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Video Denoising With Bi-Dimensional EMD Decomposition Along With Wavelet Thresholding

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ABSTRACT: For analyzing non-linear and non-stationary signals Empirical Mode Decomposition (EMD) is introduced as an adaptive method like wavelet packet best basis decomposition. Huang *et. al* introduced the empirical mode decomposition (EMD) in signal processing in 1998. In this communication we investigated the performance of video denoising using bi-dimensional EMD along with wavelet thresholding. Compressed video quality is obtained with a satisfactory signal to noise (SNR). Indeed, the reconstructed video frames include residual noise and different realizations of frames plus noise that may produce different number of modes.

Keywords : Empirical Mode Decomposition; wavelet transform; Intrinsic Mode Function; discrete cosine transform; Wiener filtering etc.

1 INTRODUCTION

Video denoising is normally done with some linear or non-linear operation on a set of neighboring pixels and the correlation between those pixels available in spatio-temporal sense. A good video denoiser should be able to preserve edges as well as to exploit inter-color and inter-frame correlations present in video sequences. Image denoising can be straightforwardly extended to video sequences by applying it to each frame independently. However, better denoising should exploit inter-frame correlations inherently present in video sequences via spatio-temporal filtering [1], such as Kalman [2] or adaptive 3D Wiener filtering [3]. Motion compensation [4] also improves the denoising performance by increasing inter-frame correlations. There are also transform-domain denoising algorithms based on wavelet transform and discrete cosine transform (DCT) [5–7]. Most transform-domain algorithms attempt to remove or reduce noise components mixed with high-frequency signals while keeping lowfrequency signals. [8] Noise from different sources affects the behaviour of image processing systems. The presence of noise produces errors in the image sequences during acquisition, broadcast or storage. Therefore, it is a priority task to filter each frame of the video sequence prior to other processing in following processing stages [9-10], reducing the amount of noisy pixels while images' edges, fine features, etc. should be preserved. In practical applications, it is important to develop denoising algorithms in some specific hardware in order to improve the execution times. DSP provides an excellent computing platform for practical applications not only due to their superior signal processing performance compared to other processor architectures, but also because of the high levels of integration. [11]

2 LITARATURE REVIEW

The Empirical Mode Decomposition (EMD) is a method of breaking down a signal without leaving the time domain. In this method [12] is an algorithm for the analysis of multicomponent signals [13] that breaks them down into a number of amplitude and frequency modulated (AM/FM) zero-mean signals, termed intrinsic mode functions (IMFs). In contrast to conventional decomposition methods such as wavelets, which perform the analysis by projecting the signal under consideration onto a number of predefined basis vectors, EMD expresses the signal as an expansion of basis functions that are signal-dependent and are estimated via an iterative procedure called sifting.It can be compared to other analysis methods like Fourier Transforms and wavelet decomposition. The process is useful for analyzing natural signals, which are most often non-linear and non-stationary. Traditional denoising schemes are based on linear methods including the discrete Fourier transform (DFT) and the wavelet transform (WT) [14]. The DFT approach uses linear filters which are not effective for nonstationary signals containing sharp edges and impulses of short duration. A main drawback of the wavelet approach is that the basis functions are fixed, and do not necessarily match varying nature of signals [15]. Huang *et. al*. [16] have proposed the Empirical Mode Decomposition (EMD) for analyzing data from nonstationary and nonlinear processes. The major advantage of the EMD is that the basis functions are derived from the signal itself, i.e. the analysis is adaptive. Signal denoising based on EMD is a novel denoising technique of nonparametric signal denoising, and it has a wide range of applications. A piecewise EMD thresholding approach for denoising mixtures with strong noise has been prpposed in [**16**]. This approach can find the noise-dominated IMFs and signal-dominated IMFs, and then use the different thresholds methods respectively.

