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A Review of Notable Studies on Using Empirical Mode Decomposition for Biomedical Signal and Image Processing

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Abstract

The data-driven empirical mode decomposition (EMD) method is designed to analyze the non-stationary signals like biomedical signals originating from nonlinear biological systems. EMD analysis produces a local complete separation of the input signal in fast and slow oscillations along with the time-frequency localization. EMD extracts the amplitude and frequency modulated (AM–FM) functions, i.e. the intrinsic mode functions (IMFs), that have been widely used for biomedical signal de-noising, de-trending, feature extraction, compression, and identification. To overcome the problems of EMD, like mode mixing, new generations of EMD have been proposed and applied for biomedical signal analysis. Besides, the bidimensional EMD (BEMD) was introduced and improved for image processing. BEMD and its modified versions have been widely used for medical image de-noising, de-speckling, segmentation, registration, fusion, compression, and classification. In this paper, a review of notable studies in the biomedical signal and image processing based on EMD or BEMD method and their modified versions were considered. The studies on using EMD and its modified versions for mono-dimensional and bidimensional(image) signal processing showed the capabilities of the improved EMD and BEMD methods on biomedical signal and image processing.

Keywords: Empirical Mode Decomposition, Mode Mixing, Bidimensional Empirical Mode Decomposition, Biomedical Signal Processing, Medical Image Processing.

1. INTRODUCTION

Fourier and wavelet transform are the most recognized decomposition techniques that break the signal into several levels of resolution or frequency. They, however, either is not suitable for non-stationary and non-linear signals or depend on a priori basis function. The Empirical Mode

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Decomposition (EMD) is a relatively new approach introduced by Huang et. al. [1] for adaptive multiresolution decomposition. Besides, EMD does not need a priori bases function. The Fourier and wavelet approaches project data onto the predefined basis functions while the bases for EMD are derived from the data [2]. EMD breaks the input signal into a number of frequency modes known as intrinsic mode functions (IMF) each, containing information about the signal behavior at a particular time scale. In other words, applying EMD, the input signal can be expressed as a sum of amplitude and frequency modulated (AM–FM) functions or IMFs, and a final monotonic trend [3].

The first IMFs reflects the high frequency/fast variations of the signal while the last IMFs contain the low frequency/slow trend of the input signal [4]. EMD, as an iterative and multiresolution process, has some significant properties that provide a better analysis of the input signal and its components. Using the locality property, EMD operates at the scale of one oscillation with no assumption on the nature of oscillations. Besides, the dynamics of IMFs' in the frequency domain is unchanged. In addition to the completeness property that enables the full reconstruction of the input signal based on its IMFs, EMD is fully data-driven and adaptive [5]. As the basic analysis tool, EMD provides the statistical analysis, extrapolation, de-noising, allocation, and removal of trend (de-trending). The representation of EMD in the time-frequency domain is a high resolution on both coordinates that offers to discover hidden amplitude and frequency modulations in signals and finding out the domains of energy concentration [5], [4].

1.1. Theoretical Background

The EMD method, also called Huang transform, has actually no complete and generally accepted theoretical framework [1]. EMD consider the input signals as "fast oscillations superimposed on slow oscillations" [4]. Hilbert–Huang transform that is the combination of EMD method with Hilbert transform applied in many different fields [6]such as system identification problems [7][8] and biomedical applications [9]. Consequently, EMD research has mainly been in two categories, modifying the sifting procedure or empirically defined configurations drastically [10]. One of the requirements of EMD method is the pure oscillation of the extracted component with mean zero. Based on this requirement, Ge et. al. suggested a theoretical principle involving the oscillation signal decomposition [10]. The validity and robustness of EMD were mathematically demonstrated by Ge et. al. in [10] and a theoretical framework for the analysis of EMD was also provided.

In this paper, the EMD and BEMD methods as well astheir inherent problems and their modified versions are considered along with their applications for medical signal and image processing. In section 2, the analytic background of EMD analysis and its generations are considered. The studies on biomedical signal processing by EMD are reviewed in section 3. Section 4 is dedicated to the application of BEMD and its modified versions on medical image processing. Discussion and conclusion sections are the next parts of this presented paper.

2. EMD ANALYSIS

The analytical formulation of EMD has not been admitted for a long time, so the theoretical analysis and performance evaluation of EMD were difficult [10]. The theoretical principle of oscillation signal decomposition was recently (2018) described by Ge et. al in [10] based on interpolation and frequency resolving ability. The best spline implementation and the optimum positions of the interpolation points are the two main concerns in EMD. The spline interpolation, that are used in the existing EMD algorithm, is not essentially the best implementation. Consequently, the produced upper (maxima) envelope or the lower (minima) envelope between the nearest two minima or maxima varies with time uniformly and bulges away from the signal smoothly [10].

Ge et. al demonstrated that, for EMD analysis of different signals with different characteristics, different spline implementations should be selected; provided that the uniform and smooth variation condition between two consecutive local minima and maxima are satisfied, the results will be the same [10]. Theoretically, a specified way to detect the optimum positions of the interpolation points has not been established [10]. The upper(maxima) envelope or the lower(minima) envelope are determined based on at least three corresponding local extrema points that cover a periodic time of the oscillation [10]. The difference between two oscillation components is the periodical difference more than two times or less than half of a time, or the frequency ratio up to 2 or less than 0.5 can be distinguishable by EMD. However, some previous studies showed that the actual separable range occurs between two oscillation components with frequency ratio larger than 1/0.6 and less than 0.6 [11], [6], [12].

