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Adaptive Signal Processing Algorithms Based on EMD and ITD

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ABSTRACT In the last two decades, both Empirical Mode Decomposition (EMD) and Intrinsic Time-Scale Decomposition (ITD) algorithms deserved a variety of applications in various fields of science and engineering due to their obvious advantages compared to conventional (e.g. correlation- or spectral-based analysis) approaches like the ability of their direct application to non-stationary signal analysis. However, high computational complexity remains a common drawback of these otherwise universal and powerful algorithms. Here we compare similarly designed signal analysis algorithms utilizing either EMD or ITD as their core functions. Based on extensive computer simulations, we show explicitly that the replacement of EMD by ITD in several otherwise similar signal analysis scenarios leads to the increased noise robustness with simultaneous considerable reduction of the processing time. We also demonstrate that the proposed algorithms modifications could be successfully utilized in a series of emerging applications for processing of non-stationary signals.

INDEX TERMS Adaptive filter bank, denoising algorithms, empirical mode decomposition, Fourier transform, Hilbert-Huang transform, internal oscillations, intrinsic time-scale decomposition, spectral analysis, wavelet transform.

I. INTRODUCTION

Majority of the observational signals considered in various fields of knowledge are non-stationary indicated by the variability of their statistical characteristics over time. In most practical scenarios, the stationarity assumption is validated for the first- and second-order moments only indicated by the time independence of both average and variance as well as the autocorrelation function having only a single time scale argument. Existing approaches to the non-stationary signal analysis and processing have several significant drawbacks.

For example, the widely used classical Fourier analysis, due to its relative calculation simplicity and fast computational algorithms availability, immediately began to overwhelm all other signal analysis methods. Despite the fact that the Fourier transform is performed under very general assumptions such as the Dirichlet boundary conditions and absolute integrability, there are several significant limitations on the signals for which it is calculated [1].

Fourier analysis has been originally suggested for strictly periodic functions that could be directly expanded in a Fourier series, i.e. represented by a superposition of multiple harmonic functions. Otherwise, the frequency domain based analysis may lead to incorrect results interpretation. It is also necessary that signals exhibiting the stationarity property for their certain characteristics such as average values and instant frequencies [1].

However, the Fourier analysis is ineffective in the study of signals with a changing frequency content (e.g. linear frequency modulated, parabolic frequency modulated, hyperbolic frequency modulated signals, from which the law of frequency change cannot be inferred from the Fourier spectrum), since the trigonometric basis contains unmodulated harmonic functions with a frequency that does not vary with time. Observational signals can include the components occupying different frequency bands and with changing instant frequency values (frequency modulation) [1].

By default, the Fourier transform is determined for the entire observational time fragment, resulting in the ignorance of the particular spatiotemporal localization of the energy dissipation. Therefore, for non-stationary scenarios, direct application of the Fourier analysis often leads to misleading results. Moreover, the most commonly used harmonic functions lead to rather low temporal resolution [1].

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Another drawback is that, due to their smoothness, the fitting harmonic functions often appear ineffective for the analysis of signals containing abrupt and/or stepwise changes. Therefore, a lot of functions may be required to provide the needed presentation accuracy. In addition, the well-known Gibbs phenomenon characterized by oscillations around gap points is often be observed [1].

To increase the accuracy and reliability of the non-stationary signal analysis, a special approach that has the adaptability property to each specific observational signal is required. One of the currently known approaches bases on the wavelet dyadic filter bank scheme partially satisfying this requirement. Moreover, its practical value can hardly be overestimated due to a set of well-developed mathematical analysis tools and fast computational algorithms leading to its wide application area [2].

Due to the wavelet basis design features (based on the scaling and shifting of the mother wavelet function along the time axis), it becomes possible to adaptively process signals by taking a rather accurate account of local time features. But the main problem is the great variety and the non-obviousness of the mother wavelet selection for solving a specific problem, especially when there is no heuristic criteria available. Nevertheless, the wavelet transform currently plays one of the leading roles in signal processing due to the presence of a large number of specially developed bases and its applicability to various important practical tasks (denoising, image, and signal compression, etc.) [2].

Matching pursuit algorithm (MPA) is another technique for spectral analysis. This algorithm allows decomposing the input signal using the following different basis functions: wavelets, sine waves, damped sine waves, polynomials, etc. These functions form the atom dictionary (the set of basic functions) where each function is localized in time and frequency domains. Generally, the atom dictionary is full (all types of functions are used) and redundant (the functions are not mutually independent). One of the main problems in this technique is the selection of basic functions and dictionary optimization. To solve this problem, a number of improvements and modifications of the classical algorithm were proposed [3], [4].

This paper will detail the adaptive technologies EMD and ITD for signal analyzing and signal processing [5]–[7]. Having properties similar to wavelet decomposition, these algorithms do not require an a priori basis choice. In other words, the decomposition according to this functions system for the purpose of subsequent analysis is carried out taking into account local features (such as signal extrema and zeros) and the internal structure (the presence of three main components in the signal – noise, trend and seasonal) of each specific signal. The basic functions are extracted directly from the original signal, therefore, such a basis is always unique (individual, does not repeat exactly for other signals), a posteriori (i.e., it becomes fully known only after data decomposition) and adaptive (i.e., it adapts to the features and data properties).

