Complex Empirical Decomposition Method in Radar Signal Processing

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Abstract—**In this paper we analyze possible application of complex Empirical Mode Decomposition (EMD) algorithm to the radar signal analysis. Presented method is applied to the analysis of experimental High Frequency Surface Wave (HFSW) radar data. Detailed procedure of extracting target signal from clutter is described. It is shown that complex EMD can extract target signal in heavy clutter environment and achieve better results compared to original, real valued EMD.**

Keywords-empirical mode decomposition; complex emd; signal processing; telecommunications; sonar; radar; border effects;

I. Introduction

Empirical Mode Decomposition (EMD) is a novel signal analysis tool which, thanks to underlying notion of instantaneous frequency, gives sharp identifications of embedded structures. It was first introduced by N.E. Huang et al (1998.) in ocean wave research [3] and since then becomes an important tool for nonlinear and non-stationary signal analysis.

Despite the fact that EMD is already very well established and widely accepted method in signal processing, the issue of being developed for real-valued data only prevents it's even wider application. On the other hand, complex representation of real data is very useful because dependences of amplitude and phase between signal components can be modeled simultaneously. Besides, several important signal processing areas (telecommunications, sonar, radar etc.) use complex-valued data structures. To overcome this defect it is necessary to develop an extension of EMD suitable for complex-valued data processing.

Extension of EMD to the domain of complex numbers is especially important in the analysis of phase-dependent processes, such as obtained from a series of sensors. The set of 69 real radar signals are analyzed in this paper and the capabilities of complex EMD in target detection are presented. Signals were obtained by monitoring the movement of aircraft King Air 200 with high-frequency surface wave (HFSW) radar.

Powerful as it is, the EMD is entirely empirical. In order to make the method more robust and rigorous, many mathematical problems need to be resolved. Some of the problems are easy and might be resolved in the next years; others are more difficult and will probably require much more effort. Despite this, EMD achieved much better results in energy-time-frequency signal representation than other traditional methods.

II. Border Effects

The EMD disadvantages are mostly related to determination of envelopes by interpolation through the maxima (minima) of the signal. Among traditional interpolation methods the best results so far are achieved using cubic spline. However, there are some known problems that are related to cubic splines, called over and under-shoot problems (situation where the envelope is above maxima or below minima which should not happen). The potential for IMFs to be corrupted by the cubic spline over and under-shooting problem may be amplified by the iterative nature of the sifting process, since the mean of the two splines is taken as step (3). More about alternative spline methodologies can be found at [3].

Another envelope related problem that we'll discuss more in this paper is a divergence at both ends of the data series. The divergence gradually influences inside of data series with the sifting procedure being carried on so that the results are very distorted. These effects are named “border effects” [2]. For the long data series, we can be sure to get the envelopes with the least distortions through throwing away the influenced segments on two ends. Signal is shortened but in return we have correct decomposition for its inner part.

Fig. 1(a) illustrates border effects. As we can see there are four maxima and minima. If we apply EMD algorithm with no technique for border effect influence reduction we will have several distortions, especially at the beginning and end of upper envelope. Since the signal is short, distortion from the borders affects the entire signal, so the result of decomposition is incorrect. The first IMF is depicted in Fig. 1(c) – blue dotted line. In comparison with actual IMF_1 (solid black line), obtained by expanding signal to the next extrema, we can see how big those amplitude deviations are. In the central inner part of considered data set differences are smaller, but still there. Because this is a short signal, throwing away influenced segments at the ends is impossible.

On the other hand, the occurrence of distortion is normal for the curve fitting by using of cubic spline function, because the cubic spline interpolation needs two neighboring data before and after the given point respectively. The only way to solve the problem is to add two additional maxima and two additional minima outside the ends of the original data series. The problem is how to determine correct positions for these artificially added maxima (minima).

We propose a simple method for signal extension: initial point (or the end point) will be declared as maxima if it's value is higher than the value of the nearest existing maxima, if this value is lower, to first (end) point is assigned the value of the nearest maxima. The same principle is used for the lower envelope. Proposed method will not give completely correct results, but the influence of border effects will be considerably reduced. Fig. 1(b) shows the signal and both envelopes calculated using this method. The corresponding IMF_1 is depicted at Fig. 1(c) – (solid red line).

This method is especially useful in long series with strong randomicity. It might be pointed out that for a series with strong randomicity it is impossible and unreasonable to extend the series accurately. The only feasible way is to let the mean envelope of the extended series near to the actual one, which is just the requirement of the EMD method. And this is exactly what we achieved here. There is a number of other more complex methods for data extension. The one based on the neural network is described in [4].