The concept of filter bank based on EMD was proposed by Flandrin et. al. [13]. They demonstrated that IMFs are combined to achieve the high-pass, low-pass and band-pass filters [13]. The similar characteristics between EMD and wavelet approaches were confirmed by Wu and Huang [14].

2.1. EMD Generations

Although EMD is one of the best signal processing techniques, it still has unsolved problems due to the nature of the EMD: ‘mode mixing’ and ‘spurious modes’. Oscillations with very disparate scales in one mode, or oscillations with similar scales in different modes i.e. “mode mixing” can be produced by EMD due to the inherent locality of this method [15]. EMD generations are shown in Table 1.

To reduce the mode mixing problem of EMD, the ensemble empirical mode decomposition (EEMD) was proposed by Wu et. al. [17]. An ensemble of noisy copies of the input signal, by adding white Gaussian noise is produced and then decomposed by EMD. The resultant modes are obtained by averaging [3]. Considering the dyadic filter bank behavior of EMD adding white Gaussian noise reduces the mode mixing by occupying the whole space of time-frequency [3]. Consequently, EEMD produces more regular modes with similar scales for the whole-time span. Although the benefits of using the EEMD method have

Table 1. ***EMD generations.***

Method	Description	Author/Year
EMD	Empirical Mode Decomposition	Huang, 1998 [1]
Complex-EMD	Complex Empirical Mode Decomposition	Tanaka, 2007 [16]
EEMD	Ensemble Empirical Mode Decomposition	Wu, 2009 [17]
CEEMD	Complementary Ensemble Empirical Mode Decomposition	Yeh, 2010 [18]
CEEMDAN	Complete Ensemble Empirical Mode Decomposition with Adaptive Noise	Torres, 2011 [19]
ICEEMDAN	Improved Complete Ensemble EMD	Colominas, 2014[3]

been demonstrated in a wide range of applications [20], it encountered some new problems. The residual noise in the reconstructed signal is the most important problem of EEMD. Besides, a different number of modes may be obtained based on the different realizations of signal plus noise that makes the final averaging difficult [3]. By adding and subtracting pairs of noise, in the Complementary EEMD [18], the reconstruction problem was drastically reduced [18]. The completeness property of Complementary EEMD has not been proven. In addition, the different number of modes are produced by the different noisy copies of the input signal that makes the final averaging difficult [3]

In order to achieve a negligible reconstruction error and solve the problem of different number of modes for different realizations of signal and additive noise, the complete ensemble empirical mode decomposition with adaptive noise (CEEMDAN) were introduced by Torres et. al. [19] that is considered as an important improvement on EEMD [3]. In spite of that CEEMDAN was applied in biomedical engineering studies, residual noise in the modes obtained based on CEEMDAN. Moreover, the signal information appears “later” than in EEMD with some “spurious” modes in the early stages of the decomposition [3]. An important amount of noise and similar scales of the signal are extracted by the first two or three modes [19],[21]. Colominas et al. proposed an improved CEEMDAN (ICEEMDAN) obtaining IMFs with less noise and more physical meaning [3]. The results of a synthesis signal decomposition using different generations of EMD are shown in Figure 1 that was demonstrated by Colominas et. al. [6].

Considering Figure 1, mode mixing in EMD results (first column from the left) are clearly visible. For instance, in the d1 mode, two different frequencies are appeared in a mode, this is also the case for d2, d3 and d4. For the noise-assisted methods the pure tone and the fast component are well extracted without mode mixing. However, in EEMD and CEEMD there are some IMFS with very small energy without representing information of the input signal. Those are no longer appeared in CEEMDAN, and ICEEMDAN. Although a “spurious” second mode appears for original CEEMDAN, the decomposition stops sooner once the IMF conditions are satisfied [3]. The number of extracted IMFs is also a notable issue, as it shows in Figure 1, for this simple input signal EMD, EEMD and CEEMD generated nine IMFs that are not informative, this dilemma is solved in CEEMDAN and its improved version (ICEEMDAN).

2.2. IMF Selection

Along with the improvements of EMD generations, a number of extracted IMF selection have been reported to improve the EMD results for different applications. Table 2 summarizes these efforts.

An improved Hilbert–Huang transform using wavelet packet transform was introduced by Peng et. al. [22]. They suggested an IMF selection based on correlation coefficients [22]. A method for IMF selection based on energy entropy was later introduced by Yu et. al. [23]. The confidence index of IMFs’ was introduced by Yi et. al. [24] for automatic IMF