The term ‘‘basis’’ is not used correctly here, because, by definition, a basis is a linearly independent set of vectors (functions) whose linear span forms the entire linear space (that is, each vector of this space can be represented as a linear combination of basis vectors) [2]. In this case, linear independence is not strictly proven and, in addition, the extracted components in most cases can only be used to process the signal from which they were extracted. Therefore, such a basis is empirical, approximate and constitutes a kind of set of ‘‘building blocks’’ for representing signals. Further, under the ‘‘basis’’ as applied to the EMD and ITD algorithms, we will just mean such an approximate basis. In some cases, when considering several signals from the same class, it is possible to decompose one of them, and then, using the obtained components and specially introduced weights for each of them, present other signals of the same type. In this case, it can be argued (after checking the linear independence of the components) that the components extracted from the signal are the basis.

In this paper, we propose a novel approach to adaptive signal processing based on EMD and ITD. This approach is used to design the adaptive filter bank based on ITD instead of EMD. The complexity of the proposed novel approach of adaptive filter bank designing is compared with EMD based approach. The use of ITD as a basis in spectral analysis algorithm using the Hilbert transform is proposed. Keeping the idea of the algorithm, we modify it to use ITD (instead of the modes obtained using EMD, we will use the modes obtained using ITD). The complexity of the algorithm, approximation errors, and energy conservation are estimated. We modify denoising algorithms to use ITD (instead of the modes obtained using EMD, we will use the modes obtained using ITD). Denoising quality and processing time of the corresponding algorithms when using the ITD algorithm as the basis instead of the EMD algorithm are compared. As test signals, we use various test non-stationary signals of MATLAB.

The paper is organized as follows. A brief review of the EMD and ITD algorithms is presented in Section II and Section III. In Section IV, the proposed novel approach to the synthesis of adaptive filter bank based on ITD is presented. In Section V and Section VI, the use of ITD as a basis in spectral analysis algorithms using the Hilbert transform and adaptive denoising algorithms is proposed. Section VII gives our conclusions.

II. ALGORITHM EMD

EMD – an algorithm for decomposing signals into functions that are called ‘‘empirical modes’’.

The EMD algorithm is an iterative computational procedure, as a result of which the original signal is decomposed into empirical modes or internal oscillations (Intrinsic Mode Functions, IMF). In contrast to harmonic analysis, that setting in advance the signal decomposition basis, empirical modes are calculated during the process, making the algorithm adaptive. The EMD algorithm allows analyzing local features, therefore, it can be used in processing non-stationary signals [5], [6].

Definitions: An empirical mode, internal oscillation, or a mode (Intrinsic Mode Functions, IMF) is a function that has the following two properties:

- The number of extrema (highs and lows) and the number of zero crossings should not differ by more than one.
- The average value, which is determined by two envelopes – upper and lower, should be equal to zero.

Empirical modes have such properties that allow applying the methods of Hilbert spectral analysis to them.

The algorithm can be written as the following sequence of steps:

Let $X(t)$ be analyzed signal.

The essence of the EMD algorithm is the sequential calculation of empirical modes c_j and residues: $r_j = r_{j-1} - c_j$, where $j = 1, 2, \ldots, n$ and $r_0 = X(t)$.

As a result, a signal decomposition is obtained:

$$X(t) = \sum_{j=1}^{n} c_j + r_n \tag{1}$$

where: n – the empirical modes number that is established during the processing.

Scheme of the Algorithm: In general terms, the algorithm is as follows (Fig. 1):

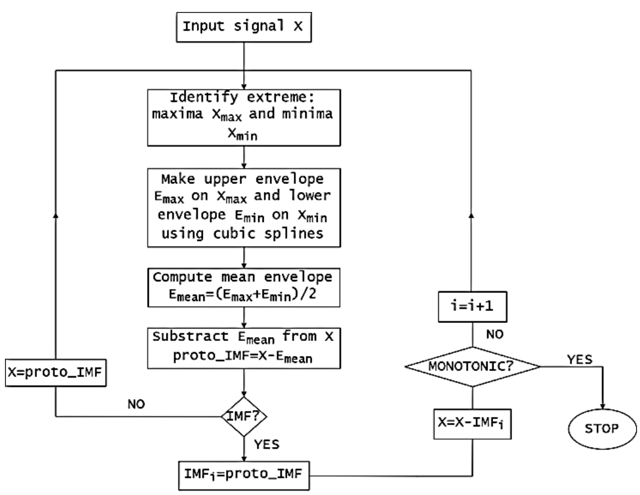

FIGURE 1. Block diagram of the EMD algorithm.

III. ALGORITHM ITD

ITD – an iterative algorithm for decomposition of the original signal into high-frequency ("proper rotation", H_t) and low-frequency ("baseline signal", L_t) components [7]:

$$L_t^0 = X_t = L_t^D + \sum_{j=1}^{D} H_t^j; \quad L_t^j = L_t^{j+1} + H_t^{j+1};\ j = 0 \ldots D \tag{2}$$

Let there be a signal X_t. We define an operator $\mathcal{L}$ that extracts the low-frequency component ("baseline signal") from the signal in such a way that the remainder is the high-frequency component ("proper rotation"). Then the signal X_t can be written as follows:

$$X_t = \mathcal{L}X_t + (1 - \mathcal{L})X_t = L_t + H_t \tag{3}$$

$L_t = \mathcal{L}X_t -$ "baseline signal"; $H_t = (1 - \mathcal{L})X_t$ – "proper rotation"

Let there is a signal $\{X_t, t \geq 0\}$ and $\{\tau_k, k = 1, 2, \ldots\}$ – its local extremes. Introduce the notation: $X(\tau_k) \equiv X_k$ and $L(\tau_k) \equiv L_k$.