2.1 The 1D empirical mode decomposition

Let a discrete time signal x(n), n = 1,2,3, … … N, where N is the sample number of the signal, the algorithm for the extraction of IMFs from real consists of the following steps [17]:

(a) $x_0(n) \leftarrow x(n)$, $h_0(n) \leftarrow x(n)$
(b) Envelopes of the maxima and minima of $h_0(n)$ using cubic splines interpolation, denote as $x_{max}(n)$ and $x_{min}(n)$ respectively.
(c) Calculate the mean of the two envelopes—

$$\mu_1^1(n) = \frac{x_{\max}(n) + x_{\min}(n)}{2} \quad (1)$$

(d) Subtract $\mu_1^1(n)$ from the original signal x(n)

$$h_1^1(n) = x_0(n) - \mu_1^1(n) \quad (2)$$

(e) Verify the residual $h_1^1(n)$ whether satisfying the definition of an IMF. If, it is not $h_0(n) = h_1^1(n)$, steps from

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(b) to (e) have to be repeated until it satisfies the definition of IMF. Thus, $h_1^k(n) = h_1^{k-1}(n) - \mu_1^1(n)$ .But if it is an IMF, the procedure stops and we get the first IMF ie. $h_1^1(n)$.

(f) After having an IMF, the new signal under examination is expressed as $h_1^1(n) = x_0(n) - x_1(n)$ and then $x_0(n) \leftarrow x_1(n)$ and $h_0(n) \leftarrow x(n)$, repeat the previous steps until the final residual is a monotonic function.Finally, EMD decomposed signal can be written as—

$$x(n) = \sum_{i=1}^{k} h_j(n) + r(n) \qquad (3)$$

where r(n) is the residual.

The criterion for the sifting process to stop can be accomplished by limiting the size of the standard deviation (SD), computed from the two consecutive sifting results as [18]:

$$SD_{ji}^2 = \sum_{n=1}^{N} \left[\frac{\left| h_{j(i-1)}(n) - h_{ji}(n) \right|^2}{h_{j(i-1)}^2(n)} \right] \qquad (4)$$

2.1 Bidimensional empirical mode decomposition (BEMD)

BEMD is a highly adaptive decomposition [19]. It is based on the characterization of the image with this decomposition in Intrinsic Mode Function (IMF) where the image can be decomposed into a redundant set of composite images called IMF and a residue. By adding all the IMFs with the residue reconstructs the original image without distortion or loss of information. The algorithm follows the following steps [20]:

(a) Initialization: $r_0 = h_0$ (the residual).

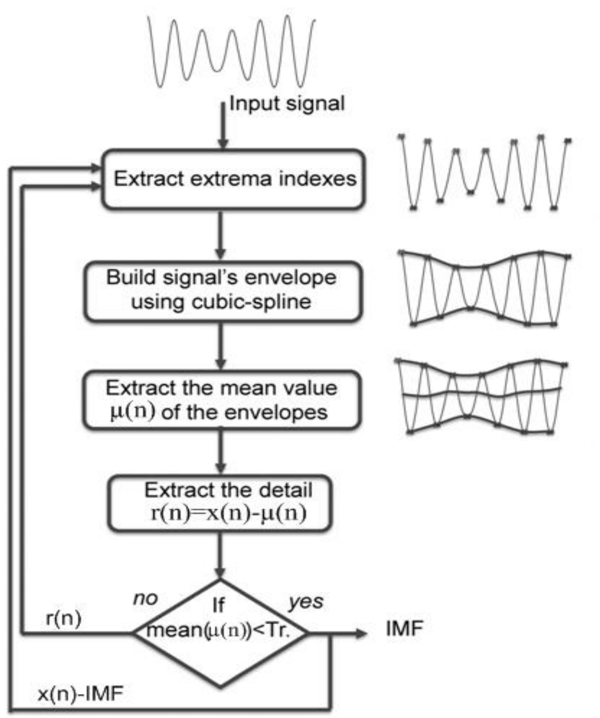

Fig. 1 Block diagram of basic EMD decomposition.

(b) Extraction : IMF: $I_k(m,n)$; where k=index number of IMF.
- $x_0(m,n) = r_{k-1}(m,n)$ and j = 1
- Extract the local extremas of $x_{j-1}(m,n)$
- Interpolate the local extremas to construct the upper and the lower envelope respectively $x_{min}(m, n)$ and $x_{max}(m, n)$.
- The average of the two envelopes:

$$\mu_1^1(m,n) = \frac{x_{\max}(m,n) + x_{\min}(m,n)}{2} \qquad (5)$$

- Update :
-

$$x_j(m,n) = x_{j-1}(m,n) - \mu_{j-1}(m,n) \qquad (6)$$

- Stopping criterion
-

$$SD(j) = \frac{1}{N} \sum_{n=1}^{N} \left[\frac{\left| x_{(j-1)}(m,n) - x_j(m,n) \right|^2}{x_{(j-1)}^2(m,n)} \right] \qquad (7)$$

- Repeat steps until $SD_i \leq SD_{max}$, and then put

$$I_k(m,n)=x_j(m,n) \qquad (8)$$

(c) Update residual

$$r_k(m,n)=r_{k-1}(m,n)-I_k(m,n) \qquad (9)$$

(d) Repeat steps (a)-(c) with j = j +1 until the number of extremas in r_j<2.

