Numerical Analysis for Iterative Filtering with New Efficient Implementations Based on FFT

Antonio Cicone, Haomin Zhou

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- Numerische Mathematik (Impact factor: 2.056) -

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Hyunsoo, Yu

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Background

- Trend of Analyzing Time series data
- EMD(Empirical Mode Decomposition)
- 1. Introduction
- 2. **IF**(Iterative Filtering) **algorithm in the continuous setting**
- 3. IF algorithm in the discrete setting
- 4. Efficient implementation of the DIF(Discrete Iterative Filtering) algorithm
- 5. Conclusions and Outlook

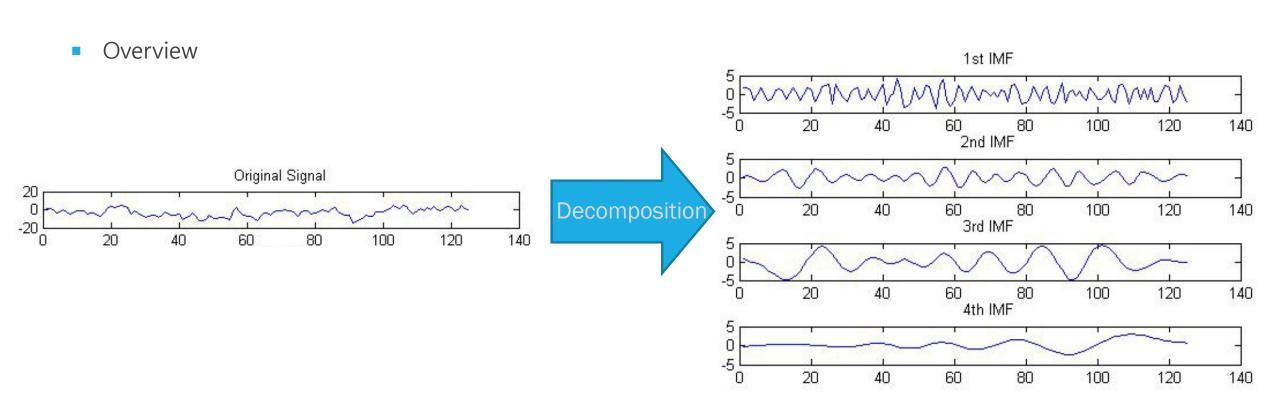
TREND OF ANALYZING TIME SERIES DATA

- FFT & Wavelet Conventional methods for analyzing Time series data
 - : linear decompositions
 - Not accurate on nonlinear & nonstationary time series data. (*Heisenberg uncertainty principle*)
 - Alternate STFT(Short Time Fourier Transform), Synchrosqueezed Wavelet Transform, and ConceFT method...
- EMD local and adaptive data-driven method
 - suitable nonlinear and nonstationary data analysis.
 - Unstable to perturbations
 - Susceptible to mode splitting and mode mixing
 - Alternate EEMD(Ensemble EMD), NA-MEMD(Noise assisted Multivariate EMD), FMEMD(Fast MEMD)
 - Solve mode mixing problem
 - Can't solve mode splitting problem
 - Alternate IF(Iterative Filtering)

BACKGROUND TREND OF ANALYZING TIME SERIES DATA

- IF(Iterative Filtering) Produce results similar to EMD-based algorithm
 - : guarantee a priori its convergence and stability
 - Using FFT leads to faster computation. (Fast Iterative Filtering)
 - Mode splitting can be avoided by tuning the value of the stopping criterion parameter.

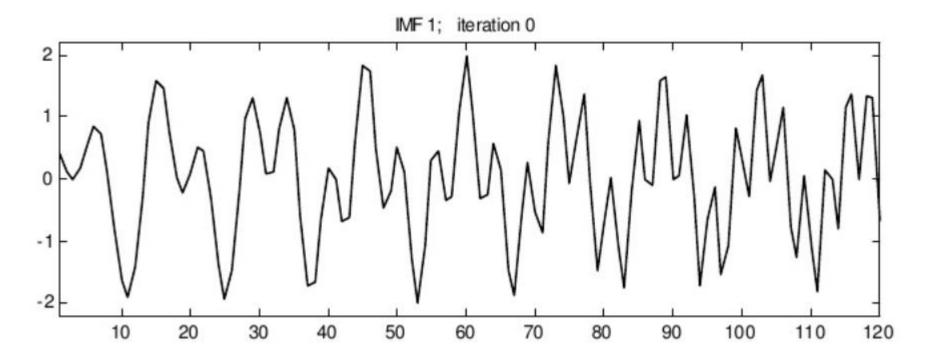
WHAT IS EMD(EMPIRICAL MODE DECOMPOSITION)?



