Bi-dimensional Empirical Mode Decomposition based Dimensionality Reduction of image using Interpolation and Smoothness Techniques

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Abstract.

Bidimentional Empirical Mode Decomposition (BEMD, or), is a new decomposition approach based on oscillatory mode signal gathering. A non-linear and non-stationary signal can be analysed using BEMD. Intrinsic Mode Functions (IMFs) are adaptively divided into oscillatory components. High computation times and other artefacts are linked with dimensional empirical mode decomposition (BEMD) approaches because of the usage of two-dimensional (2D) dispersed data interpolation methods. Computer vision problems like texture extraction and picture filtering are well-known to be demanding and complex. Using empirical mode decomposition (EMD), we were able to extract features at several spatial frequencies and at different sizes. Texture extraction and picture filtering are well-known computer vision problems that are notoriously difficult and time-consuming to solve with the EMD. After collecting the extreme points, we may use smoothness and interpolation to produce the maximum and minimum surface envelops. BEMD has tested and used a few interpolation algorithms, but many more are still under development. To help in envelope estimate in BEMD, this research compares the performance of a number of commonly used surface interpolation approaches. Different radial basis functions and Delaunay triangulations based interpolators are studied in this paper. First, a synthetic texture picture is used, and then two separate actual texture images are used for the analysis. Only interpolation methods are simulated, with little or no control over the other parameters and components in the BEMD process. A bilinear interpolation with a directionally adaptable low-pass filter is the basis for a real-time, continuous-scale picture interpolation technique. It is designed to be implemented on hardware. The standard bi-linear interpolation approach suffers from artefacts. Techniques described by the authors use directionally adaptable low-pass filtering to address this issue. Selecting low pass filter coefficients can help alleviate the problem of extreme blurring. A high-quality picture scaler for a variety of imaging systems may be realised using interpolation techniques.

Keywords: Dimensionality reduction, Bidimentional Empirical Mode Decomposition, BEMD, Interpolation, Smoothness, Image decomposition, Image processing, Feature Extraction,

1. INTRODUCTION

Dimensionality reduction of real-world data is necessary for effective data management. Dimensionality reduction is the process of reducing high-dimensional data into a more understandable form with a lower dimensionality. Ideally, the reduced representation should have the same dimensionality as the original data. The smallest number of factors required to explain the observable qualities of data is known as the inherent dimensionality of data. Many fields benefit from dimensionality reduction because it lessens the negative effects of excessive dimensionality. Because of this, dimensionality reduction may be used for a variety of purposes including data categorization, visualization, and compression. PCA and Discriminant Analysis have traditionally been used for dimensionality reduction (DA).

Empirical mode decomposition in two dimensions involves estimate of discrete data for interpolation in the method. Surface interpolation is used in the empirical mode decomposition technique. A BIMF that is more useful is the goal of the bi-dimensional empirical mode decomposition (BIMED) method. This decomposition can help guarantee that the screening process is more efficient in typical situations; The decomposition is usually used to determine the upper and lower envelopes after extracting the extreme points. The interpolation problem is complex because surface interpolation is required to complete the interpolation procedure in bi-dimensional space. As a result of this interpolation, image processing in the bi-dimensional empirical mode decomposition technique is based on it [3].

EMD's adaptiveness is a key feature that sets it apart from more classic approaches like Fourier and Wavelets. The priori basis function is not necessary for the decomposition. As a data-driven approach, the EMD employs no predetermined filtering or wavelet processing steps[4]. Extrema detection, rules for halting iterations for each individual IMF, and interpolation algorithms dictate BEMD decomposition, which results in the 2D IMFs[4]. The interpolation method may be regarded the most critical aspect in a successful decomposition. Creating 2D surfaces from dispersed data often necessitates a number of iterative steps. There may be no interpolation centres in the boundary area of the maxima or minima map in the case of BEMD, which might be more problematic for the latter modes of decomposition. As a result, effective decomposition may necessitate boundary processing that introduces extra interpolation centres at the border. The upper bounds and lower bounds of the data/image are formed by interpolating the local maxima points and the local minima points, respectively [7]. The mean or average bounds is calculated by taking the mean of the image's upper and lower bounds. By utilizing the mean envelope to create 2D IMFs with zero local means, the BEMD decomposition also helps with orthogonal decomposition. As a result, it is crucial to find a 2D dispersed data interpolation method for BEMD that is accurate in terms of both form and smoothness of the envelopes [14]. There's nothing more fundamental to interpolation than the idea that a continuous function may be represented in terms of a set of weighted and shifted basis functions. Choosing the right foundation functions is critical. Many academics have spent a lot of time and effort optimising them for the interpolation property, which is the standard perspective [19-25].