Then:

$$\mathcal{L}X_t = L_t = L_k + \frac{L_{k+1} - L_k}{X_{k+1} - X_k}(X_t - X_k) \quad t \in \{\tau_k, \tau_{k+1}\} \tag{4}$$

where:

$$L_{k+1} = \alpha\left[X_k + \left(\frac{\tau_{k+1} - \tau_k}{\tau_{k+2} - \tau_k}\right)(X_{k+2} - X_k)\right] + (1-\alpha)\, X_{k+1} \tag{5}$$

$0 < \alpha < 1-$ parameter.

We define an operator $\mathcal{H}$ that extracts the high-frequency component ("proper rotation") from the signal. After exclusion of the trend, we can calculate the remainder:

$$\mathcal{H}X_t \equiv (1 - \mathcal{L})X_t = H_t = X_t - L_t \tag{6}$$

Fig. 7 (a, b) in [7] shows the operation of the EMD and ITD algorithms, accordingly. The source signal is denoted as "raw signal". It is noticed that the ITD algorithm allows decomposition of the signal into a lower number of more stable components in comparison with the EMD algorithm. Edge effects in EMD are due to spline interpolation, and a significantly longer runtime is due to the sifting. The ITD algorithm does not have these features and can operate in real-time.

Fig. 7 (d, e) in [7] presents the operation of the EMD and ITD algorithms, accordingly. The initial signal is shown in Fig. 7 (c). It is noticed that the ITD algorithm does not introduce additional distortions in comparison with the EMD algorithm. ITD allows detecting local features (the original signal, in this case, has a series of bursts in the area of 300-350 sec) with high accuracy relative to the EMD algorithm.

IV. SYNTHESIS OF ADAPTIVE FILTER BANKS USING EMD AND ITD

Filter bank (FB) is a digital scheme that decompose the input signal, represented by a sequence of samples, using of K various digital filters into K various channel signals (for processing each of them in a certain way), from which a sequence of samples of the output signal is formed using output filters and subsequent summation (Fig. 2) [8], [9].

Filter banks are widely used in seismic monitoring, radio monitoring and hydroacoustic monitoring [10].

In the field of radio monitoring, you need to have tools to track a rapidly changing environment in real-time. A large number of emitters on the air, encryption, masking, modulation necessitate adaptive processing. For hydroacoustics,

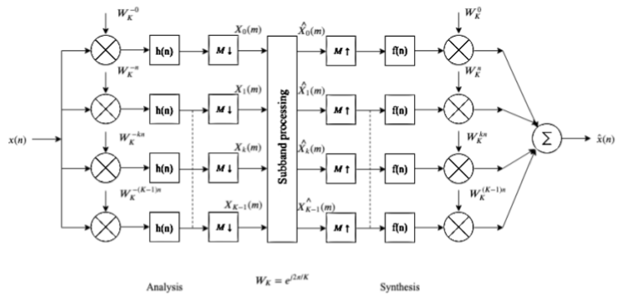

FIGURE 2. **Model of a DFT modulated filter bank based on full modulation.**

the propagation medium is of great importance, which at the slightest change in external conditions (temperature, salinity, pressure, etc.) instantly changes its properties. This fact also entails the need for adaptive processing [10].

Consider the possibility of constructing an adaptive FB using the EMD and ITD algorithms. Since both algorithms decompose the input signal into internal oscillations (Intrinsic Functions, IF) and have significant similarities, we can carry out some general considerations. In this case, adaptability is understood as the ability to fine-tune the bank to a specific type of signals taking into account local characteristics.

Obviously, the IF with the first number, extracted before all, contains the largest number of highs, lows, and zeros (in some cases, there may be no zeros if the IF turns out to be completely positive or negative definite) compared to all other components. It also contains the largest part of noise from the input mixture of the desired signal with noise. From this we can conclude that it is the highest frequency (HF). Further, when extracting the next in order IF, the number of extrema along which the upper and lower envelopes are built, is already much lower. This means that the second component of the decomposition is less HF than the first. Noteworthy is the fact that the overall dynamics persists as the IF number increases, up to obtaining the resulting residue [10], [11].

Thus, summing up the line of reasoning, the first IF is the HF itself, the second is less HF than the first, and k – less HF (lower frequency (LF)) than $k-1$. The resulting remainder may even turn out to be a constant having, by definition, a zero frequency, or this remainder may be a slowly changing trend.

If we take into account the average period IF, considering it as the inverse of the average frequency, then the dynamics will be directly opposite, that is, the first IF will have the lowest period, and the last, on the contrary, the largest until infinity (in case of a constant). This concept of a period should not be confused with a strict definition of the harmonic function period. IF does not have to be strictly periodic, even if the signal itself has this property.

Having determined the dynamics of IF properties in the time domain, we will try to transfer it to the frequency domain. For this, first of all, it is necessary to calculate the DFT for each IF. It is interesting to note that the DFT may not make sense for the signal itself (if it is non-stationary), but the DFT can nevertheless be applied to IF to obtain a qualitative view of its frequency structure. The frequency spectrum of the first IF is obviously the most wideband, since there is a large proportion of spectral components with high frequencies (mainly due to the presence of HF noise). Recall that the first IF is the highest frequency, i.e., the fastest-changing. Subsequently, as the IF number increases, the effective width of its Fourier spectrum decreases, which is associated with a decrease in the total number of oscillations in its temporal realization. Finally, the last IF has the narrowest spectrum explaining its pronounced monotonic nature [11], [12].

The spectral representation features allow us to draw the following important conclusions. The spectrum of the first IF is band-pass, i.e., the transmission of the input signal through a filter with a magnitude response that coincides with the DFT module of the first IF, and a phase response that matches the DFT phase of the first IF, allows this IF to be extracted from the input signal. The spectrum of the second IF, as a rule, also is a band-pass, however, it is shifted in frequency compared to the first case towards low frequencies. And again, a filter based on the calculated DFT spectrum allows one to extract the corresponding IF from the signal. With an increase in the number of components, the frequency response of the corresponding filters becomes lower and lower due to a decrease in the effective spectral width of the corresponding IF.