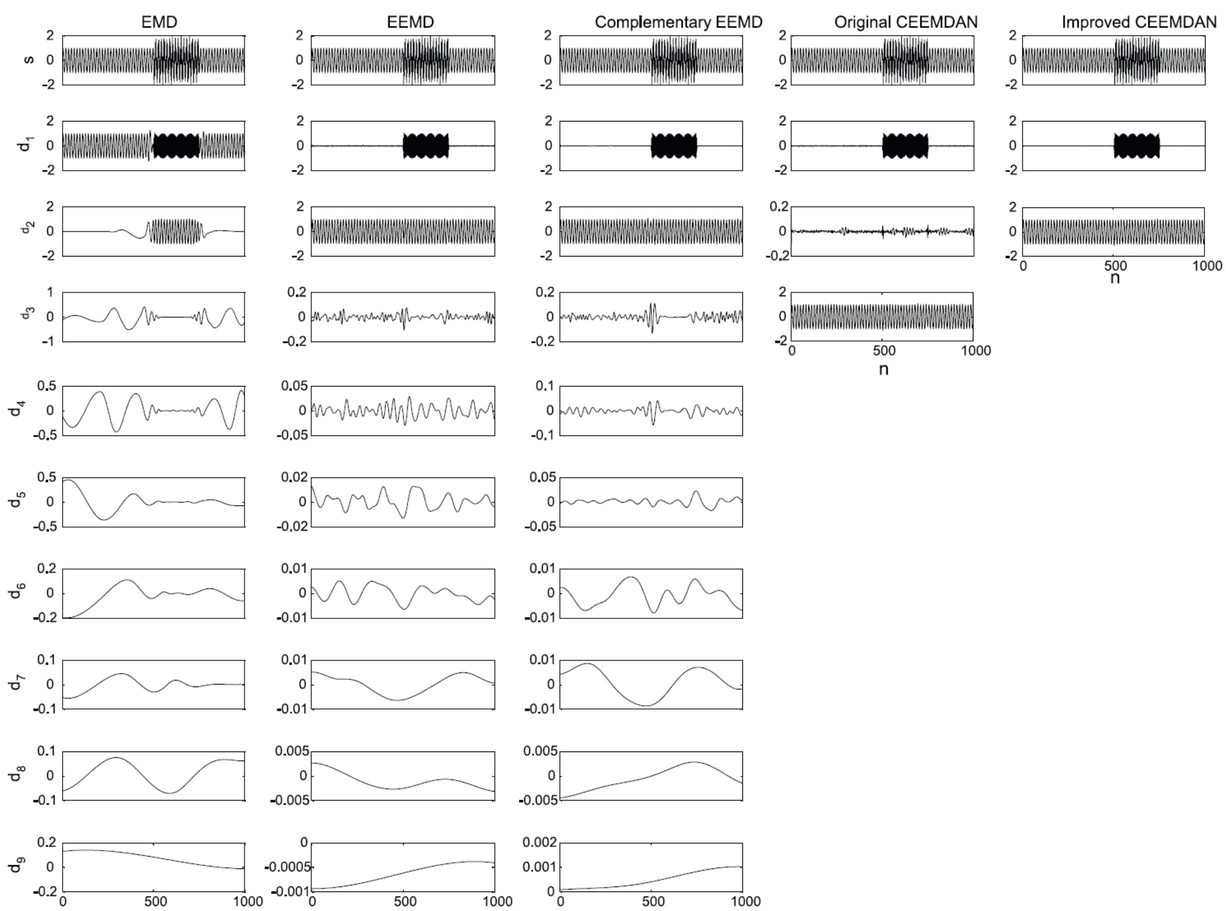


Fig. 1. Decomposition of the synthesis signal by EMD, EEMD, CEEMD, CEEMDAN and ICEEMDAN [3].

Table 2. ***Proposed methods for IMF selection*****.**

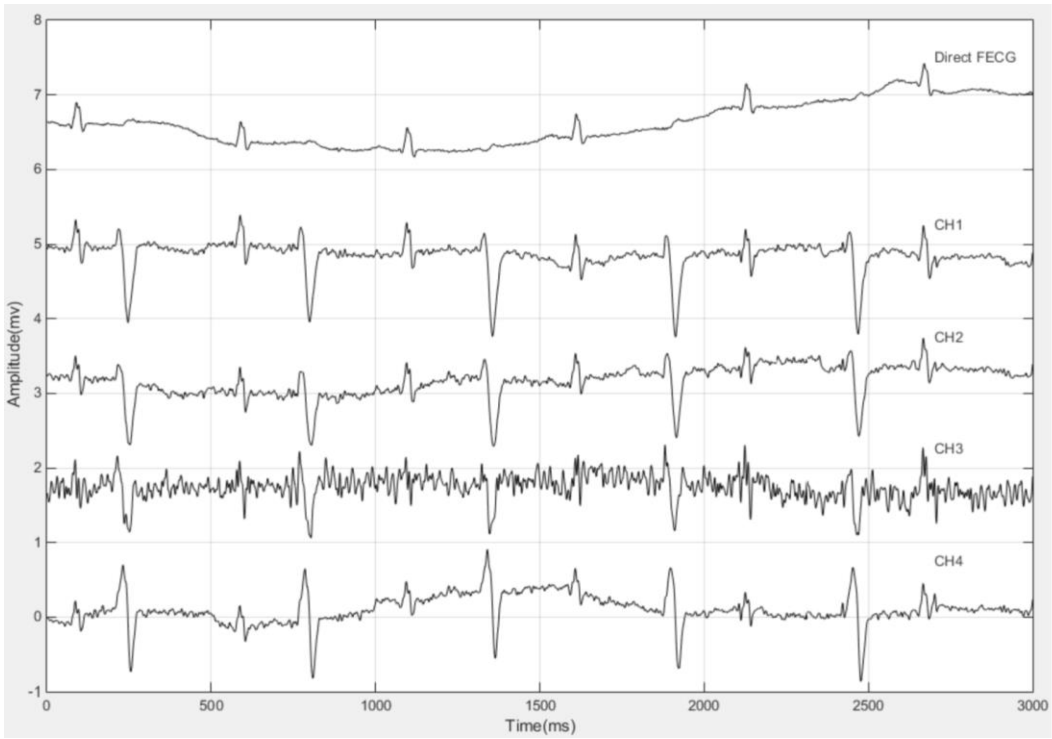
IMF selection Method	Author/Year
Correlation Coefficients	Peng et. al. , 2005[22]
Energy Entropy	Yu et. al., 2006 [23]
Confidence Index	Yi et. al., 2015 [24]
Statistical Significance of Information Content	Wu et. al., 2004 [14]