III. COMPLEX EMD

In order to have complex valued data decomposed by complex EMD we first split it into its positive and negative frequency components. Later on, applying basic transformations to those frequency components we get two analytical signals. Owing to the well-known properties of signal representations in the complex domain (Fourier), this

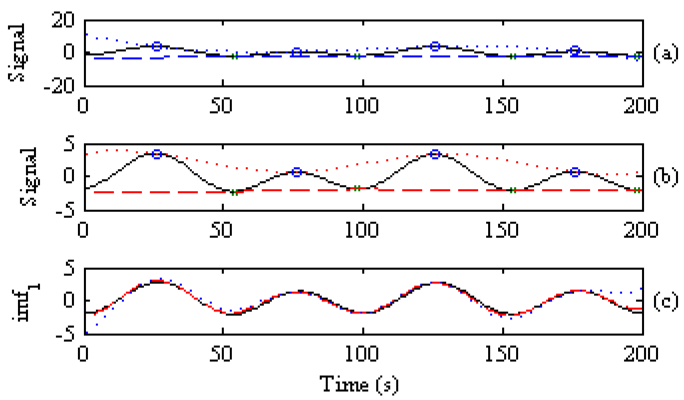

Figure 1. Border effects in EMD: (a) data set and corresponding envelopes with no technique for border effects influence reduction (b) data set and corresponding envelopes with proposed method for border effects influence reduction (c) IMF_1 for those particular cases of envelopes and the actual one.

provides us with an opportunity to deal with only the real part of such signal and without loss of information.

Let $x[n] \in C$ be a complex valued time sequence, and $X(e^{j\omega})$ its discrete-time Fourier transform. If $x[n]$ is already an analytic signal, its negative spectrum values equals 0, we can analyze only the real part of $x[n]$. Generally $x[n]$ is not going to be analytic signal. That's why we propose to extract positive and negative frequency components from $x[n]$. We can do it using ideal band-pass filter with transfer function defined as

$$W(e^{j\omega}) = \begin{cases} 1, 0 \le \omega < \pi \\ 0, -\pi \le \omega < 0 \end{cases} \quad (1)$$

Two analytic signals, representing positive (negative) frequency component we obtain by

$$X_+(e^{j\omega}) = W(e^{j\omega}) X(e^{j\omega}) \quad (2)$$

$$X_-(e^{j\omega}) = W(e^{j\omega}) X^*(e^{-j\omega}) \quad (3)$$

where $X^*(e^{j\omega})$ denotes the complex conjugate of $X(e^{j\omega})$.

Applying inverse Fourier transform $\left(F^{-1}[\cdot]\right)$ we obtain

$$x_+[n] = \Re F^{-1}\left\{X_+(e^{j\omega})\right\} \quad (4)$$

$$x_-[n] = \Re F^{-1}\left\{X_-(e^{j\omega})\right\} \quad (5)$$

where $\Re$ denotes the operator that extracts the real part of a complex function. Now, since $x_+[n]$ and $x_-[n]$ are real valued, we can apply standard EMD to decompose them. Following results are obtained

$$x_+[n] = \sum_{i=1}^{N_+} x_i[n] + r_+[n] \quad (6)$$

$$x_-[n] = \sum_{i=-N_-}^{-1} x_i[n] + r_-[n] \quad (7)$$

where $\sum_{i=1}^{N_+} x_i[n]$ and $\sum_{i=-N_-}^{-1} x_i[n]$ denote sets of corresponding IMFs, to $x_+[n]$ and $x_-[n]$, respectively, and $r_+[n]$ and $r_-[n]$ are associated residuals.

The reconstruction of so-decomposed complex-valued signal is accomplished by

$$x[n] = \left(x_+[n] + jH\{x_+[n]\}\right) + \left(x_-[n] + jH\{x_-[n]\}\right)^* \quad (8)$$

where $H[\cdot]$ denotes the Hilbert transform operator [3].

Like in standard EMD, complex-valued signal can be represented by summing corresponding IMFs and the residual

$$x[n] = \sum_{i=-N_-, i\neq 0}^{N_+} y_i[n] + r[n] \quad (9)$$

where $r[n]$ denotes residual, and $y_i[n]$ are complex-valued IMFs defined as

$$y_i[n] = \begin{cases} \left(x_+[n] + jH\{x_+[n]\}\right), i = 1,\ldots,N_+, \\ \left(x_-[n] + jH\{x_-[n]\}\right)^*, i = -N_-,\ldots,-1. \end{cases} \quad (10)$$

This is the final step of the complex EMD algorithm, which, as we can see retained generic form of standard EMD [5]. The transfer function from (1) can't be realized in practice, so it needs to be approximated.

IV. Complex EMD in Radar Signal Processing

The set of 69 complex-valued radar signals were used in our analysis. Those signals are obtained experimentally by detecting the maneuvering aircraft King-Air 200 using high-frequency surface wave radar (HFSWR).