If one place the frequency response of all filters on the same frequency axis, then it becomes clear that the decomposition process is, in fact, a synthesis of a combination of bandpass filters that overlap in frequency with an effective band that decreases in width and shifts toward the low frequencies as the number of the corresponding IF increases. This approach allows us to create filter banks based on specific signals and use them both to quickly emphasizing specific IFs and to analyze signals similar in properties. Thus, it is possible to significantly increase the hardware and software costs.

As a test signal, we will use the observational signal [13] (a seismograph record) shown in Fig. 3. We perform the

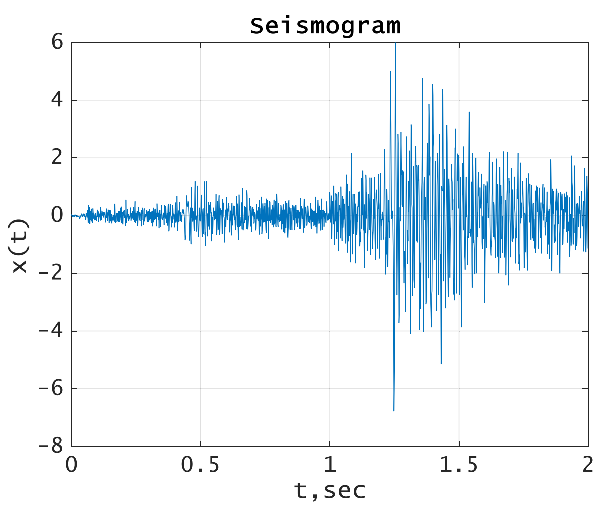

FIGURE 3. **Testing signal.**

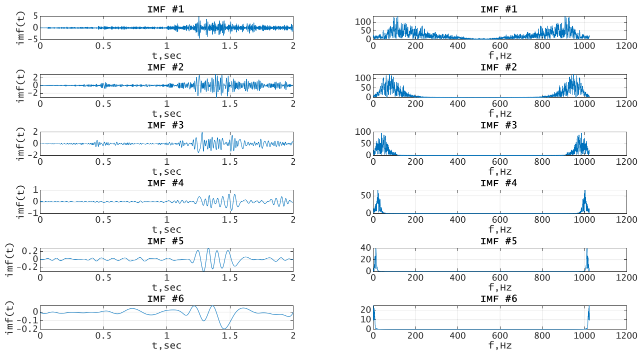

FIGURE 4. EMD: modes and their corresponding spectra.

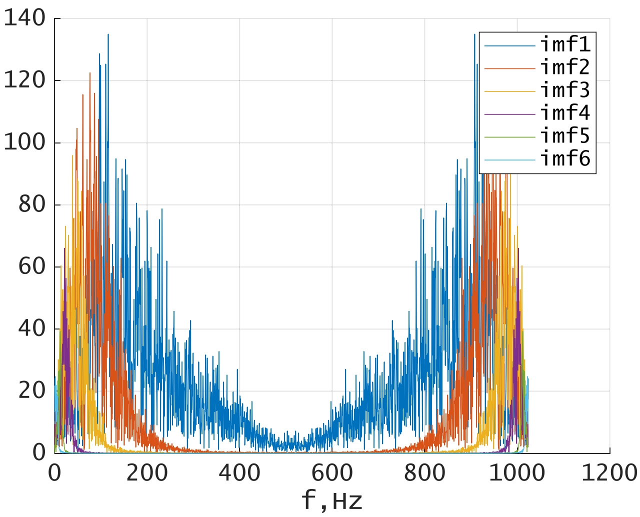

FIGURE 5. Filter bank based on EMD.

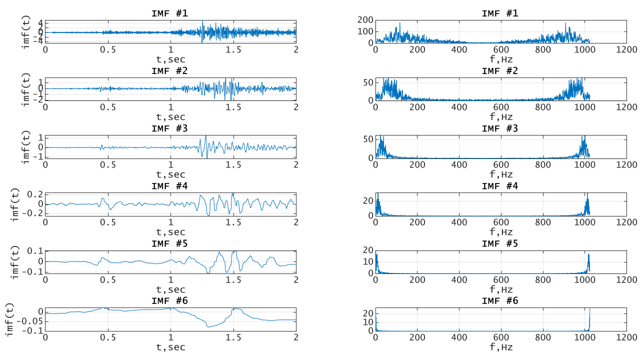

FIGURE 6. ITD: modes and their corresponding spectra.

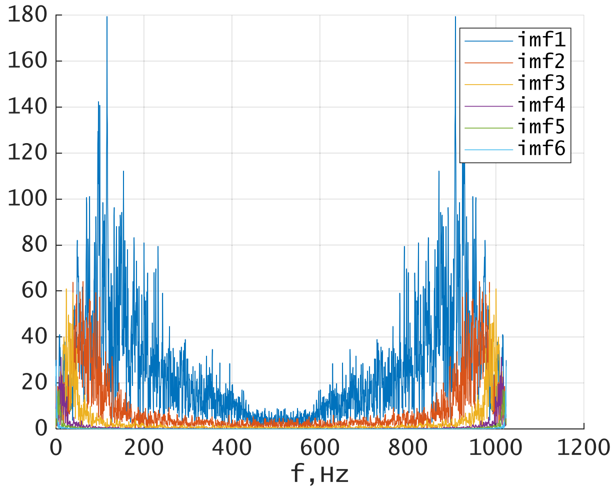

FIGURE 7. Filter bank based on ITD.