IMF(Intrinsic Mode Function)

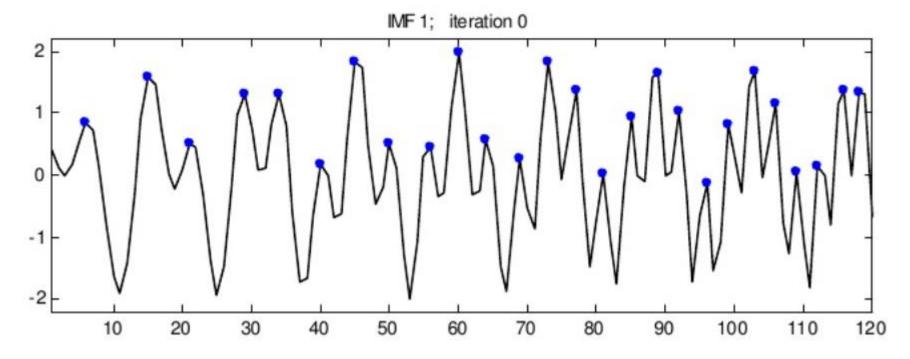
WHAT IS EMD(EMPIRICAL MODE DECOMPOSITION)?

- Method : Sifting Process
 - Signal x(t)



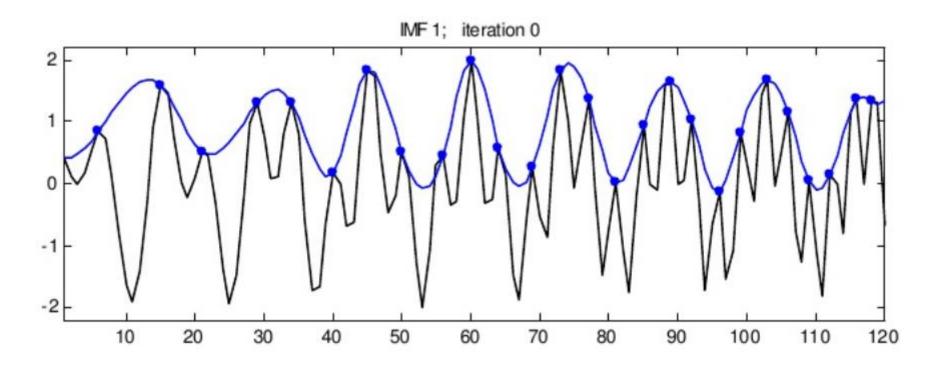
WHAT IS EMD(EMPIRICAL MODE DECOMPOSITION)?

- Method : Sifting Process
 - Get upper extrema of x(t)



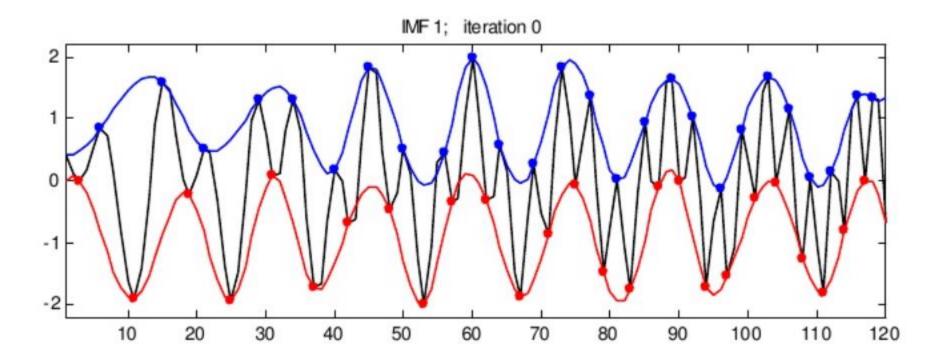
WHAT IS EMD(EMPIRICAL MODE DECOMPOSITION)?

