International Journal of Science and Research (IJSR)
ISSN (Online): 2319-7064
Index Copernicus Value (2013): 6.14 | Impact Factor (2013): 4.438

A Review on Bidimensional Empirical Mode Decomposition

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Abstract: ***The Bidimensional Empirical Mode Decomposition (BEMD) is an adaptive decomposition technique for the decomposition of images into a number of intrinsic Mode functions (IMF). The use of BEMD in various image processing techniques is promoted by the fact that it has better quality than Fourier, Wavelet, and other decomposition techniques. The BEMD technique is used for the removal of noise in the images. The watermarking techniques using BEMD is more robust against various attacks and signal processing operations.***

Keywords: Bidimensional Empirical Mode Decomposition, Intrinsic Mode Function, Robustness, Texture Analysis, Watermarking.

1. Introduction

The Empirical mode decomposition(EMD), originally developed by Huang et al. [1], is a data driven signal processing algorithm that has been established to be able to perfecty analyze nonlinear and non-stationary data by obtaining local features and time-frequency distribution of the data. Empirical Mode Decomposition (EMD) is newly introduced adaptive algorithm. The BEMD is a 2D extension of EMD, which can decompose non stationary and non linear signals into basis functions called intrinsic mode functions (IMFs). During the first step of BEMD method, the signal is decomposed into characteristic intrinsic mode functions (IMFs), while the second step finds the time frequency distribution of the signal from each IMF by utilizing the concepts of Hilbert transform and instantaneous frequency.

The EMD is hinged on the idea of instantaneous frequency; instantaneous frequency becomes valid only in the event the signal is made symmetric with respect to the local zero-mean line. Upper and lower envelopes, which cover all local maxima and local minima, respectively, are constructed, and then their mean iteratively removed in order to force local symmetry about the zero mean line; the procedure has been termed sifting. The sifting process results in the generation of basis functions known as intrinsic mode functions (IMFs), which are adaptively derived from the signal within the local time scale of the signal; IMFs have instantaneous frequency defined for them at every point. The decomposition is based on the assumptions [4]:

1) The signal has at least two extrema-one maximum and one minimum;
2) The characteristic time scale is defined by the time lapse between the extrema.
3) If the data were totally devoid of extrema but contained only inflection points, then it can be differentiated once or more times to reveal the extrema. Final result be obtained by integration of the components.

Given a signal x(t), the effective algorithm of EMD [5] can be summarized as follows:

1) Identify all extrema of x(t).
2) Interpolate between the maxima and connect them by a cubic spline curve. The same applies for the minima in order to obtain the upper and lower envelopes $e_{max}(t)$ and $e_{min}(t)$ respectively.
3) Compute the mean of the envelopes.
   $m(t) = (e_{max}(t) + e_{max}(t)) /2$
4) Extract the detail:
   $d(t) = x(t) - m(t)$
5) Iterate steps 1-4 on the residual until the detail signal $d_k(t)$ can be considered an IMF: $c_1(t) = c_k(t)$
6) Iterate steps 1-5 on the residual $r_n(t) = x(t) - c_n(t)$ in order to obtain all the IMFs of the signal.

The pictorial representation of EMD is shown in Figure 1. An important step in the EMD process is the construction of the maxima and minima envelopes; research has shown that the cubic spline is the best fit for 1D EMD. The success of the 1D EMD prompted research into a 2D version, which may be used for image processing. Linderhed first introduced 2D EMD, which has been called bidimensional empirical mode decomposition (BEMD).

The rest of the paper is organized as follows. In Section 2, we present an overview of the BEMD. In Section 3, the experimental results are highlighted. And in Section 4 we discuss applications of the proposed watermarking technique. Finally Section 5, summarizes this paper with some concluding remarks.