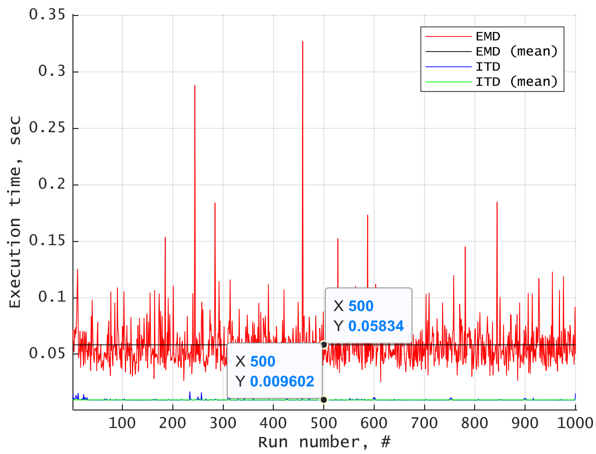

FIGURE 8. EMD vs ITD: runtime with averaging over 1000 measurements.

signal decomposition into internal oscillations using EMD and ITD (Fig. 4-7):

Fig. 4 shows the signal decomposition using the EMD algorithm (left: modes; right: corresponding DFT spectra).

Fig. 5 shows the frequency response of an adaptive FB using the EMD algorithm.

Fig. 6 shows the signal decomposition using the ITD algorithm (left: modes; right: corresponding DFT spectra).

Fig. 7 shows the frequency response of an adaptive FB using the ITD algorithm.

Fig. 8 shows the dependence of the execution time of the considered algorithms on the run number and the average value (averaging over 1000 measurements).

Comments: Fig. 8 illustrates the stability of the ITD algorithm in comparison with the EMD algorithm (due to the lack of sifting and interpolation by splines) and a significant reduction in the computation time ($\sim$ 6.08 times) of the ITD algorithm in comparison with the EMD algorithm.

V. SPECTRAL ANALYSIS OF SIGNALS USING EMD, ITD AND HILBERT TRANSFORM

Once the EMD algorithm has been applied to decompose the input signal into a set of IF, one may now analyze the IFs to extract instantaneous amplitude, phase, and frequency information. The conventional approach to obtain instantaneous amplitude, A_t, instantaneous phase, θ_t and instantaneous frequency, f_t, information from IF, R_t, is based on the application

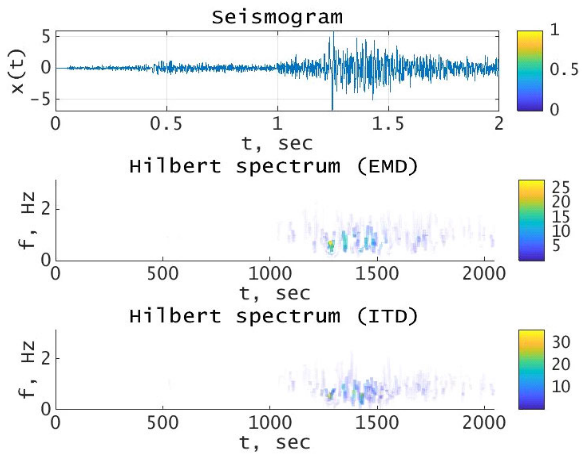

FIGURE 9. Seismogram No̲ 1 (maximum 10 modes).

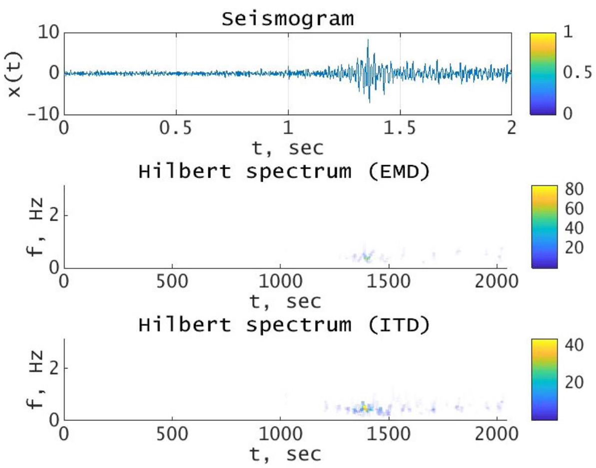

FIGURE 10. Seismogram No̲2 (maximum 10 modes).

of the Hilbert transform, $h[\cdot]$, as follows:

$$\begin{cases} A_t \equiv \left| R_t + ih\left[R_t\right] \right| \\ \theta_t \equiv angle\left(R_t + ih\left[R_t\right]\right) \\ f_t \equiv \dfrac{1}{2\pi}\dfrac{d\theta_t}{dt} \end{cases} \tag{7}$$

here:

$$h\left[R_t\right] = P.V. \left[\frac{1}{\pi} \int_{-\infty}^{\infty} \frac{R_\tau}{t-\tau} \right] \tag{8}$$

and 'P.V.' denotes the Cauchy principal value of the integral.

In the Hilbert-Huang transform, at the first stage, the signal is decomposed using EMD, then the Hilbert transform [5], [6] is performed.

Keeping the idea of the algorithm, we modify it to use ITD (instead of the modes obtained using EMD, we will use the modes obtained using ITD).

Consider a series of seismograms (16 records were used in total) and their Hilbert spectra (first 3 records) obtained using EMD and ITD (Fig. 9-11).

