

# A New Wavelet-Based Mode Decomposition for Oscillating Signals and Comparison with the Empirical Mode Decomposition

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- **Decomposing** time series into several **modes** has become more and more popular and **useful** in signal analysis.
- Methods such as EMD or SSA (among others) have been successfully applied in **medicine, finance, climatology, ...**
- Old but gold: **Fourier** transform allows to decompose a signal as

$$f(t) \approx \sum_{k=1}^K c_k \cos(\omega_k t + \phi_k).$$

- Problem: often **too many components** in the decomposition.
- Idea: Considering the **amplitudes and frequencies as functions of  $t$**  to decrease the number of terms.
- Development of an empirical wavelet mode decomposition (**EWMD**) method which can be used in numerous ways.

Edit: EWMD becomes **WIME** (wavelet-induced mode extraction).

- 1 Methods: EMD and WIME
- 2 Reconstruction skills
- 3 Period detection skills
- 4 Real-life data
- 5 Recent improvements
- 6 Conclusion

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- 1 **Methods: EMD and WIME**
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## Empirical Mode Decomposition (EMD) in a nutshell

1. Given a signal  $f$ , compute  $m$  the mean of its upper and lower envelopes.
2. Compute  $h = f - m$  and repeat steps 1. and 2. with  $h$  instead of  $f$  until  $h$  is “stable enough” and becomes an “intrinsic mode component” (IMF),  $f_1$ .
3. Repeat the whole process with  $f - f_1$  instead of  $f$ .
4. The procedure always stops and the IMFs successively extracted reconstruct  $f$  accurately.

Main drawbacks include: lack of solid mathematical theoretical background, high sensitivity to noise, mode-mixing problems.

Improvements made are computationally expensive, not intuitive.

## Empirical Wavelet Mode Decomposition (EWMD) – WIME

- The **wavelet used** in this study is the function

$$\psi(t) = \frac{e^{i\Omega t}}{2\sqrt{2\pi}} e^{-\frac{(2\Omega t + \pi)^2}{8\Omega^2}} \left( e^{\frac{\pi t}{\Omega}} + 1 \right)$$

with  $\Omega = \pi\sqrt{2/\ln 2}$ , which is similar to the **Morlet** wavelet. The **Fourier** transform of  $\psi$  is given by

$$\hat{\psi}(\omega) = \sin\left(\frac{\pi\omega}{2\Omega}\right) e^{-\frac{(\omega-\Omega)^2}{2}}.$$

- The **wavelet transform** of the signal is computed as:

$$Wf(a, t) = \int f(x) \bar{\psi}\left(\frac{x-t}{a}\right) \frac{dx}{a},$$

where  $\bar{\psi}$  is the complex conjugate of  $\psi$ ,  $t \in \mathbb{R}$  stands for the location/**time** parameter and  $a > 0$  denotes the **scale** parameter.

## Empirical Wavelet Mode Decomposition (EWMD) – WIME

- a) Perform the continuous **wavelet transform**  $Wf(a, t)$  of  $f$ .
- b) Compute the **wavelet spectrum**  $\Lambda$  associated to  $f$ :

$$\Lambda(a) = E |Wf(a, \cdot)|$$

where  $E$  denotes the mean over time. Then look for the **scale**  $a^*$  at which  $\Lambda$  reaches its global **maximum**.

- c) **Extract** the component related to  $a^*$ :

$$c_1 = R_\Psi^{-1} |Wf(a^*, t)| \cos(\arg Wf(a^*, t))$$

where  $R_\Psi \approx 1.25$  is a reconstruction constant.

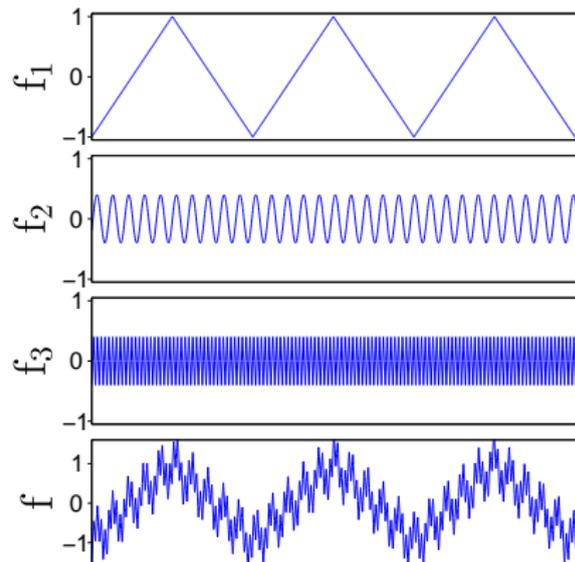
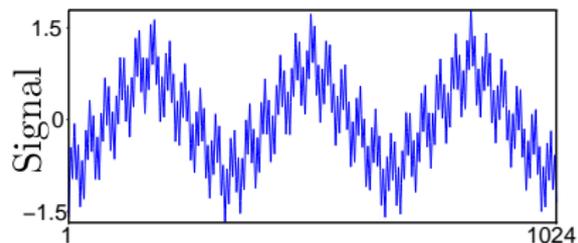
- d) **Repeat** steps (a) to (d) with  $f - c_1$  instead of  $f$ .
- e) **Stop** the process when  $\Lambda(a^*) < \varepsilon$  for a threshold  $\varepsilon$  or at your convenience. The components successively extracted **reconstruct**  $f$  accurately.