Different methods are used to extract target component from radar signal. The one based on eigenvector analysis is studied in detail in [6]. Basic results of classical EMD application is presented in [7].

We applied complex EMD on the same experimental dataset. The procedure for target detection is described through the following steps:

1. Decompose two analytic signals to corresponding standard IMFs and residuals as described in relations (1) – (7).
2. Calculate the instantaneous frequency (IF) of the IMF_1 (potential target) using Hilbert transform [3], Fig. 2.
3. Determine threshold - the criterion for decision weather the component belong to the target or clutter.
4. Apply standard EMD to the part(s) of IMF_1 where IF is below threshold (5-22s Fig. 2).
5. Concatenate first IMF(s) calculated in step 4 to the part of IMF_1 where IF was above threshold (22-256s Fig. 2).
6. If none of the stopping criterions is satisfied repeat steps 1-5 with new data set from step 5. as an argument.
7. Show results, as time-frequency representation (TFR) of the target signal.

Having in mind properties of the radar system used in our research and the target observed, we can expect for the received target signal to have the highest frequency. This hypothesis is confirmed experimentally with all of the 69 radar signals - target signal was contained in the first IMF in all cases.

Further more, the instantaneous frequency of the signal reflected from moving objects is *chirp* like. Regarding this, we can define threshold (step 3 of the proposed procedure) in order to separate low-frequency region (clutter) from target region as presented in Fig. 2.

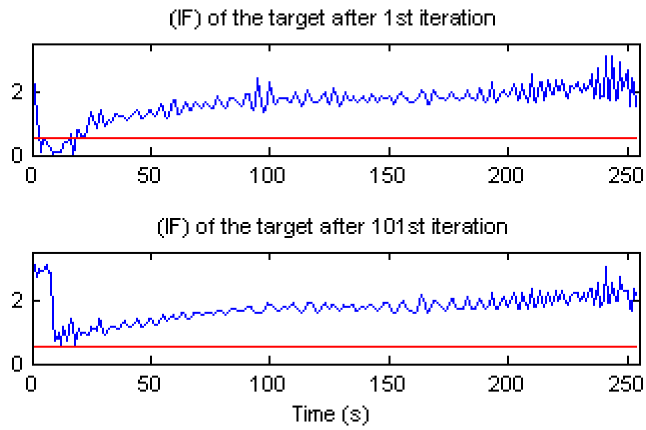

Figure 2. Instantaneous frequency (IF) of the target signal and corresponding threshold for complex-valued radar signal No.43

This threshold is used in order to avoid situation where part of clutter component is included in the first IMF. The threshold is determined empirically. Analyzing all radar signals it is confirmed that the best results in extracting target signal from noise are achieved using the mean value of the minimums from the signal obtained at step 2 for threshold.

In further lines we'll see the results of described procedure applied on the radar signal No.43 (position number of the King-Air 200). Regarding relations (1)-(7) we have two analytical signals, as shown in Fig. 3 and Fig. 4 (signal), that are time domain representatives of positive (negative) frequency component.

As described in (8)-(10) we have those signals decomposed. Corresponding complex-valued IMFs are plotted in the same Figures. Notice that the number of IMFs is different. This phenomenon is directly related to the lack of precise mathematical IMF derivation.