2. OVERVIEW OF BEMD:

Nonlinear and non-stationary data may now be analysed using a brand-new approach. In this approach, the 'Empirical Mode Decomposition' is the most important aspect. These 'intrinsic mode functions,' which permit well-behaved Hilbert transformations, may be used to deconstruct any complex data collection or signal [4]. The adaptive nature of this decomposition approach makes it incredibly efficient. Nonlinear and non-stationary processes can be decomposed using the internal features time scale of the data. There are exactly the same number of extrema and zero crossings in each IMF. Once EMD has been applied, a new set of low-frequency IMFs may be retrieved from the signal. It is always the first IMF that has a high frequency component and the final IMF that has a monoatomic function. Following are the conditions that each of these oscillatory modes has to meet [8]:

(1) The total count of extrema and zero crossings must be equal in order for them to be similar or different by one.

(2) Envelopes with local peaks and minima must have zero mean values. For the signal X (t) to be decomposed into IMF, the first step is to detect all local extrema, then use cubic spline to determine the maximums in the upper and lower portions of the envelope. Following the decomposition, the following formulae can be used to reconstruct the signal.

$$X(t) = \sum_{j=1}^{n} Cj + rn$$

2.1.Bi-Dimensional Empirical Mode Decomposition:

In the event of a multidimensional signal, a multidimensional approach to EMD is necessary. EMD in 2D known as Bidimensional EMD (BEMD) [2] Sifting is used to calculate IMFs in both BEMD and EMD. Input signals are analysed to identify multiscale inherent vibrations. However, rather than a single set of intrinsic mode functions, we got two-dimensional signals using the approach of Huang [4].

A two-dimensional matrix signal f can be seen as an image (x, y). The following are the specifics of the BEMD decomposition method.

1. Using the cubic spline approach, locate all f(x,y) local maxima and minima.

2. Emax(x, y) and Emin(x, y) are the maximum and minimum envelope surfaces that may be interpolated using the extrema from step 1. (x, y).

A two-dimensional matrix signal f can be seen as an image (x, y). BEMD is a decomposition method that follows these steps.

1. using the cubic spline approach, locate all f(x, y) local maxima and minima.

2. Use the extrema from step 1 to perform surface interpolation to get a bounded surface Emax(x, y) and a bounded surface Emin(x, y) (x, y).