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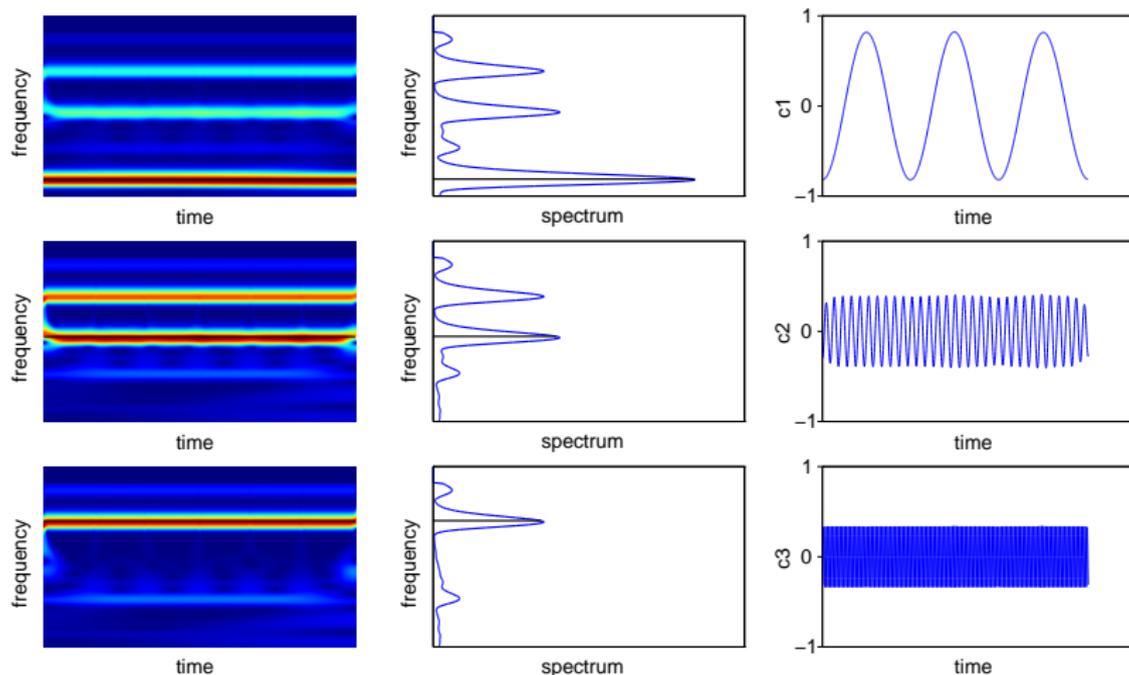
## Reconstruction skills

First example:



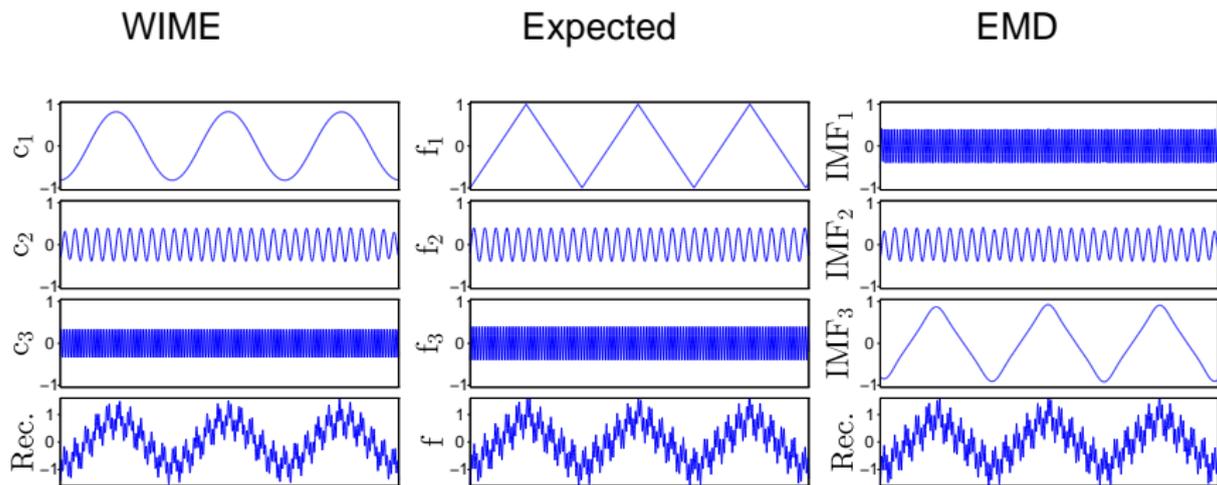
Sum of 2 triangular waveforms and a sine wave (classic example of the EMD).

