection methods such as spectral analysis techniques and band-pass filters, certain characteristics of flight data are examined to detect any damage. Since flight data are nonlinear and non-stationary, it is essential for aircraft damage detection systems to use signal processing methods which are suitable for these characteristics.

The Empirical Mode Decomposition (EMD) presented in 1998 by Huang et al. [6] is a signal processing method appropriate for analyzing nonlinear and non-stationary signals. Hence, the EMD has been employed quite successfully in the field of the fault diagnosis, failure detection, damage identification and health monitoring, so far [7–10]. Nevertheless, as we know, it has not been utilized in the aircraft damage detection. To be appropriate for real-time applications, including the aircraft damage detection, the EMD should be enhanced. Therefore, the aim of this paper is to propose a local and online EMD algorithm.

The main objective of the EMD is to decompose nonlinear and non-stationary signals of real systems into physically meaningful narrowband components. These mono-component elementary signals are termed the Intrinsic Mode Functions (IMFs). The definition of an IMF is still controversial. Originally, every IMF should satisfy both the "symmetric profile" and "zero local mean" conditions. However, these conditions are questionable [11]. An IMF is a more general form of a harmonic function, because its amplitudes and frequencies are varied during the signal. The IMFs are data-driven, rather than pre-defined; thus, the EMD is capable of analyzing nonlinear and non-stationary signals, adaptively.

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Despite significant advantages, the EMD suffers from lack of a theoretical foundation. Whereas the EMD is totally empirical, it is difficult to develop its analytical formulation. Therefore, particular features of the EMD algorithm are arbitrary. In the literature, several problems associated with the EMD algorithm have been addressed, and some solutions have been offered to these problems [12]. For instance, numerous techniques have been employed for stopping criteria of the sifting process [13–15] and the boundary estimation problem [13,16,17]. Moreover, several methods have been utilized to improve the spline envelopes [18–20]. Furthermore, some new algorithms have been presented for the EMD [21]. Finally, many studies are conducted to present new sifting processes. This paper is focused on the latter.

One branch of the newly developed sifting processes utilizes the local approach. Reference [13] proposes a local EMD algorithm, for the first time. In this algorithm, parts of the signal containing non-zero mean values are identified, and the sifting process is applied only to those parts. By this technique, the algorithm protects other parts from over-decomposition. Reference [22] introduces a method to extract the local mean signal, directly. This method acquires the local mean signal by fitting a cubic spline to inflection points. Then the sifting process is performed by solving a fourth-order parabolic differential equation. Reference [23] presents another method to construct the direct mean envelope of the signal through a quadratic programming problem with equality and inequality constraints. Reference [24] determines optimal locations of interpolation points using the genetic algorithm. Then, different piecewise interpolating polynomials are utilized for the optimal formation of the upper and lower envelopes.

The second branch of the newly developed sifting processes utilizes the online approach. Reference [13] provides an online EMD algorithm by limiting the span of the sifting process to blocks containing a finite number of exterma. Reference [25] presents an online method for the cubic spline interpolation through data reuse in overlapped windows with optimal length. Reference [26] utilizes sliding overlapped windows to perform the EMD algorithm in real-time.

Reviewing the available literature on the EMD algorithms demonstrates a need for a local and online method. This paper aims to propose such an improved EMD algorithm which is suitable for real-time applications.

This paper is organized as follows: In Section 2, the EMD algorithm is described, briefly; then, shortcomings of the classical EMD are explained. Section 3 describes the concept of the VSSS, principals of two smoothing filters, and fundamentals of variable-span smoothing filters. In Section 4, comparative studies are carried out between the results of the classical and proposed methods for some benchmark problems. In Section 5, the VSSS is applied to the aircraft damage detection problem. Finally, Section 6 concludes the paper.

2. EMD

2.1. The algorithm

In this subsection, a quick review of the EMD algorithm is conducted based on Reference [6]. The EMD algorithm includes two loops. The inner loop is called the *sifting process*. The main task of the sifting process is to view the investigated signal as the *approximation* and *detail* parts, and to separate them from each other. For this purpose, the sifting process identifies the approximation part (i.e., the *local mean*) of the signal, and eliminates it from the signal:

$$h_{1,1}(t) = x(t) - m_{1,1}(t) \tag{1}$$

in which x is the original signal, and $m_{i,j}$ and $h_{i,j}$ are the local mean and high-frequency parts of the signal, respectively, in the jth iteration of the sifting process for obtaining the ith IMF.

Performing the sifting process only once may not be adequate to separate the local mean signal. Therefore, the process should be iterated until a stopping criterion is satisfied:

$$\begin{aligned} h_{1,2}(t) &= h_{1,1}(t) - m_{1,2}(t) \\ &\vdots \\ h_{1,k}(t) &= h_{1,(k-1)}(t) - m_{1,k}(t) \end{aligned} \tag{2}$$

In this paper, a convergence-based stopping criterion is employed which terminates the iteration when the difference of consecutive acquired detail part is lesser than a certain epsilon value.

Finally, the detail (i.e., high-frequency) part of the signal is detected as an IMF, and the residual is obtained by removing it from the signal:

$$\begin{aligned} c_1(t) &= h_{1,k}(t) \\ r_1(t) &= x(t) - c_1(t) \end{aligned} \tag{3}$$

where $c_i$and r_i are the ith IMF and residual, respectively.

The residual can be treated as the original signal. In the outer loop, the above procedure is repeated, until no other IMF can be acquired.

Finally, the signal reconstruction will be completed, as follows:

$$x(t) = \sum_{j=1}^{n} c_j(t) + r(t) \tag{4}$$

in which $r(t) = r_n(t)$, and the successive IMFs are sorted in a descending frequency order.