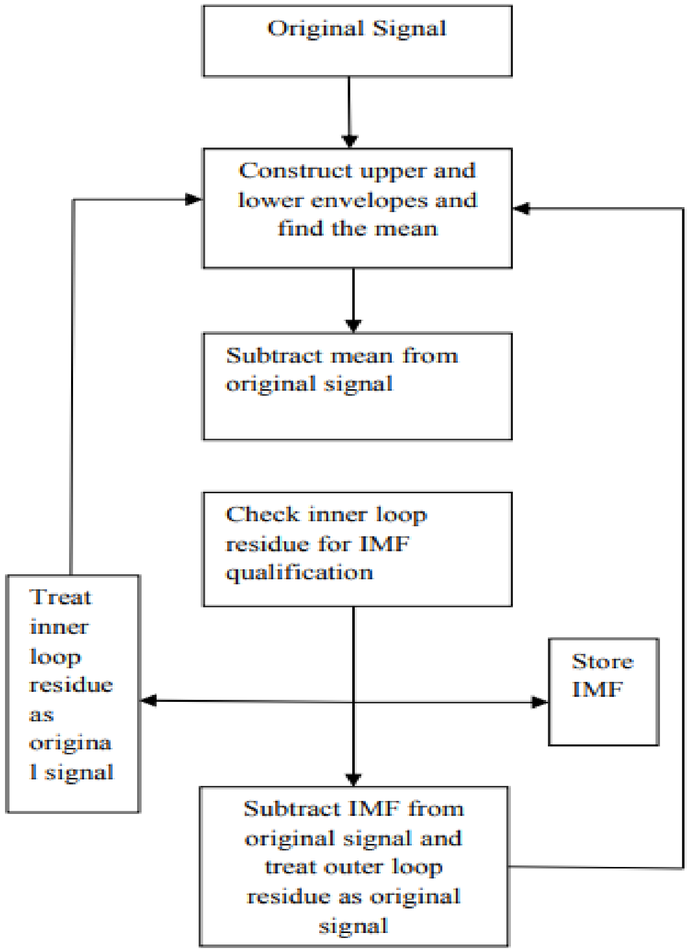

Figure 1. Graphical representation of BEMD

A 2D matrix signal f can be seen as an image (x, y). BEMD is a decomposition method that follows these steps.

1. Using the cubic spline approach, locate all f(x, y) local maxima and minima.
2. using the extrema from step one, perform surface interpolation to generate a maximum and a minimum bounded surface Emax(x, y).
3. The average envelope surface Avg(x, y) will be calculated on the basis of the maximum and minimum envelope surfaces.
4. When the mean bounded surface is subtracted from the original signal, the jth iteration of the ith sifting process is called Hij.
5. If the stop criteria are met, go to the next step. If this is the case, then repeat steps 1 through with Hij as f(x, y). A single repetition is all that is required to complete this task. IMFi can be obtained by meeting the stop criteria [7].

2.2 Stoppage criteria

The conditions for a stoppage in many circumstances,

BEMD's IMFs do not meet the criteria of an IMF. When the convergence criteria is modest, further iterative decomposition cannot yield any more information. The approach can also be used with an empirical stop criterion as an alternative. Use Equation to determine the SD criteria in accordance with Huang's (1998) approach where r is a constant that is set by the end-user (between 0.2 and 0.3) and is used in this article as the stop criterion[4].

$$SD = \sum_{i=0}^{x}\sum_{j=0}^{y} \frac{|H_{i(j-1)}(x,y) - H_{i,j}(x,y)|^2}{H^2{}_{i(j-1)}(x,y)} < r$$

3. Image Interpolation and Smoothness

In general, there are two phases involved in image interpolation:

The initila step is to create a new pixel location, and the later step is to give a pixel value to it.

Interpolation algorithms are summarised in this section. Interpolation using convolutions. The zero-order hold technique is another name for the closest neighbour interpolation. The interpolation is accomplished via convolution of a M x N input picture with a suitable kernel, represented by H [17]. For example, the kernel for two-fold interpolation may be stated as follows:

$$H = \begin{bmatrix} 1 & 1 \\ 1 & 1 \end{bmatrix}.$$

The first-order approach, which uses a bi-linear interpolation to estimate intensity from an image, is also known as the first-order method.

$$H = \begin{bmatrix} \frac{1}{4} & \frac{1}{2} & \frac{1}{4} \\ \frac{1}{2} & 1 & \frac{1}{2} \\ \frac{1}{4} & \frac{1}{2} & \frac{1}{4} \end{bmatrix}.$$

For horizontal and vertical convolution, the bi-linear interpolation is identical to convolution with the kernel twice. A basic construction makes the closest neighbour and bi-linear interpolations popular choices for low-cost, compact imaging systems. Since functions are the best kernel for interpolation because they were established by Shannon in the 1940s. However, because of its infinite impulse response (IIR), it cannot be used in implementations with finite impulse responses (FIR) [20].

3.1 Edge Detection

To determine the representative direction of the current pixel, the method utilises an LR Image as its input. The spatial gradient or directional frequency analysis can be used to choose the representative direction. The precision of the frequency-domain analysis approach is sacrificed for computing efficiency [16]. The spatial-domain technique, on the other hand, is capable of detecting a wide range of orientations with a significant computing burden. A bi-lateral or epsilon filter, for example, as well as other directional low-pass filters, demand a significant amount of processing and memory. As a result, five Gaussian filters are employed in the suggested technique [19].