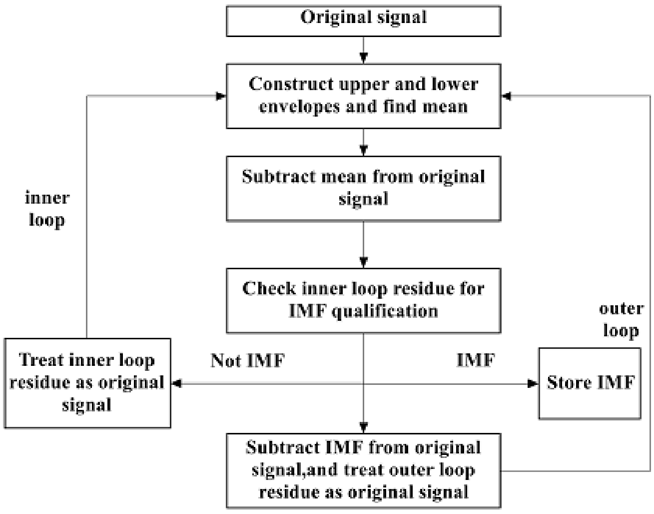

Figure 1: Pictorial representation of EMD

2. Bidimensional Empirical Mode Decomposition

The BEMD is a 2D extension of EMD. The basic steps in BEMD are the same as for the EMD, only in two dimensions. Of much importance is the envelope construction for maxima and minima; in this case, scattered data interpolation (SDI) is used to construct 2-D surfaces. Various SDI methods have been used to construct maxima and minima envelopes. However, Linderhed preferred radial basis functions (RBFs) with thin-plate splines. The appropriate SDI method would depend on the objective of the BEMD analysis. Before SDI can be performed, appropriate extrema detection needs to be carried out. Detection of extrema has been achieved with methods including morphological reconstruction based on geodesic operators, and neighboring windows. The stopping criteria for BEMD are similar to that for the 1-D EMD.

The BEMD is performed by using a sifting process. The sifting procedure decomposes a sampled signal by means of the EMD. The sifting procedure is based on two constraints:

- Each IMF has the same number of zero crossings and extrema.
- Each IMF is symmetric with respect to the local mean.

Furthermore, it assumes that it has at least two extrema.
Bidimensional Sifting process

The EMD is performed by using a sifting process. To extract the 2D IMF during the sifting process, morphological reconstruction is used to detect the image extrema and Radial basis function (RBF) is used to compute the surface interpolation [2].

1) Identify the extrema (both maxima and minima) of the image I by morphological reconstruction based on geodesic operators.
2) Generate the 2D envelope by connecting maxima points with a RBF.
3) Determine the local mean m1; by averaging the two envelopes.
4) Since IMF should have zero local mean, subtract out the mean from the image: $I - m_1 = h_1$
5) repeat as h_1 is an IMF.

- Extrema detection
  Morphological reconstruction is a very useful operator provided by mathematical morphology. Its use in hierarchical segmentation proves its efficiency in all the steps of the process, from extrema detection to hierarchical image construction [8]. The image extrema have been detected by using morphological reconstruction based on geodesic operators.

- Surface interpolation by RBF
  Huang proposed to use cubic spline interpolation on non-sampled data. There is a choice to use the RBF rather than the bicubic spline for different reasons developed. One of the technical problems is that cubic spline fitting creates distortion near the end points. RBFs are presented as a practical solution to the problem of interpolating incomplete surfaces derived from three-dimensional (3D) medical graphics. The radial basis approximation method offers several advantages over piecewise polynomial interpolants. The geometry of the known points is not restricted to a regular grid. Also, the resulting system of linear equations is guaranteed to be invertible under very mild conditions [3].

Finally, polyharmonic RBFs have variational characterizations, which make them eminently suited to interpolation of scattered data, even with large data free regions. These applications include geodesy, geophysics, signal processing, and hydrology. RBFs have also been successful employed for medical imaging and morphing of surfaces in three dimensions.

The BEMD acts as dyadic filter. It has been observed that the first IMF constitutes most of the noise in signal. Hence removal of first IMF reduces the highest spatial frequency. The filtering occures in time space rather than in frequency space. Therefore any non-linearity and non stationarity present in the data can be preserved. Although the IMF has been observed to contain most of the noise, the removal of first IMF and reconstructing the image by using remaining IMFs and residue will tends to denoise the image. Although, first IMF contains a lot of noise, still the first few IMFs from the BEMD process also contains significant amount of noise. The number of IMFs to be removed depends on the amount of noise in the image. If the image contains more noise, more number of highest spatial frequency IMFs are required to be removed. If the image contains less noise, less number of highest spatial frequency IMFs are required to be removed [4].