The original frame will be [21]:

$$A(m,n) = \sum_{j=1}^{N} I_j(m,n) + r(m,n) \qquad (10)$$

3 Frame Denoising

Digital noisy frame can be represented as—

$$x(t) = \tilde{x}(t) + n(t) \qquad (11)$$

where $\tilde{x}(t)$ is the estimated denoised frame and $n(t)$ is the Additive White Gaussian Noise. The noise variance is considered to be unity. But it may be categorized as parametric or nonparametric depending on the predefined parametric model of $\tilde{x}(t)$.

3.1 Wavelet Based Denoising

The discrete wavelet transform is a filter bank algorithm iterated on the low-pass output [22]. A filter bank is a pair of lowpass and highpass filters followed by downsampling by two. The lowpass filtering produces an approximation of the signal, which is expressed by the scaling coefficients, while the highpass filtering reveals, the differences between two successive approximations that are expressed by the wavelet coefficients. At the reconstruction, the scaling and the wavelet coefficients are first up-sampled by introducing a zero between each two samples and then filtered with a lowpass and a highpass filter, respectively, followed by summation of the filtered outputs. If the wavelet transform is orthogonal, the reconstruction high-pass and the lowpass filter coefficients are simply the mirrored versions of their counterparts at the decomposition stage. The conventional separable two-dimensional 2D DWT follows from applying the filter bank algorithm successively to the rows and to the columns of a video frame [23]. The wavelet based video denoising scheme is depicted in Fig. 2

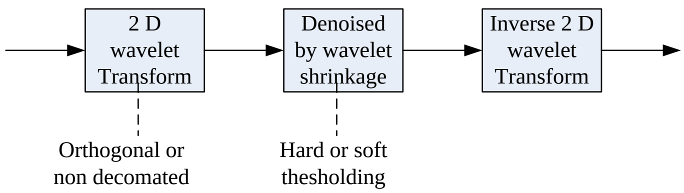

Fig. 2 wavelet based video denoising scheme.

The discrete wavelet transform (DWT) whether critically sampled or non-decimated employed for noise reduction is commonly done by wavelet thresholding. The magnitude of each coefficient is reduced by a given amount depending on the noise level and depending on how likely it is that a given coefficient represents an actual discontinuity. A common used approach is hard thresholding [21, 24], which sets the wavelet coefficients with small magnitudes to zero. While the remaining ones are set for soft-thresholding. Thresholding with a uniform per subband threshold is attractive due to its simplicity. Of course, the performance is limited and the denoising quality is often not satisfactory. [23]

The DWT—

$$\bar{c} = W\bar{x} \tag{12}$$

where,

$$\bar{c} = [c_1, c_2, \quad , c_N];\ \bar{x} = [x_1, x_2, \quad , x_N]$$

and W is a N×N matrix.

The coefficients c_i follow normal distribution. Since the signal under consideration is sparse in the wavelet domain, the DWT distributes the total energy of $\tilde{x}(t)$ in few wavelet components with high amplitudes. Therefore, the amplitude of most of the wavelet components is attributed to noise. Thus wavelet thresholding is set to zero to all the components that are lower than a threshold related to the noise level

The hard and soft thresholding are defined by—

$$\rho_{hard}(y) = \begin{cases} y, & |y| > T \\ 0, & |y| \le T \end{cases} \tag{13}$$

and

$$\rho_{soft}(y) = \begin{cases} \operatorname{sgn}(y)(|y| - T), & |y| > T \\ 0, & |y| \le T \end{cases} \tag{14}$$

Using the thresholding, the estimated denoised signal is given by

$$\hat{\bar{c}} = W^T \hat{\bar{x}} \tag{15}$$

where, $\bar{c} = [\rho(c_1), \rho(c_2), \quad , \rho(c_N)]$ and

W^T is the transpose matrix of *W. T*he universal threshold is—

$$T = \sigma\sqrt{2\ln N} \tag{16}$$

where σ= variance.