## Reconstruction skills



First row:  $|Wf(a, t)|$ , spectrum of  $f$ , first extracted component  $c_1$ . Second and third rows: the same for  $f - c_1$  and  $f - c_1 - c_2$ .

## Reconstruction skills



First column: components extracted with WIME. Second column: the real (expected) components. Third column: the IMFs extracted with the EMD. The reconstruction  $c_1 + c_2 + c_3$  has a correlation of 0.992 with the original signal and a RMSE of 0.085.

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## Period detection

We consider the AM-FM signal  $f(x) = \sum_{i=1}^4 f_i(x)$  where

$$f_1(x) = \left( 1 + 0.5 \cos \left( \frac{2\pi}{200} x \right) \right) \cos \left( \frac{2\pi}{47} x \right) \quad (1)$$

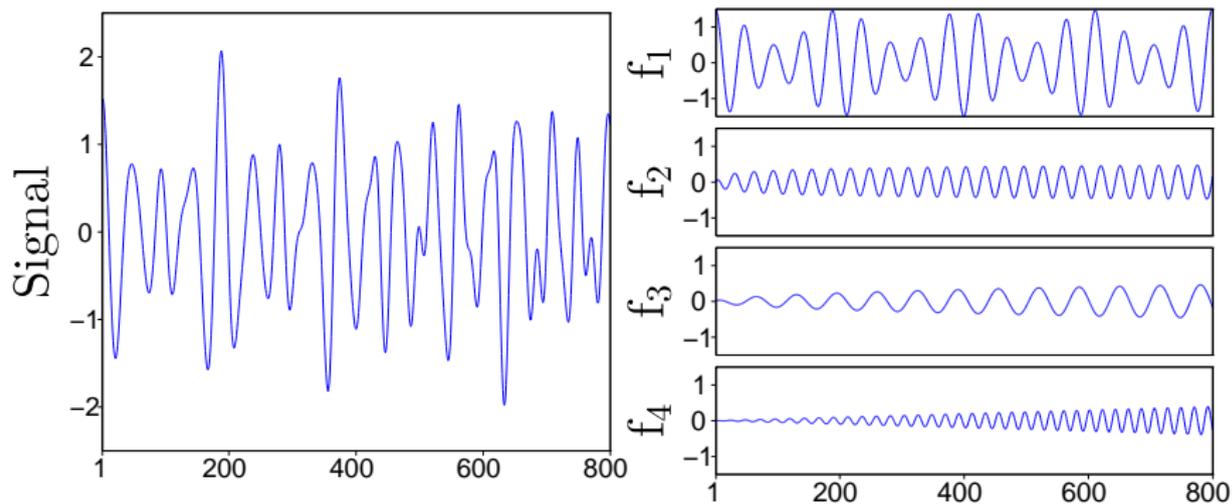
$$f_2(x) = \frac{\ln(x)}{14} \cos \left( \frac{2\pi}{31} x \right) \quad (2)$$

$$f_3(x) = \frac{\sqrt{x}}{60} \cos \left( \frac{2\pi}{65} x \right) \quad (3)$$

$$f_4(x) = \frac{x}{2000} \cos \left( \frac{2\pi}{23 + \cos \left( \frac{2\pi}{1600} x \right)} x \right) . \quad (4)$$