3. Simulation Results

The proposed system is implemented in MATLAB 8.1.0.197613. The image is decomposed adaptively by using BEMD process. The input image to the BEMD process is shown in Figure 2. By performing BEMD on the input image, it decomposes into a number of IMFs and a residue. Here the number of iterations for BEMD process is selected as three. Thus three IMFs and a residue is obtained as output. The results obtained by performing BEMD is shown in Figure 3. The first mode IMF extracts the locally highest spatial frequency in the image while the second IMF holds the locally next highest spatial frequency [8]. The Residue contains lowest spatial frequency. The original image is reconstructed by adding three IMFs and Residue and is shown in Figure 4.

Figure 2: The input image to the BEMD process

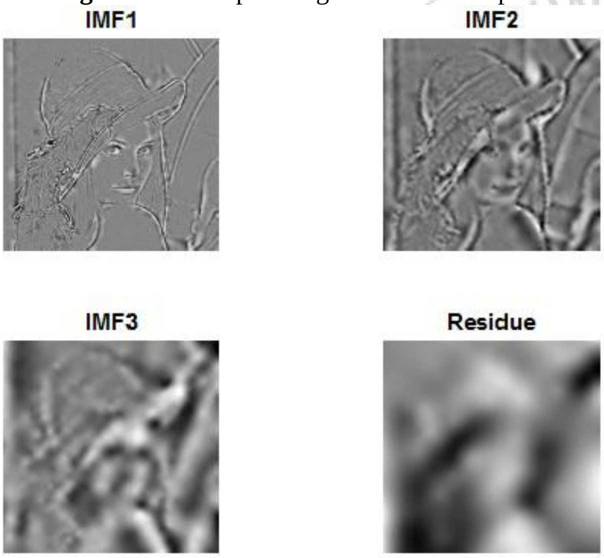

Figure 3: The results obtained by the BEMD process

Figure 4: The image reconstructed by adding IMFs and Residue

4. Applications

Various applications of image watermarking are

- The BEMD is an adaptive signal decomposition technique which decomposes the image in time domain.
- The BEMD is a 2D extension of EMD which can decompose non linear and non stationary signals into basis functions called IMFs; the set of IMFs are complete; so that by adding the IMFs together with the residue will reconstruct the original image without any distortion [5].
- The BEMD is an efficient tool to address the geometrical attacks issue.
- The BEMD acts as a dyadic filter. In case of very noisy images, by removing first few IMFs, the amount of noise in the image can be removed.
- By using BEMD filtering occures in time space rather than in frequency space, therefore any non linearity and non stationarity present in the data can be preserved.
- The BEMD is used in many of the image watermarking techniques along with DCT, DWT and SVD.
- Various image compression methods makes use of BEMD process. Because the coarsest component of the image obtained by BEMD is highly robust under JPEG compression.
- The BEMD technique is used for texture analysis.

5. Conclusion

The BEMD is a 2D extension of EMD which can decompose non linear and non stationary signals into basis functions called IMFs. It is a powerful decomposition technique used for the adaptive decomposition of signals. The BEMD is an efficient tool to address the geometrical attacks issue. The BEMD decomposes an image into 2D IMFs [4]. The BEMD method is used as a dyadic filter, by removing the first few IMFs will remove a large amount of noise in the image. In BEMD the filtering is done in time space, thus it is helpful for preserving the non linearity and non stationarity of the data. An advantage of BEMD over Gaussian filtering is that it does not involve any convolution process, and it is a local method of denoising the image. The BEMD is used for pavement crack detection, texture analysis, and compression techniques etc. The BEMD technique is also used in many of the robust watermarking techniques, it is due to the fact that it has better quality than Fourier, Wavelet, and other decomposition techniques [7]. The coarsest component of the image or the mean trend obtained by the BEMD method is highly robust against various distortions, JPEG compression, and signal processing operations. The decomposition of images of great size using the BEMD consumes more computational time. This problem can ovecome by using a technique called LBBEMD (Lapped Block Bidimensional Empirical Mode Decomposition) [9]. LBBEMD accelerates the decomposition process and minimizes the computational time.

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