3.1 EMD Based Denoising With Wavelet Thresholding

Yannis *et. al.* [27] proposed the thresholding for EMD denoising algorithm. In this technique wavelet thresholding is used to denoise the frames and is referred to as EMD thresholding. The thresholding is done by the following formula—

$$T_n = C\sqrt{E_n 2\ln N} \tag{17}$$

where C is a constant experimentally found to be in between 0.7 and 1.0 depending on the type of signal, N is the sample number of the signal and

$$E_n = \frac{E_1}{\beta}\rho^{-n}, \qquad n = 2,3,4\cdots$$
$$E_1 = \frac{1}{N}\sum_{n=1}^{N}(IMF_1)^2 \tag{18}$$

where E_1 is the energy of the first IMF. β and ρ are parameters and Flandrin et al[9] specifically defined the values of β and ρ are 0.719 and 2.01 respectively for AWGN.[17]

4 Results

Three Additive White Gaussian Noise (AWGN) corrupted videos namely, gflowersg15.avi (flower garden), gsalesmang15.avi (salesman) and gstennisg15.avi (tennis player) [25] are used for extensive simulations. Empirical Mode Decomposition in two dimensions typically generates a residue with many extrema points. In this paper we decomposed video frames into a number of Intrinsic Mode Functions and a residue image with a minimum number of extrema points. Four IMFs are shown in the simulation result while only the first IMF is used to denoise the frames. First IMF has been subtracted from the AWGN corrupted noisy frames and then hard and soft theshlding is applied to have more visual quality frames. The visual quality will depend on the frame rate and motion speed of the videos. Table I shows the SNR (dB) of the 10^{th} frame of the different videos. The average of all frames was not reported here as the deviation of SNRs amongst the frames are not that much significant [26].

TABLE I. SNR (dB) of the10-th frame

Videos	Hard Thresholding	Soft Thresholding
gflowersg15.avi	24.7	23.9
gsales-mang15.avi	20.9	20.3
gstennisg15.avi	23.4	23.2

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Fig. 3. Noisy frame of Flower Garden (10-th frame).

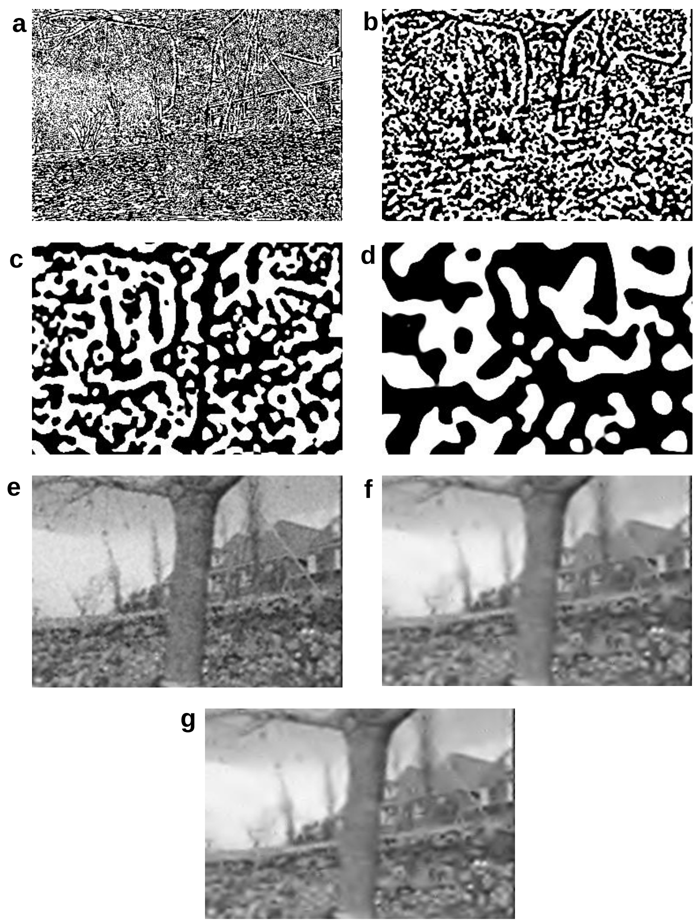

Fig. 4. Flower Garden (10-th frame).(a) 1st IMF (b) 2nd IMF (c) 3rd IMF (d) 4th IMF (e) Noisy frame -1st IMF (f) Denoised frame with hard thresholding obtained from **e**.(g) Denoised frame with soft thresholding obtained from **e**.