selection. An effective statistical test was proposed by Wu et. al. [14] to distinguish the noisy IMFs and informative ones, that assigns the statistical significance of information content for each IMF components [14]. Wu et. al [14] tested the uniformly distributed white noise as an input signal to EMD method and found out that the obtained IMFs as a dyadic filter are all normally distributed, and their Fourier spectra are all identical and cover the same area on the semi-logarithm period scale. Wu et. al. also demonstrated that the product of the energy density of the IMF and its corresponding mean period is a constant and that the energy density function is Chi-squared distributed [14]. Wu et. al. establish a method to assign the statistical significance of information content for IMF components from any noisy data [14]. ICEEMDAN was used to decompose a noisy Fetal Electrocardiogram (FECG) by Nejad and Yousefi Rizi [25]. The noisy IMFs were then evaluated by the statistical test introduced by Wu et. al. [14]. The extracted IMFs from the first independent component of a sample noisy fetal electrocardiography (FECG) signal by ICEEMDAN are shown in Figure 2 and the statistical test results are shown in Figure 3.

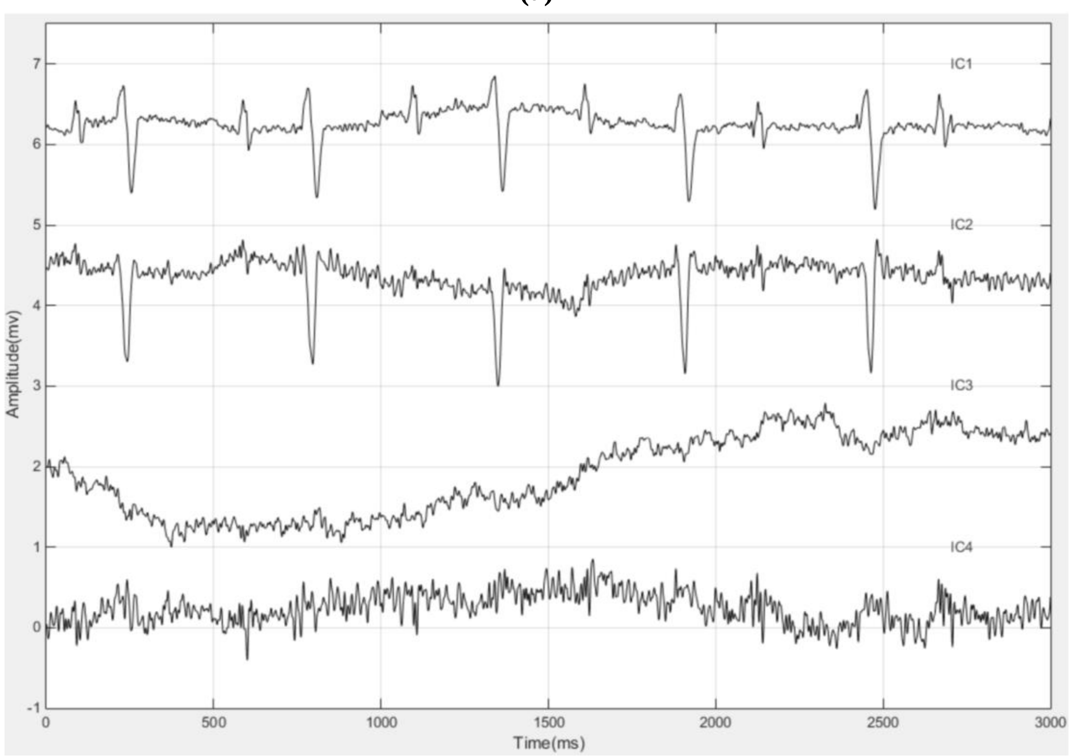
In spite of the fact that the first several IMFs are generally considered to be noisy, the significance of the test showed that they might contain useful information. For instance, in Figure 3, IMF1 and IMF2 of the noisy FECG signal, contaminated with noise, but do not locate within the 99% confidence line, so they may contain some signal components[25]. They were then candidate to be further de-noised (Figure 3). IMF3-IMF7 are located far from the confidence line, it represents that they are mainly useful information which needs to be reserved. IMF8 and IMF9 are close or within the confidence line, hence they are noise dominant IMFs and need to be de-noised by wavelet shrinkage (WS). Finally, IMF10-IMF14 are mainly trends baseline wander that are discarded. FECG were reconstructed by summing up the de-noised and reserved IMFs[25].

3. EMD FOR MEDICAL SIGNAL PROCESSING

EMD has been proven to be a reliable mono-dimensional method for medical signal processing. EMD-based signal filtering for signal de-noising was realized by Boudraa and Cexus [26]. The efficiency of EMD



(a)



(b)