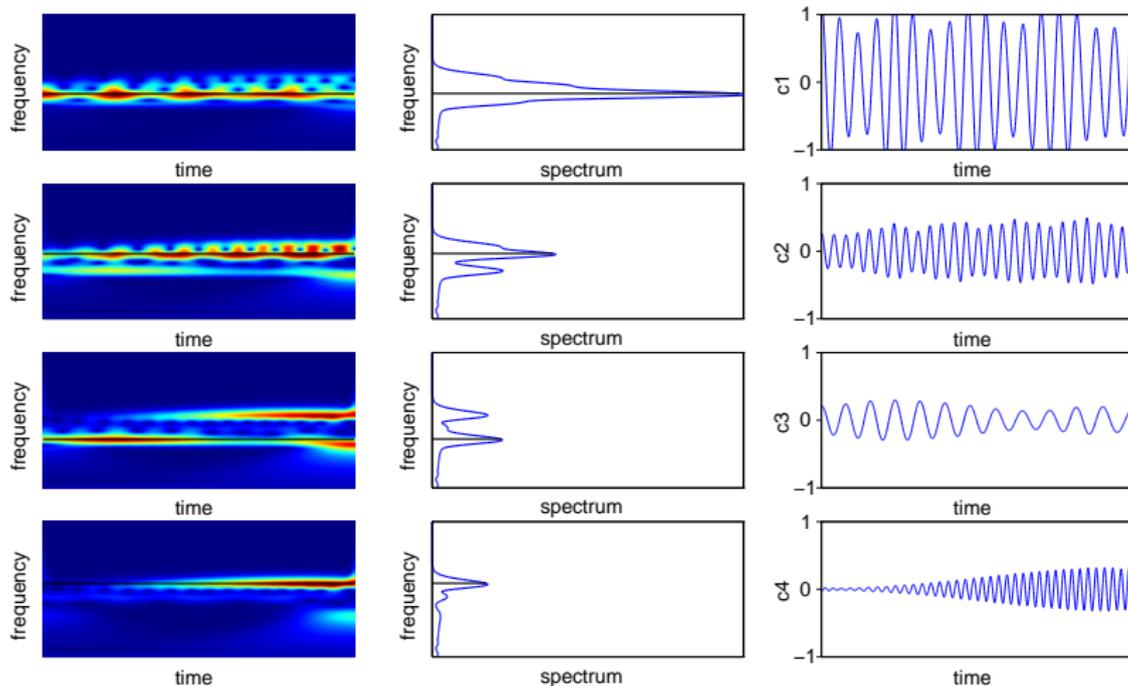
Target periods:  $\approx 23, 31, 47, 65$  units.

## Period detection



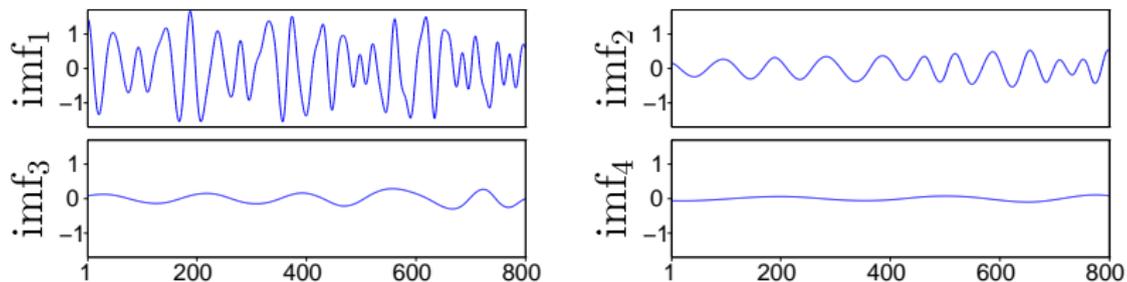
Target periods:  $\approx 23, 31, 47, 65$  units.

## Period detection - WIME



Target periods:  $\approx 23, 31, 47, 65$  units. Detected periods corresponding to  $a^*$ :  
 46.4, 30.6, 65.5 and 21.6 units. Correlation: 0.996. RMSE: 0.069.

## Period detection - EMD



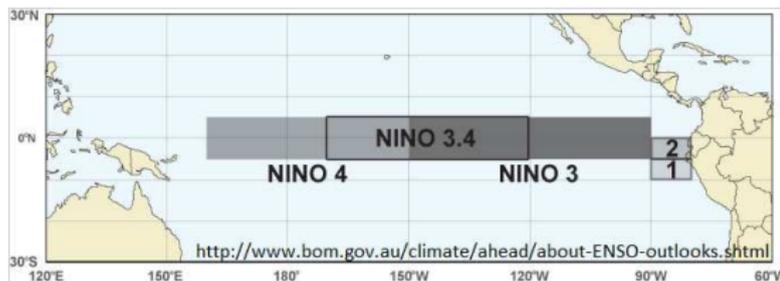
Target periods:  $\approx 23, 31, 47, 65$  units. Periods extracted from the Hilbert-Huang transform: 41, 75, 165, 284 units.