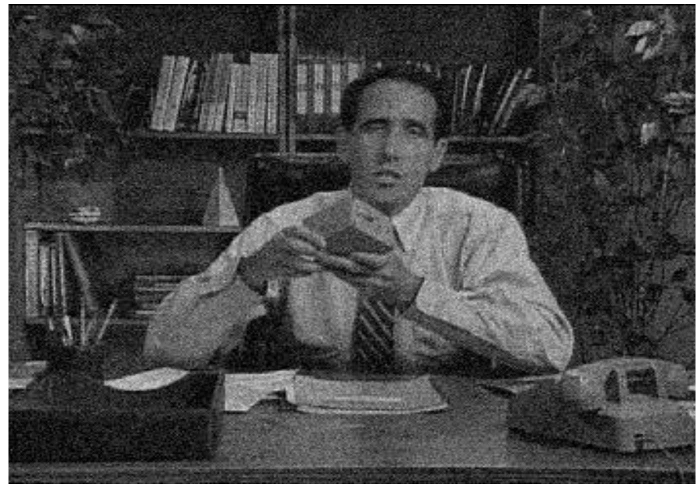

Fig. 5. Noisy frame of Salesman (10-th frame).

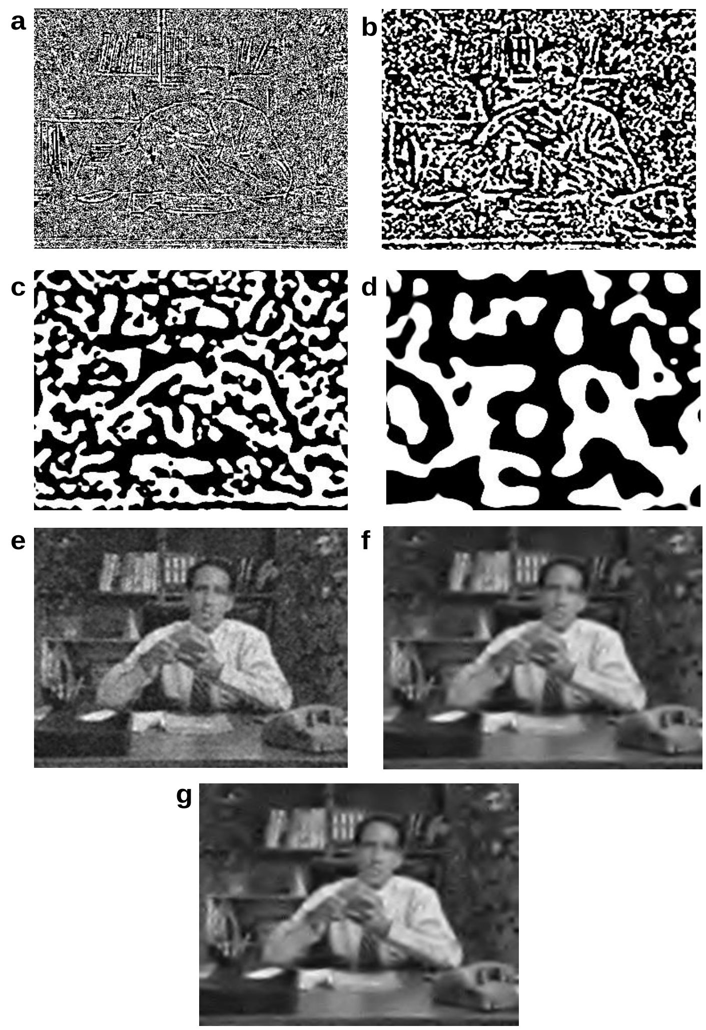

Fig. 6. Salesman (10-th frame).(a) 1st IMF (b) 2nd IMF (c) 3rd IMF (d) 4th IMF (e) Noisy frame -1st IMF (f) Denoised frame with hard thresholding obtained from **e**.(g) Denoised frame with soft thresholding obtained from **e**.