- Method : Sifting Process
 - Interpolate(spline interpolation) the local maxima to form an upper envelope u(x)



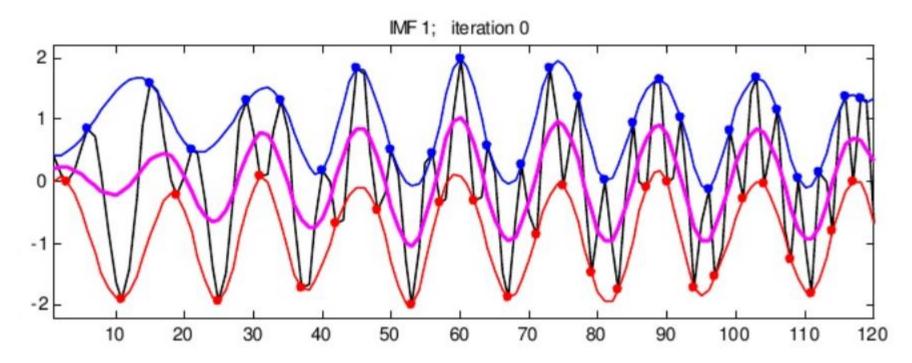
WHAT IS EMD(EMPIRICAL MODE DECOMPOSITION)?

- Method : Sifting Process
 - Get a lower envelope(l(x) with same way.



WHAT IS EMD(EMPIRICAL MODE DECOMPOSITION)?

- Method : Sifting Process
 - Calculate the mean envelope m(t) = [u(t) + l(t)]/2

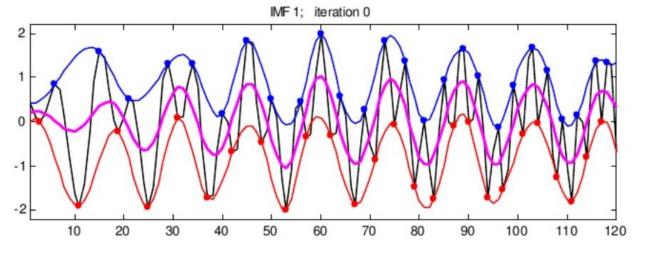


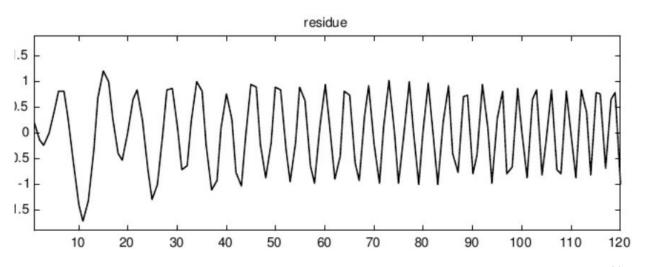
WHAT IS EMD(EMPIRICAL MODE DECOMPOSITION)?

- Method : Sifting Process
 - Subtract the mean from the signal : h(t) = x(t) m(t)

- Repeat until h(t) satisfy the IMF condition (Inner loop)
- Get All IMF components

(Outer loop)
$$X(t) = \sum_{i=1}^{N} \text{IMF}_{i}(t) + r_{N}(t)$$





INTRODUCTION

- Most real-life signals are non-stationary and non-linear.
 - : Standard techniques(FFT, Wavelet) can't capture their **hidden features** properly.
- EMD allows to unravel the hidden features of a non-stationary signals by iteratively decomposing it into a finite sequence of simple components(IMF).

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- But EMD is difficult to analyze mathematically.
- Alternate : many methods based of IF(Iterative Filtering)

IF ALGORITHM IN THE CONTINUOUS SETTING

- To get IMF, IF algorithm approximate the moving average of s (signal) and subtract it from s itself.
 - The approximated moving average is computed by convolution of s with a filter function w.
- w: filter/window

$$\int_{\mathbb{R}} w(z) dz = \int_{-L}^{L} w(z) dz = 1$$

 $-\ell_m$: filter length

$$\mathcal{M}_m(s_m) = s_m - \mathcal{L}_m(s_m) = s_{m+1}$$

$$IMF_1 = \lim_{m \to \infty} \mathcal{M}^m(s)(x) = \int_{-\infty}^{\infty} \hat{s}(\xi) \chi_{\{\hat{w}(\xi) = 0\}} e^{2\pi i \xi x} d\xi$$