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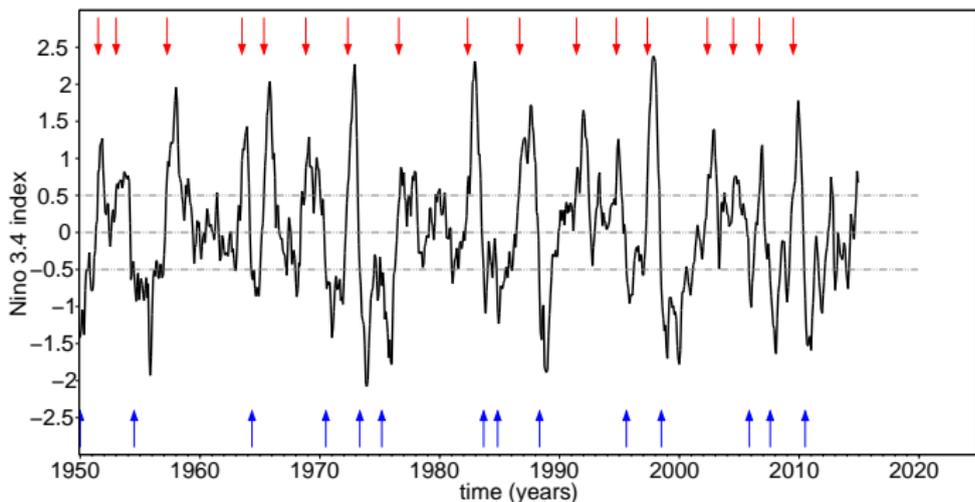
## ENSO index

- Analyzed data: Niño 3.4 time series, i.e. monthly-sampled sea surface temperature anomalies in the Equatorial Pacific Ocean from Jan 1950 to Dec 2014 (<http://www.cpc.ncep.noaa.gov/>).



## ENSO index

- Niño 3.4 index:

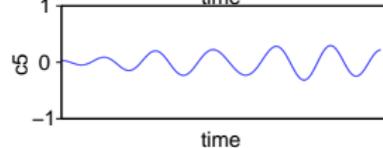
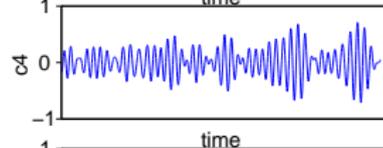
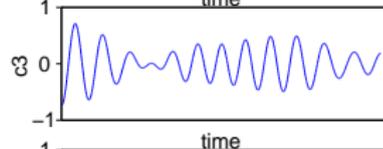
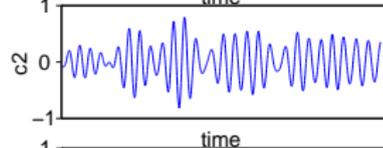
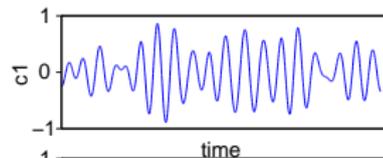
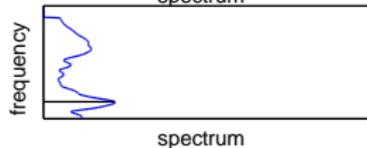
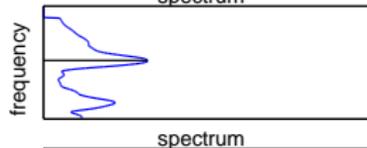
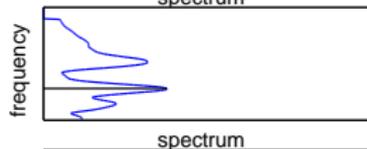
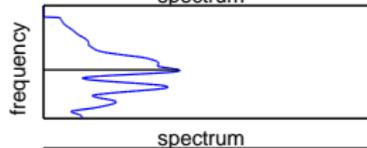
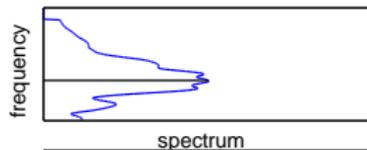
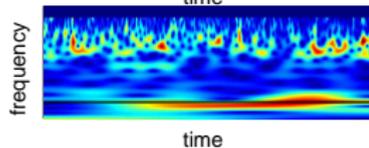
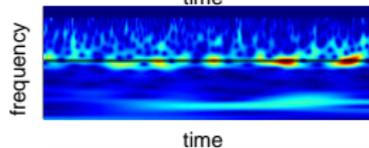
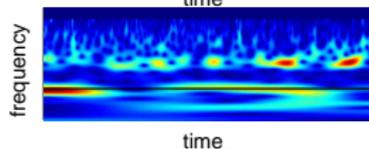
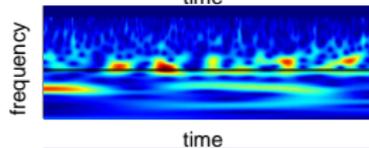
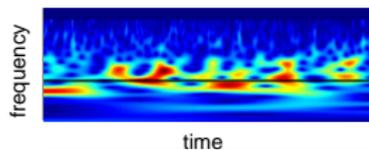


- **17 El Niño events:** SST anomaly above  $+0.5^{\circ}\text{C}$  during 5 consecutive months.
- **14 La Niña events:** SST anomaly below  $-0.5^{\circ}\text{C}$  during 5 consecutive months.