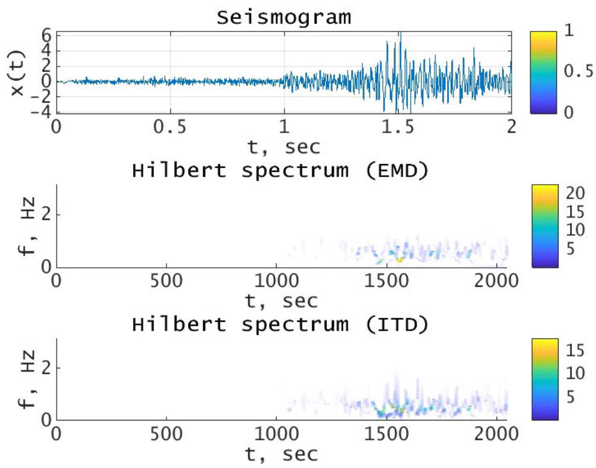

FIGURE 11. Seismogram No̲3 (maximum 10 modes).

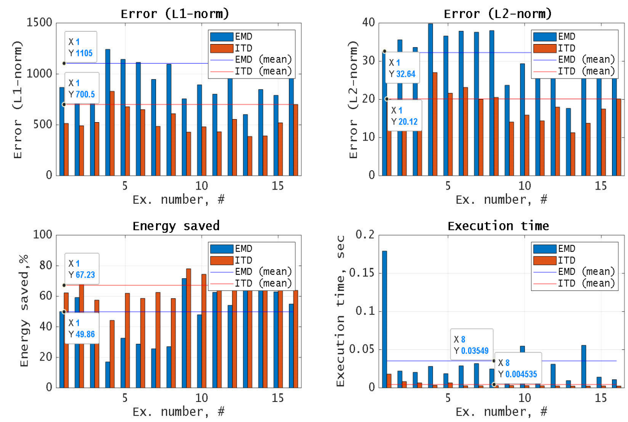

FIGURE 12. EMD vs ITD (modes number: 1): approximation errors, energy conservation, and runtime.

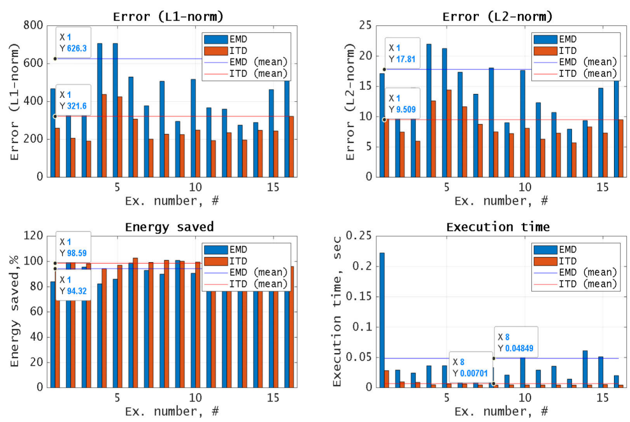

FIGURE 13. EMD vs ITD (modes number: 2): approximation errors, energy conservation, and runtime.

Comments: Fig. 9-11 illustrate the signal representation improvement in the time-frequency-energy domain. Hilbert spectra constructed using ITD have a higher degree of correlation with the original signal in the sense of energy conservation than Hilbert spectra constructed using EMD. Fig. 12-14 show approximation errors, energy conservation rates, and runtimes for all 16 records using the EMD and ITD

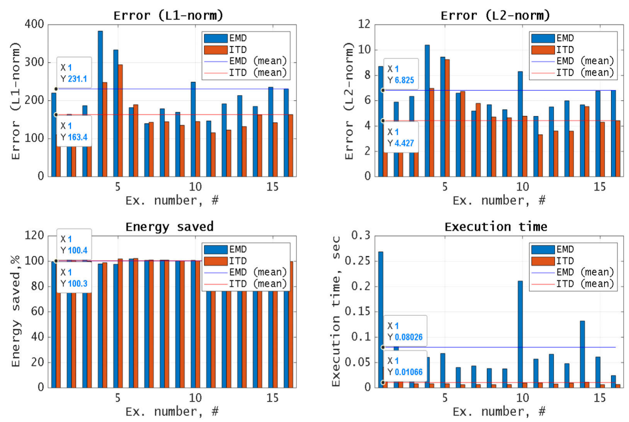

FIGURE 14. EMD vs ITD (modes number: 3): approximation errors, energy conservation, and runtime.

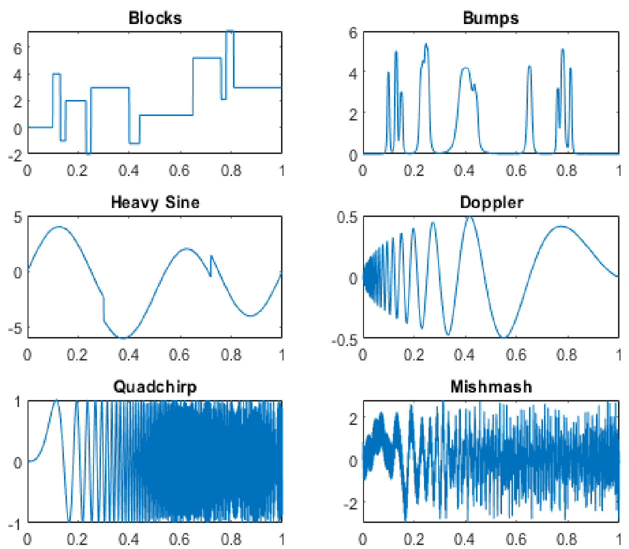

FIGURE 15. Testing signals.

algorithms. The norms of the error vector e were calculated by the following formulas:

$$\|e\|_p = \left[\sum_{k=1}^{N} |e_k|^p\right]^{1/p}; \quad p=1,2; \; \|e\|_\infty = \max_i |e_i|; \; p=\infty; \tag{9}$$

Comments: Fig. 12-14 illustrate the reduction of approximation energy loss. Hilbert spectra constructed using ITD have a higher correlation degree with the signal in the sense of an approximation error than Hilbert spectra constructed using EMD (~1.68 times). Therefore, such spectra can be used, for example, as classification features in convolutional neural networks (CNN) [14] with a significant reduction in time costs (~7.42 times).