Algorithm 1 Iterative Filtering IMF = IF(s) $IMF = \{\}$ while the number of extrema of $s \ge 2$ do $s_1 = s$ while the stopping criterion is not satisfied do compute the filter length l_m for $s_m(x)$ $s_{m+1}(x) = s_m(x) - \int_{-l_m}^{l_m} s_m(x+t)w_m(t)dt$ m = m + 1Moving average end while $\mathcal{L}_m(s_m)$ $IMF = IMF \cup \{s_m\}$ $s = s - s_m$ end while

 $IMF = IMF \cup \{s\}$

- Signals which we are dealing with are discrete.
- w : filter

$$\int_{\mathbb{R}} w(z)dz = \int_{-L}^{L} w(z)dz = 1 \quad \text{discrete} \quad \sum_{p=1}^{n} w_p = 1$$

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$$s_{m+1}(x_i) = s_m(x_i) - \int_{x_i - l_m}^{x_i + l_m} s_m(y) w_m(x_i - y) dy$$

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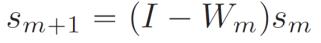
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Matrix form

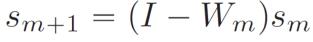
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$$j=0,\ldots,n-1$$

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$$\frac{1}{x_{j}=x_{i}-l_{m}} = \frac{1}{x_{j}} \frac{$$

$$IMF_1 = \lim_{m \to \infty} \mathcal{M}^m(s)(x)$$

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 discrete $IMF_1 = \lim_{m \to \infty} (I - W_m)s_m$



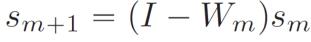
 $W_m = W$ for every m

$$IMF_1 = \lim_{m \to \infty} (I - W)^m s$$

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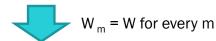




$$s_{m+1}(x_i) = s_m(x_i) \left[-\int_{x_i - l_m}^{x_i + l_m} s_m(y) w_m(x_i - y) dy \right] \approx s_m(x_i) \left[-\sum_{x_j = x_i - l_m}^{x_i + l_m} s_m(x_j) w_m(x_i - x_j) \frac{1}{n} \right], \quad j = 0, \dots, n-1$$

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$$IMF_1 = \lim_{m \to \infty} (I - W)^m s$$

Algorithm 2 Discrete Iterative Filtering IMF = DIF(s)

```
IMF = {} while the number of extrema of s \ge 2 do s_1 = s while the stopping criterion is not satisfied do compute the function w_m(\xi), whose half support length l_m is based on the signal [s_m(x_i)]_{i=0}^{n-1} s_{m+1}(x_i) = s_m(x_i) - \sum_{j=0}^{n-1} s_m(x_j) w_m(|x_i - x_j|) \frac{1}{n}, i = 0, \ldots, n-1 m = m+1 end while IMF = IMF \cup \{s_m\} s = s - s_m end while IMF = IMF \cup \{s\}
```

W: digonalizable

 $W = UDU^T$ D: diagonal matrix containing in its diagonal eigenvalues of W

$$(I - W) = U(I - D)U^T$$

$$\lim_{m \to \infty} (I - W)^m = \lim_{m \to \infty} U(I - D)^m U^T = UZU^T$$

$$\mathit{IMF}_1 = \lim_{m \to \infty} (I - W)^m s = U Z U^T s$$

Z: diagonal matrix

U : Consists of u_p as columns

$$u_p = \frac{1}{\sqrt{n}} \left[1, \ e^{-2\pi i p \frac{1}{n}}, \dots, \ e^{-2\pi i p \frac{n-1}{n}} \right]^T$$

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$$W_m = \begin{bmatrix} c_0 & c_{n-1} & \dots & c_1 \\ c_1 & c_0 & \dots & c_2 \\ \vdots & \vdots & \ddots & \vdots \\ c_{n-1} & c_{n-2} & \dots & c_0 \end{bmatrix}$$

: Discrete convolution operator <= circulant matrix

Circulant matrix's eigenvalues

$$\lambda_j = c_0 + c_{n-1}\omega_j + \dots + c_1\omega_j^{n-1}$$

$$\lambda_j = c_0 + 2\sum_{k=1}^{\frac{n-1}{2}} c_k \cos\left(\frac{2\pi jk}{n}\right)$$