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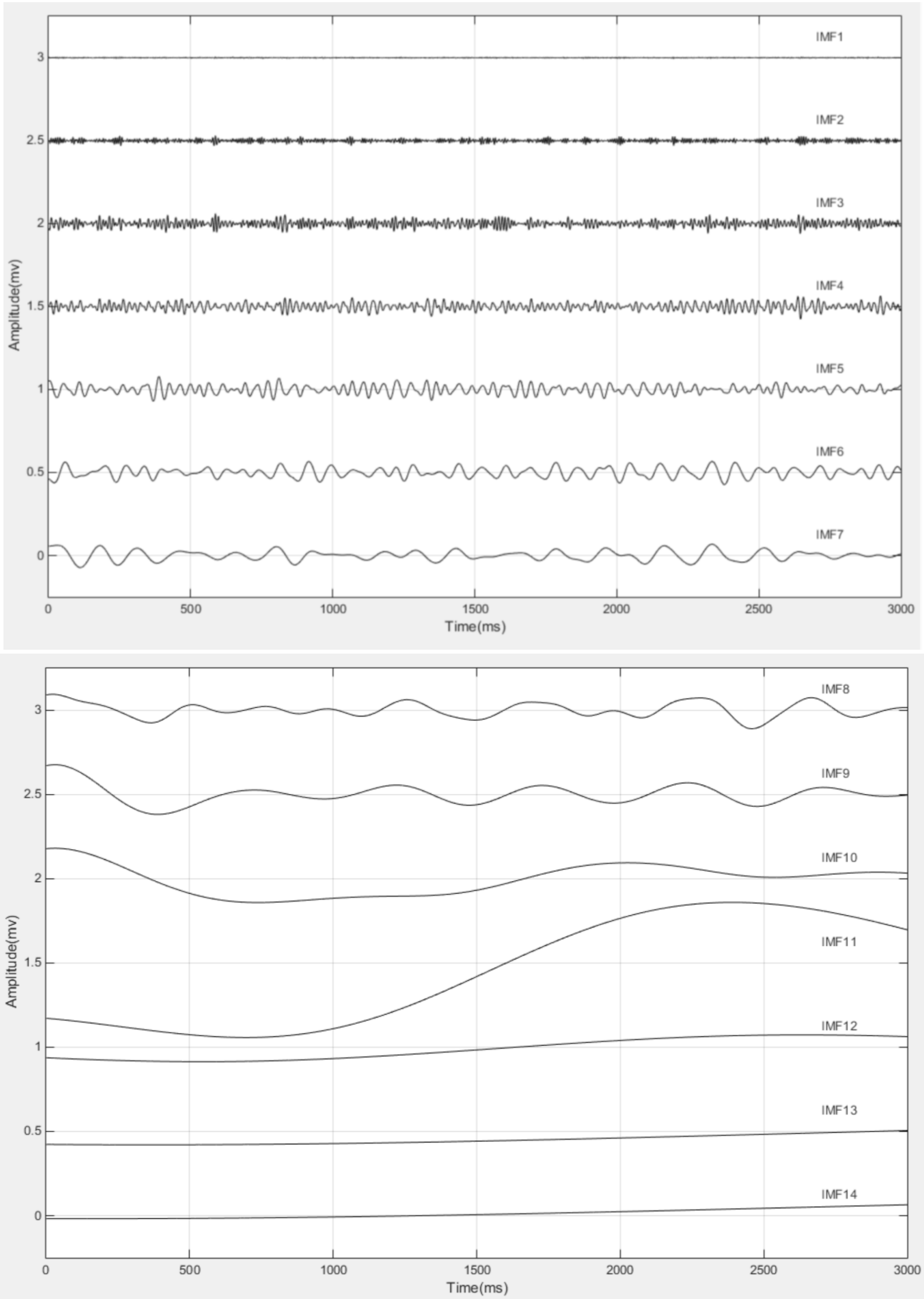

(c)

Fig. 2. FECG signal decomposition (a) Sample abdominal and direct FECG signals, (b) The independent components of a sample FECG signal extracted by efficient fast independent component analysis (EFICA) [25] (c) IMFs of first independent component(IC1) of FECG signal decomposed by ICEEMDAN [25].

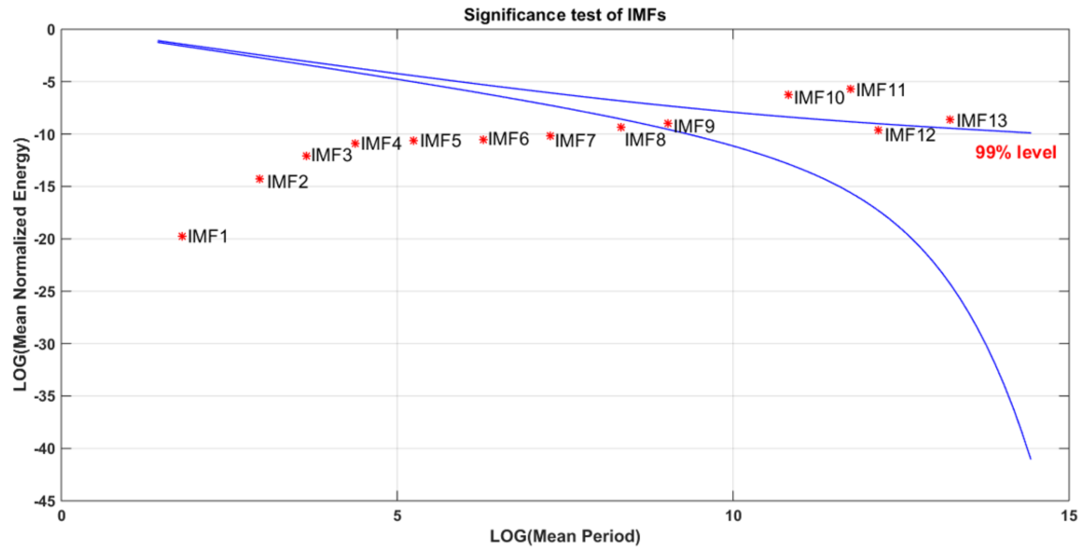

Fig. 3. Significance test of IMFs of No. r10. The stars are IMFs and the curves are 99% confidence intervals. This diagram is used to determine the informative and noisy IMFs[25].

approaches for de-noising applications has been considered in many studies, some of the recent and significant EMD-based approaches are gathered in Table 3.