VI. DENOISING USING EMD AND ITD

Based on the EMD algorithm, the researchers proposed a number of denoising algorithms: Ensemble EMD (EEMD) [15], Conventional EMD (CEMD) [16], Iterative EMD (IEMD) [16], Exponential EMD (EXP-EMD) [17] and

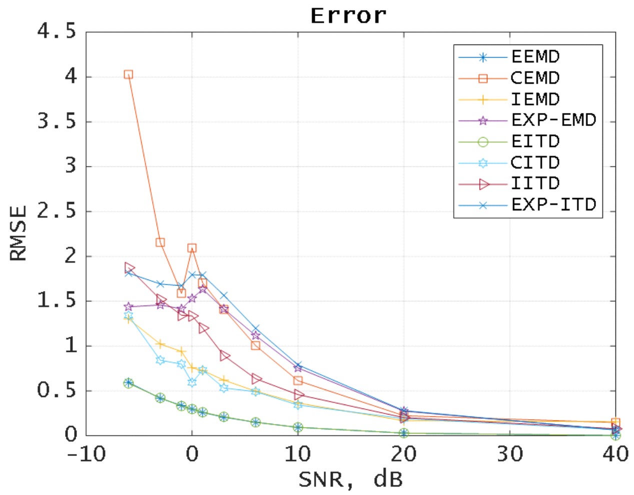

FIGURE 16. Comparison of various denoising algorithms for the "Blocks" signal.

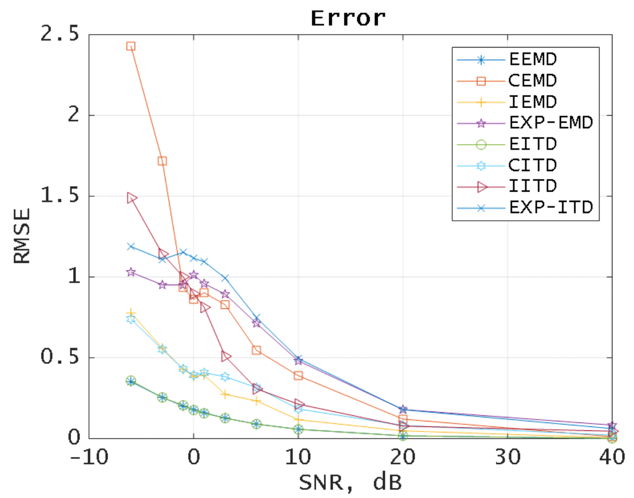

FIGURE 17. Comparison of various denoising algorithms for the "Bumps" signal.

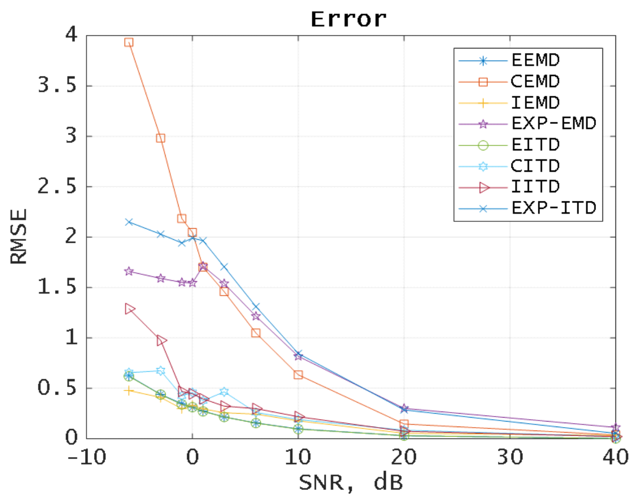

FIGURE 18. Comparison of various denoising algorithms for the "Heavy Sine" signal.

their various modifications [18]. All algorithms use so called modes in their work, so we could modify them as follows: keeping the structure of the algorithms, we modify them with

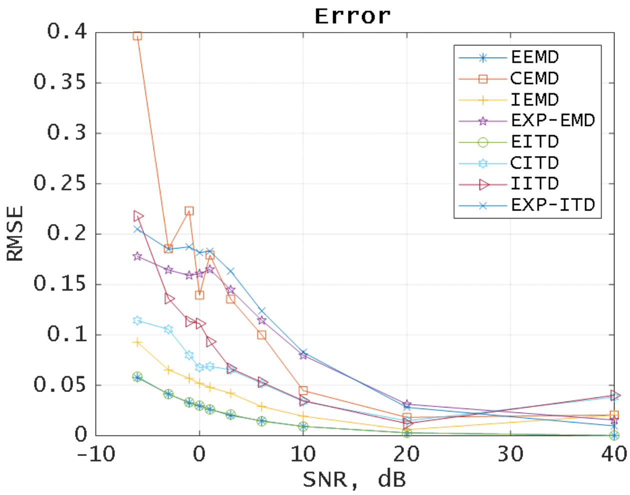

FIGURE 19. Comparison of various denoising algorithms for the "Doppler" signal.