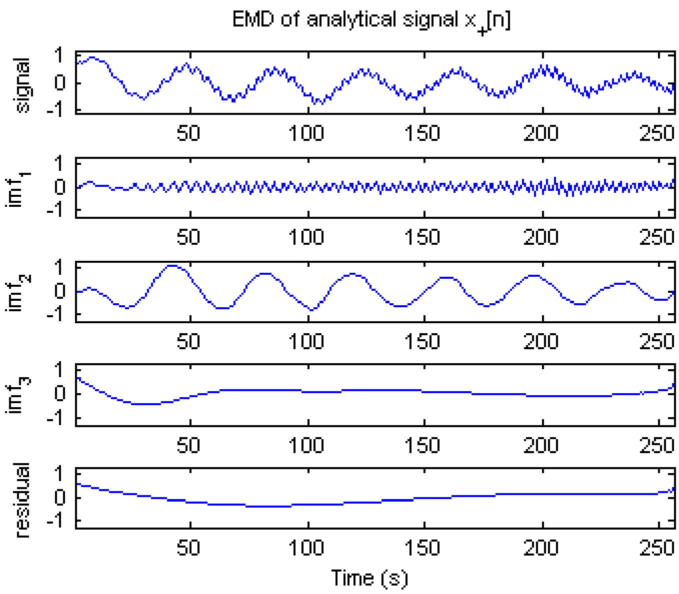

Figure 3. IMFs of complex-valued signal - positive frequency

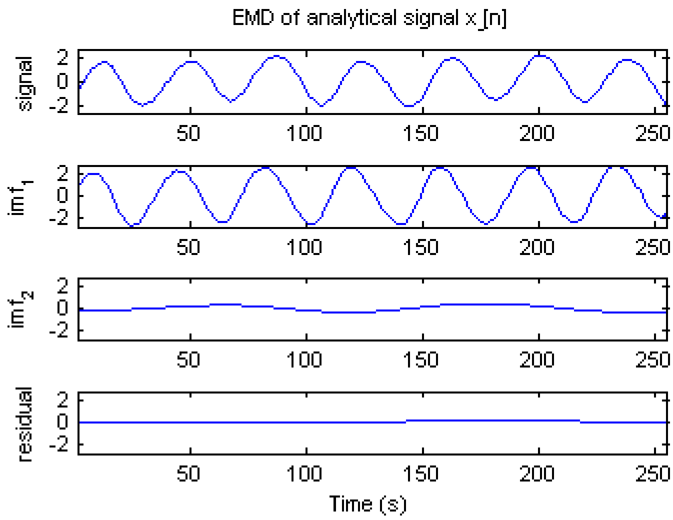

Figure 4. IMFs of complex-valued signal - negative frequency

Fig. 5 confirms that obtained complex-valued IMFs indeed have physical meaning and truly represent instantaneous frequency and power of observed signal. The IMF_1, from analytic signal corresponding to positive frequency component represent the target – Fig. 5(b). All other IMFs from both, positive and negative frequency components, represent noise – middle part of Fig. 5(a).

After analysis of the whole data-set we obtained satisfactory decomposition in all cases when complex EMD algorithm is applied. Two examples are presented in Fig. 6. TFR of analyzed signal is presented in the first column (a), result of decomposition that correspond to target component obtained by complex EMD is given in column (b) while classically obtained result is presented in the last column (c). Note that in the first signal (first row in Fig. 6), target component passes through clutter while in the second case target component is very close to the clutter.

IV. CONCLUSION

It is shown that complex EMD is efficient method for analysis of non-stationary complex-valued data. In this paper we analyze experimentally obtained HFSW radar data.

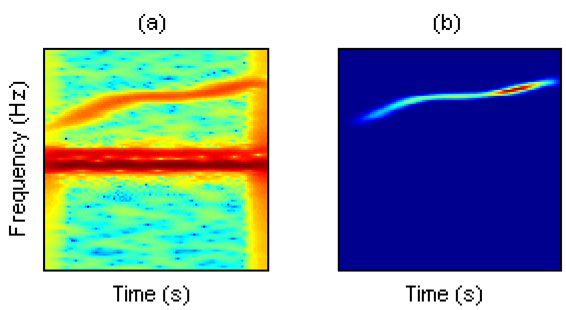

Figure 5. Complex EMD applied on signal No.43: (a) TFR of the original data set – sea clutter in the middle and target on the upper part (b) TFR of extracted target signal (IMF_1 from Fig. 3)

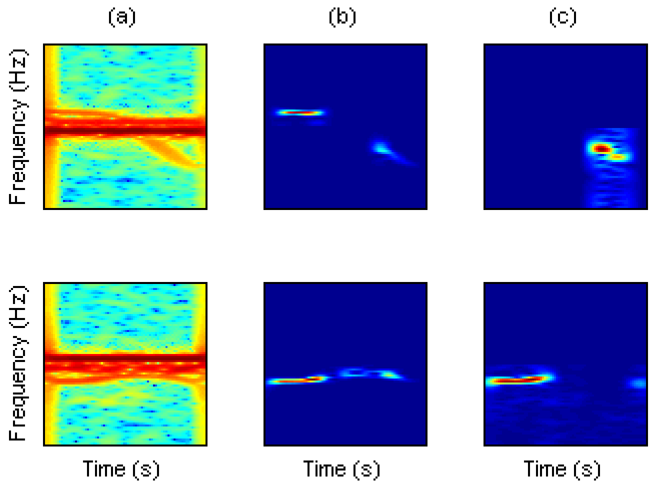

Figure 6. Complex EMD and classical EMD comparison: a) TFR of the original signal (logarithmic scale), b) TFR of the target component obtained by complex EMD, c) TFR of the target component obtained by classical EMD, 1) Signal No. 41, 2) Signal No. 7.

We developed a procedure for decomposition of experimental radar signals based on complex EMD presented in [1]. Along with this procedure a novel simple method for avoiding "border-effects" is presented.

Proposed procedure is applied to the experimental data in order to separate target signal from the heavy sea clutter. Obtained results are promising and can be used as starting point for further research in this area. Lack of theoretically based analysis is important drawback of complex EMD as well as of all EMD methods.

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