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Approximated IMF1

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$$\overline{\mathrm{IMF}}_1 = (I-W)^{N_0} s = U(I-D)^{N_0} U^T s^{N_0}$$
 : minimum Natural number

$$W_m = \begin{bmatrix} c_0 & c_{n-1} & \dots & c_1 \\ c_1 & c_0 & \dots & c_2 \\ \vdots & \vdots & \ddots & \vdots \\ c_{n-1} & c_{n-2} & \dots & c_0 \end{bmatrix}$$

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$$\lim_{\substack{m\to\infty\\ m\to\infty}} (I-W) = U(I-D)U^T$$

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$$IMF_1 = \lim_{\substack{m\to\infty\\ m\to\infty}} (I-W)^m s = UZU^T s$$

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 [Cpq]'s eigenvectors

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$$\lambda_p = \sum_{q=0}^{n-1} c_{1q} e^{-2\pi i p \frac{q}{n}}$$

DFT of {C₁₀} & [Cpq]'s eigenvalues₂₅

IMPLEMENTATION OF THE DIF ALGORITHM

$$\lim_{\substack{m \to \infty \\ m \to \infty}} (I - W)^m = \lim_{\substack{m \to \infty \\ m \to \infty}} U(I - D)^m U^T = UZU^T$$

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$$\overline{\mathrm{IMF}}_1 = (I-W)^{N_0} s = U(I-D)^{N_0} U^T s$$
 , which is a substant $\mathrm{IMF}_1 = (I-W)^{N_0} s = U(I-D)^{N_0} U^T s$.

$$\begin{split} \mathrm{IMF} &= \sum_{k=0}^{n-1} u_k (1-\lambda_k)^{N_0} \sigma_k = \mathrm{IDFT} \left((I-D)^{N_0} \mathrm{DFT}(s) \right) \\ &: \mathsf{FIF} \text{ (Fast Iterative Filtering)} \end{split}$$

 σ_k : the k-th element of the DFT of the signal s

Circulant matrix's eigenvalues

$$\lambda_j = c_0 + c_{n-1}\omega_j + \ldots + c_1\omega_j^{n-1}$$

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$$\lambda_p = \sum_{q=0}^{n-1} c_{1q} e^{-2\pi i p \frac{q}{n}}$$

DFT of {C10} & [Cpq]'s eigenvalues $_{26}$

CONCLUSIONS AND OUTLOOK

- We prove that the DIF is also convergent.
- We show that each IMF is a smart summation of eigenvectors of a circulant matrix.
- The DIF algorithm and the explicit formula for the IMFs derive FIF(Fast Iterative Filtering)
 - It increase its efficiency and reduce its computational complexity.
 - It decompose a signal by means of the FFT
 - Instantaneous analysis of non-stationary signals.

APPENDIX

[HTML] A fast iterative filtering decomposition and symmetric difference analytic energy operator for bearing fault extraction

Y Xu, F Fan, X Jiang - ISA transactions, 2021 - Elsevier

The fault vibration signals extracted from defective bearings are generally non-stationary and non-linear. Besides, such signals are extremely weak and easily buried by inevitable background noise and vibration interferences. Thus, the development of methods capable of ...

☆ ワワ 2회 인용 관련 학술자료 전체 4개의 버전 no code implementation

[HTML] Schizophrenia detection technique using multivariate iterative filtering and multichannel EEG signals

K Das, RB Pachori - Biomedical Signal Processing and Control, 2021 - Elsevier

A new approach for extension of univariate iterative filtering (IF) for decomposing a signal into intrinsic mode functions (IMFs) or oscillatory modes is proposed for multivariate multi-component signals. Additionally the paper proposes a method to detect schizophrenia (Sz) ...

☆ ワワ 전체 3개의 버전 no code implementation

Multidimensional iterative filtering: a new approach for investigating plasma turbulence in numerical simulations

E Papini, <u>A Cicone</u>, <u>M Piersanti</u>, <u>L Franci</u>... - Journal of Plasma ..., 2020 - cambridge.org Turbulent space and astrophysical plasmas exhibit a complex dynamics, which involves nonlinear coupling across different temporal and spatial scales. There is growing evidence that impulsive events, such as magnetic reconnection instabilities, lead to a spatially ...

☆ ワワ 7회 인용 관련 학술자료 전체 6개의 버전 ⋙ no code implementation

Impact factor: 4.035

Impact factor: 3.137

Impact factor: 1.91