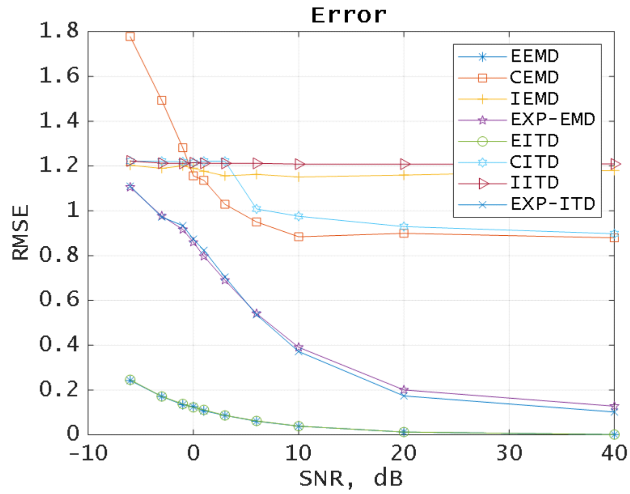

FIGURE 21. Comparison of various denoising algorithms for the "Mishmash" signal.

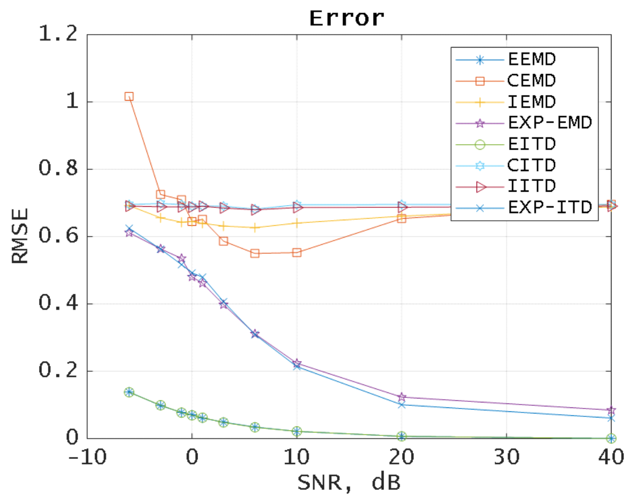

FIGURE 20. Comparison of various denoising algorithms for the "Quadchirp" signal.

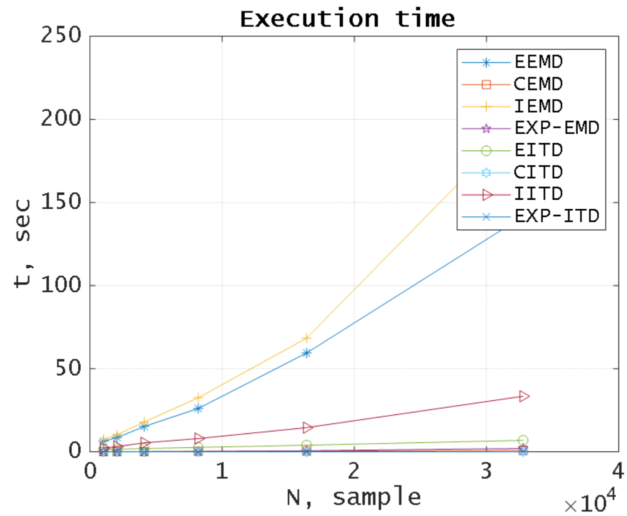

FIGURE 22. Comparison of computational complexity for various denoising algorithms.

using ITD (instead of the modes obtained using EMD, we will use the modes obtained using ITD). As test signals, we use various test non-stationary signals of MATLAB (Fig. 15):

Additive white Gaussian noise is used in the paper:

$$z(t) = x(t) + \eta(t) \tag{10}$$

$x(t)$– initial signal; $z(t)$– noisy signal; $\eta(t)$– noise itself.

We use the standard RMSE metric (Root Mean Square Error) to estimate the filtering quality:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N} (x_i - \tilde{x}_i)^2}{N}} \tag{11}$$

x_i– initial signal; $\tilde{x}_i$– noised signal; N – number of samples.

Compare the denoising quality using various algorithms based on EMD and ITD (RMSE vs SNR) (Fig. 16-21):

Fig. 22 shows the dependence of the execution time for the considered algorithms on the number of input signal samples.

Comments: Fig. 16-21 and 22 illustrate the improvement in the denoising quality and/or the reduction of the processing time of the corresponding algorithms when using the ITD algorithm as the basis instead of the EMD algorithm in most experiments over the entire signal-to-noise ratio. Note that the most effective algorithm in terms of denoising, speed and stability was EITD.

VII. CONCLUSION

The paper provided a brief mathematical description of EMD and ITD algorithms. The comparative algorithm analysis was made. The possibility of building an adaptive filter bank using ITD was considered. The use of ITD as a basis in spectral analysis algorithms using the Hilbert transform and adaptive denoising algorithms was proposed. The computational complexity of the algorithms was estimated. The use of ITD algorithm instead of EMD allowed, depending on the application, to improve the signal representation quality in the time-frequency-energy domain or to improve the denoising quality, as well as significantly reduce the processing time.

All experiments were performed using real seismic and hydroacoustic data. The simulation was performed on a PC with the following architecture: OS Win 10 64-bit, CPU Intel Core i7 Skylake 4.0 GHz, RAM DDR4 Kingston HyperX Fury 64 GB 2.4 GHz, GPU NVIDIA GeForce GTX 1080 1.7 GHz DDR5 8 GB 10 GHz, CUDA kernel 2560, MATLAB R2018b 64-bit.

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