Moreover, EMD and its family were widely used for biomedical signal processing like feature extraction for classification or compression. Some of the studies on the use of IMFs for feature extraction and compression along with other applications of EMD for medical signal processing are demonstrated in Table 4.

Some of the significant studies are gathered in Table 4.

4. EMD FOR MEDICAL IMAGE PROCESSING

EMD technique has been extended to analyze bidimensional images, known as Bidimensional EMD (BEMD), image EMD (IEMD), 2D EMD, etc. [67]. The bidimensional empirical mode decomposition (BEMD) is introduced by Nunes et. al. [68] as the 2D extension of the EMD. BEMD was reported repeatedly to be used for image segmentation [69], [70] image fusion [71], edge detection [72], noise reduction [73], [74], [75], texture synthesis [76], image compression [77] and image watermarking [78], [79]. In spite of these wide applications, there are some problems using BEMD method. As a consequence,, several modifications and improvements of BEMD have been developed [80]. BEMD like EMD is time-consuming since each IMF is extracted by several iterations that each of which contains the extrema detection and interpolation. In the previous studies, the multilevel B-spline [69], different types of radial basis functions [68], [69], Delaunay triangulation [81], finite-element method [82], order statistics filters [83] were reported to be used for 2D scattered interpolation. Nunes et. al. [68] applied BEMD for texture extraction and image filtering. In their proposed method, regional maxima were detected by using morphological operators and the bidimensional sifting process completed by radial basis function for surface interpolation [68]. A bidimensional decomposition of a brain MRI is shown in Figure 4. The generations of BEMD are gathered in Table 5.

Yeh et. al. [80] proposed a new method for computing complex bidimensional empirical mode decomposition (BEMD).

Table 3. ***Some studies on biomedical signal de-noising using EMD based methods (in chronological order).***

Author/year	Signal	EMD application
Nimunkar, 2007 [27]	ECG	EMD-based 60-Hz noise filtering of the ECG
Tang, 2007 [28]	ECG	Hilbert-Huang Transform for ECG De-Noising
Blanco, 2008 [29]	ECG	ECG signal de-noising and baseline wander correction
Chang, 2010 [30]	ECG	Ensemble empirical mode decomposition for high-frequency ECG noise reduction
Wu, 2011 [31]	EEG	Frequency recognition in an SSVEP-based brain-computer interface using EMD and refined generalized zero-crossing
Kabir 2012 [32]	ECG	De-noising of ECG signals
Pal, 2012 [33]	ECG	Empirical mode decomposition-based ECG enhancement
Agrwal, 2013 [34]	ECG	Fractal and EMD based removal of baseline wander and power line interference
Jenitta, 2013 [35]	ECG	De-noising of ECG signal based on EMD and EEMD
Navarro, 2015 [36]	EEG	De-noising EEG by signal decomposition and adaptive filtering
Sucheta, 2017 [37]	ECG	EMD based filtering methods for 50 Hz noise cancellation in ECG signal
Zhou, 2018 [38]	ECG	EMD Based Hierarchical Multiresolution Analysis via DCT with Applications to ECG De-noising and QRS Point Enhancement
Kumar, 2018 [39]	ECG	De-noising of ECG by using EMD with non-local mean
Rakshit, 2018 [40]	ECG	ECG de-noising EMD and adaptive switching mean filter
Srivastava, 2018 [41]	EMG	AWGN Suppression Algorithm in EMG Signals Using EEMD
Liu, 2018, [42]	ECG	De-noising of ECG Signal with Power Line and EMG Interference Based on EEMD
Yang, 2018 [43]	EMG	Study On De-Noise of Electromyography (EMG) Signal
Tiwari, 2018 [44]	EMG	Combination of EEMD and Morphological Filtering for Baseline Wander Correction in EMG Signals
Saha, 2019 [45]	EEG	A Filtering Approach to Clean EEG Signal Based on EMD-DF to Improve Classification Accuracy during Hands Movement
Mucarquer, 2019 [46]	EMG	Improving EEG Muscle Artifact Removal using EEMD and canonical correlation analysis

Table 4. ***Some studies on biomedical signal processing using EMD based methods (in chronological order).***

Author	Signal	EMD application
Nimunkar, 2007 [9]	ECG	R-peak Detection and Signal Averaging for Simulated Stress ECG using EMD
Rizi, 2014[47] [48]	RF	Vibration extraction from estimated motions of carotid artery wall based on ultrasound RF signals using EMD
Wang, 2016[49]	ECG	ECG compression based on combining of EMD and wavelet transform
Hassan, 2016[50]	EEG	Automatic identification of epileptic seizures from EEG signals using linear programming boosting based on EMD features
Mishra, 2016 [51]	EMG	Discrimination between Myopathy and normal EMG signals using IMFs
Mishra, 2016 [52]	EMG	Analysis of ALS and normal EMG signals based on EMD
Mishra, 2017 [53]	EMG	An efficient method for analysis of EMG signals using improved EMD
Izci, 2018 [54]	ECG	Arrhythmia Detection on ECG Signals by using EMD
Zhang, 2018 [55]	EEG	EEG-based classification of emotions using EMD and autoregressive model
Jacob, 2018 [56]	EEG	Automated Diagnosis of Encephalopathy Based on Empirical Mode EEG Decomposition
Moctezuma, 2018 [57]	EEG	EEG-Based Subjects Identification Based on Biometrics of Imagined Speech Using EMD
Pryia, 2018 [58]	EEG	Efficient method for classification of alcoholic and normal EEG signals using EMD
Bueno, 2018 [59]	EEG	Analysis of Epileptic Activity Based on Brain Mapping of EEG Adaptive Time-Frequency Decomposition by EMD
Mert, 2018 [60]	EEG	Emotion recognition from EEG signals by using multivariate EMD
Islam, 2018 [61]	EEG	Optimal IMF Selection of EMD for Sleep Disorder Diagnosis using EEG Signals
Kaleem, 2018 [62]	EEG	Patient-specific seizure detection in long-term EEG using signal-derived EMD based dictionary approach
Huang, 2018 [63]	ECG	Energy-efficient ECG compression in wearable body sensor network by leveraging EMD
Zeng, 2019 [64]	EEG	Classification of focal and non-focal EEG signals using empirical mode decomposition (EMD), phase space reconstruction (PSR) and neural network
Babiker, 2019 [65]	EEG	EEG in classroom: EMD features to detect situational interest of students during learning
Hansen, 2019, [66]	EEG	Un-mixing Oscillatory Brain Activity by EEG Source Localization and EMD