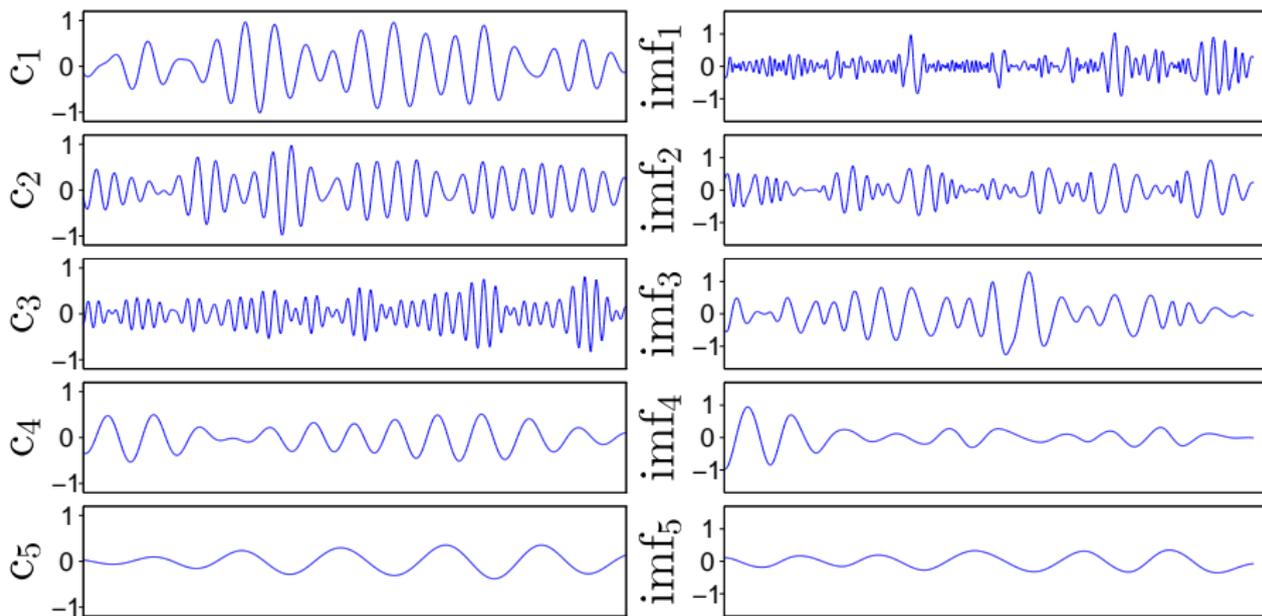
## ENSO index

- **Flooding** in the West coast of South America
- **Droughts** in Asia and Australia
- **Fish kills** or shifts in locations and types of fish, having **economic impacts** in Peru and Chile
- Impact on snowfalls and **monsoons**, drier/hotter/wetter/cooler than normal conditions
- Impact on **hurricanes/typhoons** occurrences
- Links with famines, increase in **mosquito-borne diseases** (malaria, dengue, ...), civil conflicts
- In Los Angeles, increase in the number of some species of mosquitoes (in 1997 notably).
- ...

## ENSO index



## ENSO index



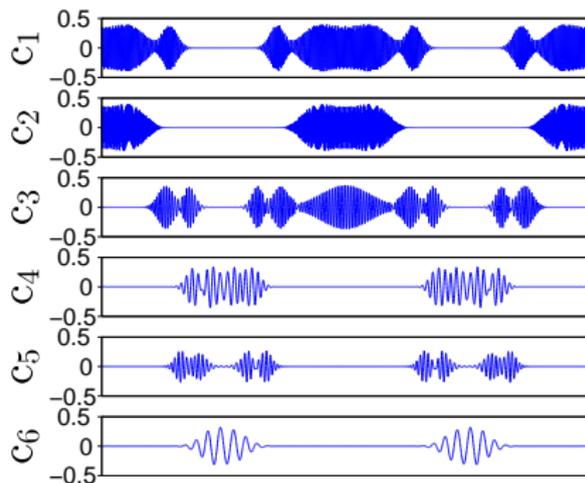
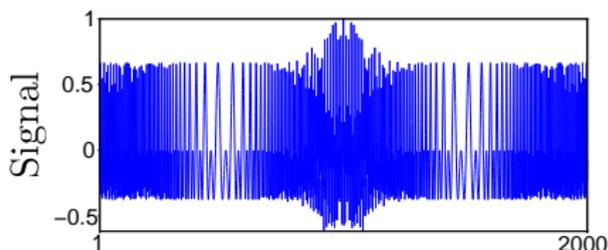
Components extracted with WIME and the IMFs from the EMD. Periods: 44.8, 28.6, 17, 65.6, 140.6 months (WIME) and 9.8, 21, 38.6, 75.9, 138.4 (EMD). Those from WIME are more in agreement with some previous works.