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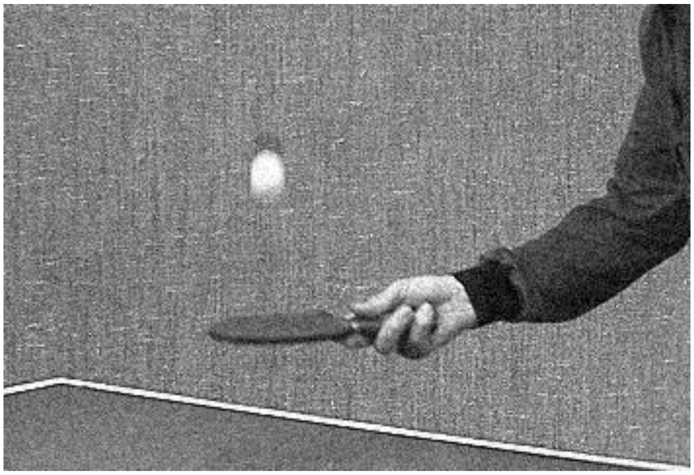

Fig. 7. Noisy frame of Tennis Player (10-th frame).

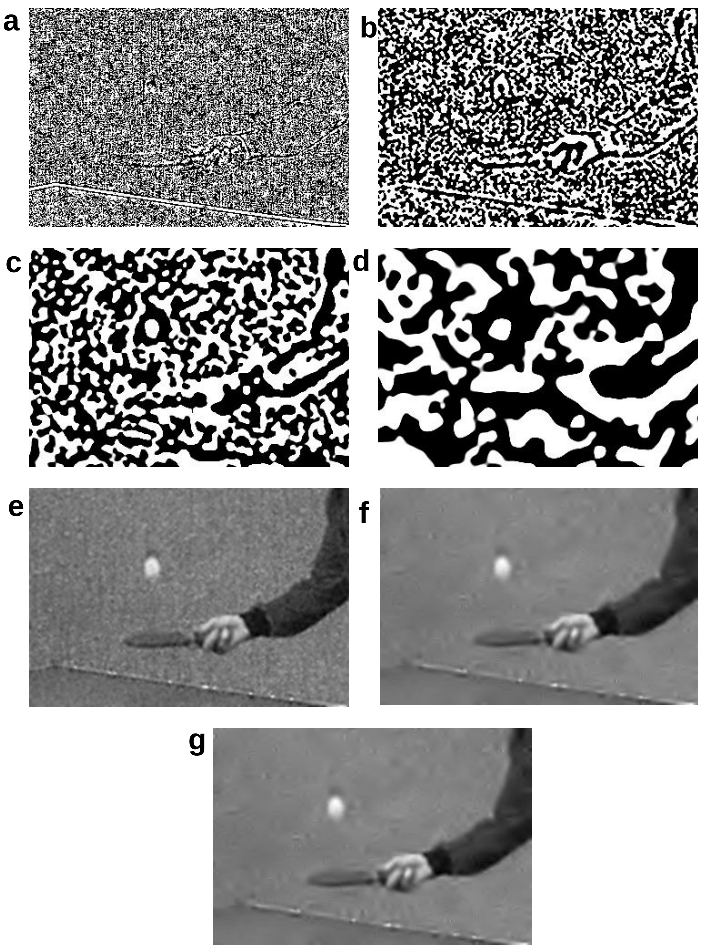

Fig. 8. Tennis Player (10-th frame).(a) 1st IMF (b) 2nd IMF (c) 3rd IMF (d) 4th IMF (e) Noisy frame -1st IMF (f) Denoised frame with hard thresholding obtained from **e**.(g) Denoised frame with soft thresholding obtained from **e**

4 Conclusion

A real and structured noise model is essential for high-quality video denoising. Simulation results show that the systems can play significant role with the state of the art in removing AWGN and structured noise. EMD can be interesting technique in the compression perspective. The IMFs represents the frames in a very compact way, in well behaved signals, leading to a clean representation by a few components. The 2D EMD offers a new and promising way to decompose and extract texture features without parameter. We observed that the performance degradations that result from making the wavelet domain filtering along with BMED part is less complex for both hard and soft-thresholding. Further improvements are expected from using a more sophisticated recursive temporal filter.

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