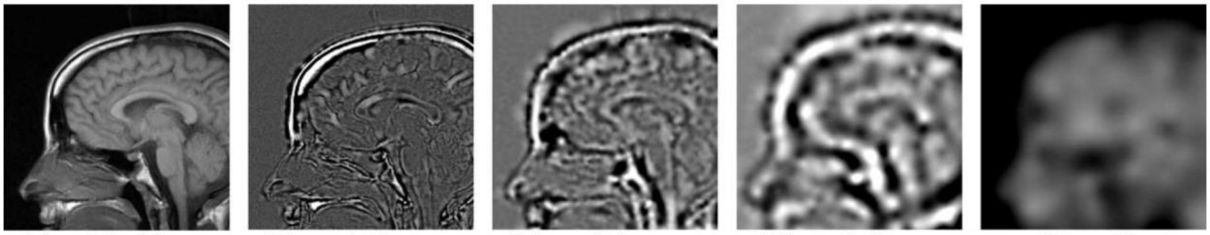

Fig. 4. Obtained modes of BEMD method applied to a brain MRI image [68].

Table 5. ***Some bidimensional EMD versions.***

Method	Description	Author /Year
BEMD	Bidimensional EMD	Nunes 2003[68]
FABEMD	Fast and adaptive bidimensional empirical mode decomposition	Bhuiyan 2008 [83]
MEEMD	Multidimensional EEMD	Wu, 2009 [84]
Complex-BEMD	Complex bidimensional empirical mode decomposition	Yeh, 2012 [80]
MCEEMDAN	Multi-Dimensional Complete Ensemble Empirical Mode Decomposition with Adaptive Noise	Humeau-Heurtier, 2015 [73]

The obtained IMFs of complex-BEMD are 2D complex-valued. By alleviating the mode mixing, complex-BEMD would be successful for color image processing and image fusion [80]. Chen et. al. proposed a mean approach to accelerate BEMD [85]. A modified mean filter was used by Chen et. al. to approximate the interpolated envelope along with the convolution algorithm based on singular value decomposition (SVD) for further reduction of computation time [85]. Bhuiyan et. al. [83] introduced a fast and adaptive BEMD (FABEMD) method. It was demonstrated that FABEMD is faster, adaptive and more efficient than original BEMD considering the quality of the bidimensional IMFs [83]. Pan et. al. used the mean points in the sifting process of BEMD as centroid point of neighbor extrema points in Delaunay triangulation and proposed using mean approximation instead of the mean envelope [86]. Recent developments of BEMD enhanced the applicability of BEMD [87]. BEMD have been used for infrared and visible images and video [88], [89], [90], multispectral images [91], and remote sensing images [92]. Alshawi et. al. in [93] investigated the utilization of BEMD process in medical imaging to decompose CT and MRI images and fuse the output components by using various fusion rules. In [94], Ahmed et. al. used FABEDM to fuse images on common spatiotemporal scales and also to solve the problem of multi-focus images fusion [94]. For image de-noising, the BEMD algorithm was successful. The noise components are usually appearing as high-frequency details in the bidimensional IMFs [95], [74]. In the image decomposition by BEMD, fine details and edges also appear in the high frequency IMFs, the informative components should be distinguished by IMF selection methods (such as the methods were mentioned before in Table 2 for signal processing applications) that have not been well established yet for BEMD and its improved versions. A sample application of FABEMD for image registration is shown in Figure 5 from [96]. Some studies on using BEMD for medical image processing are gathered in Table 6.

5. DISCUSSION

EMD was introduced and improved by Huang et al. [1] and Du et al. [113] and many researchers for one-dimensional analysis of non-stationary and non-linear signals based on the instantaneous frequency. Signal decomposition using EMD and its different versions can be used to de-noise the medical signals, reduce the amount of artifact and feature extraction for classification and pattern recognition. Based on the literature, EMD cannot be used 3D data analysis [87]. The two-dimensional extension of the EMD approach mainly used for medical image processing, segmentation, image de-noising, pattern recognition, image enhancement, image registration and compression [87].