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## Recent improvements

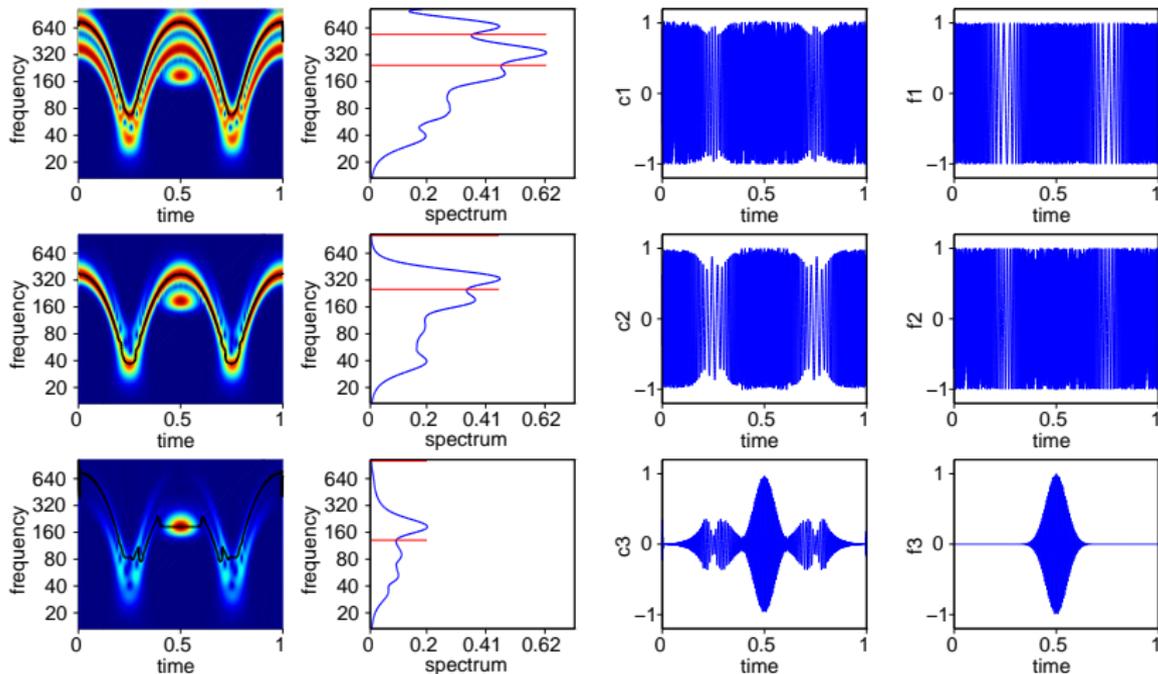
Problems with “highly” non-stationary components (classic example of the EMD):



Reconstruction is excellent ( $\text{RMSE} = 0.08$ ,  $\text{PCC} = 0.97$ ) but components are not correct.

## Recent improvements

Solution: add flexibility, follow ridges of maxima.



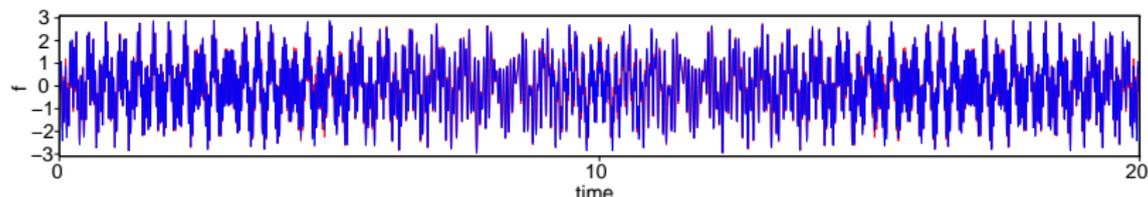
## Recent improvements

Crossings in the TF plane:

$$f_1(t) = 1.25 \cos \left( -(t-3)^3 + 180t \right) \quad (5)$$

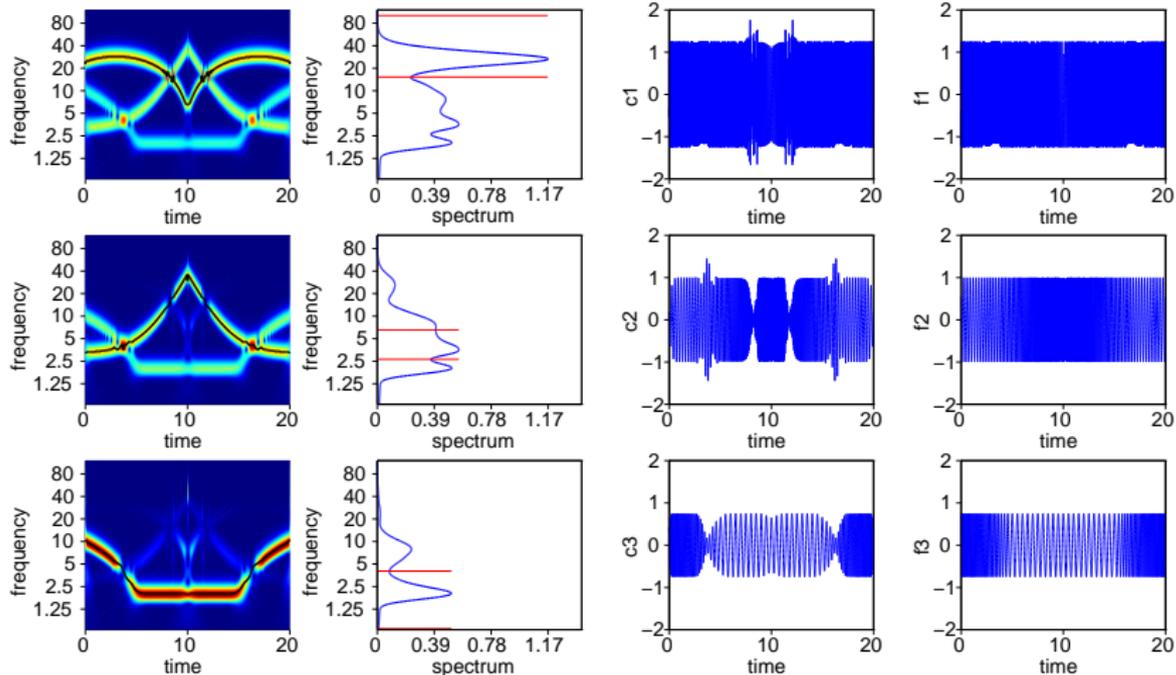
$$f_2(t) = \cos (1.8^t + 20t) \quad (6)$$

$$f_3(t) = \begin{cases} 0.75 \cos(-1.6\pi t^2 + 20\pi t) & (t < 5) \\ 0.75 \cos(4\pi t) & (t \geq 5) \end{cases} \quad (7)$$



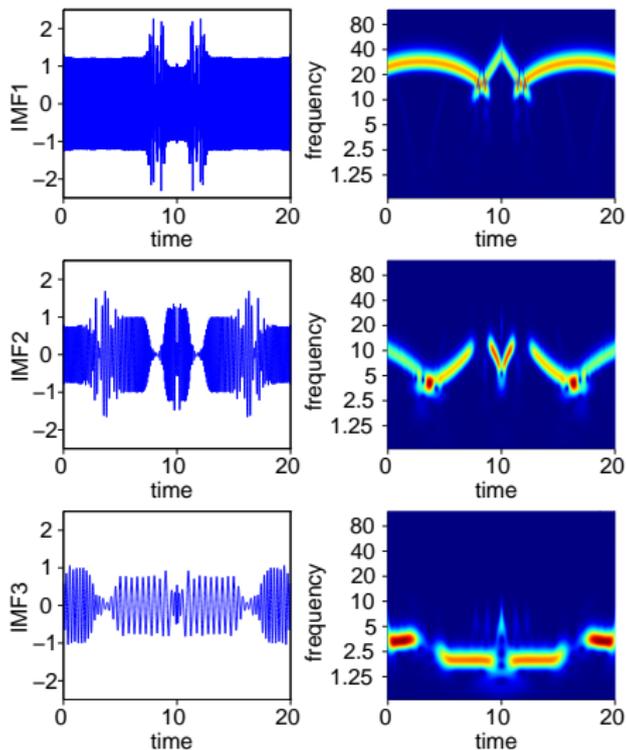
## Recent improvements

## WIME



## Recent improvements

## EMD



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## Conclusion

### WIME

- is a wavelet-based **decomposition** method
- has **reconstruction skills** comparable to the EMD
- has **period detection skills** better than the EMD in mode-mixing problems
- handles **crossing patterns** in the TF plane
- gives accurate results with **real-life** signals

Future works: study the mathematical properties of the method, test its tolerance to noise, limit edge effects,...

Thanks for your attention.

Please refer to the paper for relevant references.