As we discussed earlier in this paper, EMD has been widely used in different signal and image processing areas; more importantly, to process the medical signal and image with that are inherently non-linear and non-stationary. In this study, our attempt is to gather the significant and recent EMD applications on biomedical data processing including de-noising, classification, compression and feature extraction of medical signals. The

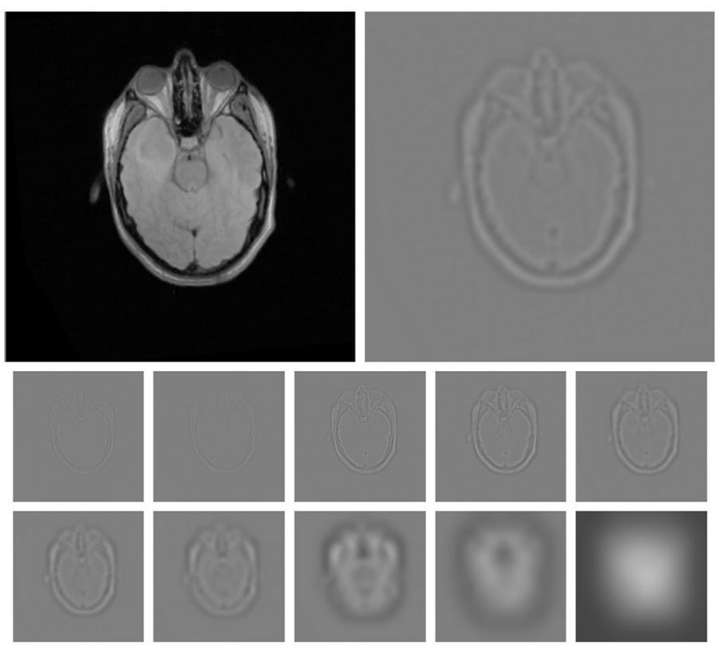

Fig. 5. An example of the FABEMD of an MRI image. The input image (top left), the most representative mode (top right), intrinsic modes (bottom) [96].

Table 6. ***Some studies on using BEMD for medical image processing (in chronological order)*.**

Author/year	BEMD Application
Nunes, 2003 [68]	Image analysis by BEMD
Shicun, 2006, [97]	Medical image edge detection based on the EMD method
Liu, 2007[98]	Medical Image Retrieval Based on BEMD
Qin, 2008 [99]	Medical Image Enhancement Method Based on 2D EMD
Wu, 2009 [84]	The Multi-Dimensional EEMD Method
Feng, 2009, [100]	MRI Medical Image de-noising Based on BEMD and Wavelet Thresholding
Lia, 2010 [101]	Potential contrast improvement in ultrasound pulse inversion imaging using EMD and EEMD
Yi, 2012, [74]	DWI de-noising method based on BEMD and adaptive Wiener filter
He, 2013 [102]	EIT Image Processing Based on 2-D EMD
Zemzami, 2013 [67]	Decomposition of 3D medical image based on FABEMD
Rojas, 2013 [103]	Application of EMD on DaTSCAN SPECT images to explore Parkinson Disease
Zhang, 2014, [104]	A medical image fusion method based on energy classification of BEMD components
Guo, 2014, [105]	Self-adaptive image de-noising based on BEMD
Bashar, 2015, [106]	EMD based GRAPPA reconstruction algorithm for parallel MRI
Humeau, 2015, [73]	Analysis of microvascular perfusion with multi-dimensional complete ensemble empirical mode decomposition with adaptive noise algorithm
Gavriloaia, 2015 [107]	Thermal image filtering by BEMD
Humeau, 2015, [73]	Multi-Dimensional Complete Ensemble Empirical Mode Decomposition with Adaptive Noise Applied to Laser Speckle Contrast Images
Khaliluzzaman, 2016, [108]	Analyzing MRI segmentation based on wavelet and BEMD using fuzzy c-means clustering
Dilmaghani, 2017, [109]	A new MRI and PET image fusion algorithm based on BEMD and HIS methods
Guryanov, 2017 [96]	Fast medical image registration using BEMD
Mostafiz, 2018 [95]	Speckle noise reduction for 3D ultrasound images by optimum threshold parameter estimation of BEMD using Fisher discriminant analysis
Ding, 2018, [110]	BEMD image fusion based on PCNN and compressed sensing
Ma, 2018, [111]	Fast BEMD based on variable neighborhood window method
Gudigar, 2019 [112]	Automated categorization of multi-class brain abnormalities using decomposition techniques with MRI images: A comparative study.

enhancement, classification, feature extraction, segmentation, de-speckling, compression, registration and fusion of medical images in CT, MRI, US, and infrared modalities were also reported as BEMD applications. The modified versions of one-dimensional and bidimensional EMD helped to improve the performance and overcome the mode mixing problem and reduce the processing time. In addition to the number of informative IMFs and stopping, criteria were amended in the new versions.

6. CONCLUSION

Considering the studies about EMD method, it can be concluded that the adaptability, locality, completeness and multiresolution characteristics of the EMD method make EMD as one of the best techniques for medical signal and image processing. Besides the dynamics of IMF are unchanged in the frequency domain, consequently, the statistical analysis, extrapolation, extraction of the additive noise component with the successive noise removal, allocation, and removal of trend (de-trending) are possible by using EMD. This time-frequency domain decomposition has a high resolution on both coordinates, and its final spectrum is convenient to detect the hidden amplitude modulation and frequency modulation. Based on the studies on biomedical signal processing and medical image processing using EMD and its family methods, it can be concluded that this time-frequency analysis suits well the inherent non-stationary and nonlinear biological data and in many medical signal and image processing cases outperforms wavelet transform as a localized time-frequency analysis and other time-domain or transform domain analysis. Modified versions of EMD coped with the mode mixing problem, besides the informative extracted modes should be selected by IMF selection methods like significance test in both medical signal and image processing application of EMD.

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