3.2 Interpolation and Low-pass Filtering

As a result of the interpolation ratio, both interpolation and directionally adaptive filtering were used to detect edges. The interpolated picture must be remembered before filtering if the two operations are separated. There's a difficulty with hardware implementation due of the extra memory. Interpolation with a ratio of 5/3 is seen in Fig. 4. Low-resolution images can be represented by dotted lines, while full circles depict the areas that need to be filtered. [18].There are two interpolation scale factors known as SX and SY, and they are specified as

$$SX = \frac{(ori\_width-1)}{(inter\_width-1)},$$
$$SY = \frac{(ori\_height-1)}{(inter\_height-1)}$$

where ori_width, inter_width, ori_height and inter_height respectively represent the widths and heights of the lowresolution and high-resolution in Both SX and SY are equal to ½ [10].

3.3 Texture smoothing:

When it comes to texture smoothing, we rely on smoothing spline interpolation. As previously stated, only areas that were classified as texture regions are subjected to smoothing spline interpolation. Because it interpolates between all points in a table, and controls overfitting, smoothing spline interpolation is an excellent choice for data interpolation in this situation. Spline interpolation is simple and stable, and they are the key advantages. spline f smoothing reduces [11]:

$$p\sum_{j=1}^{n} w(j)|y(j) - f(x(j))|^2 + (1-p)\int \lambda(t)|D^2 f(t)|^2 dt$$

There are n data points, and the integral occurs across the shortest interval including all entries of x. Here, |y(j) = f(x(j))|2 represents the total of all data points' square errors. The default value for data points is 1, and as the number of data points increases, so do the error estimations. As a tuning parameter, the smoothing parameter is commonly referred to as the smoothing parameter[14] [16]. Smoothing reduces for 0 while increasing for smoothness. The piecewise constant weight function comes with a default value ω is one. Also known as the second derivative, D2f indicates the function f's second derivative. Between 0 and 1, the smoothing parameter p is set. Data points are fitted with a straight line using least squares if p = 0. If p is set to 1, the interpolation will be a cubic spline, which is the best match to the data, thus we've set p to 0.5 for our interpolation .As part of the CSAPS MATLAB function that conducts the smoothing interpolation and allows the choice to set the value of the smoothing parameter p, we employ it to accomplish smoothing for an input picture [17].

4. Experimental Results

A performance evaluation and comparison of the suggested interpolation method is presented in this section. The suggested technique employs both sharp and smooth filters in this experiment. Subsampling alone, without the use of low pass filtering, produced the lowscale image.

Interpolation Method	Interpolation Ratio	Red channel [db]	Green channel [db]	Blue channel [db]
Bi linear	3.0	29.162	26.543	27.342
Cubic Sharp	3.0	29.372	27.041	27.312
Cubic Smooth	3.0	29.564	27.102	27.571
New Sharp	3.0	29.016	26.301	27.463
New Smooth	3.0	28.872	26.315	27.561

Table 1: PSNR values of five interpolation methods with Interpolation ratio 2.0.

5. Challenges of BEMD

Creating BEMCs from a pixel-by-pixel picture is not a new idea, however. For each BIMF, the number of BEMCs and their properties are determined by the method used to detect extrema, the interpolation method used, and the stopping conditions [12]. As a result, each image has an endless number of BEMC sets. For interpolating the extrema points, scattered data interpolation has been used to form the upper and lower bounds. For each BIMF, the SD threshold criterion is most commonly used [15].

6. Conclusion and Future Enhancements:

The cubic natural spline approach has been used to create BEMD, which is both simple and adaptable. Non-stationary and non-linear signals are no problem for BEMD. Wavelet, Fourier, and other classic decomposition methods pale in comparison to this one. The IMF's calculations are critical to the BEMD's implementation. The term "IMF" refers to an oscillation that is distinct from the accompanying signal. An iterative and filtering method are used to compute the IMF. When the stoppage criterion equation is met, the iteration and filtering process is halted. The correlation coefficient is used to assess the extraction on a variety of pictures under assault. The suggested approach has been proven to be more resistant to JPEG compression, filtering, and noise addition after simulation. Using the BEMD, you may extract the brain MRI's spatial frequency components as well. There are 1025 distinct spatial scales, ranging from the finest to the coarsest, described by J.C. Nunes and colleagues in Image and Vision Computing (1019–1026). Non-linear and non-stationary data may be analysed using this approach, which is generated from picture data and completely unsupervised. Both natural and synthetic textures have yielded promising outcomes in our experiments. We can focus on simply one or a few modes (individual or multiple spatial frequency components) rather than the complete image when we have access to these representations of sceneries or objects. 2D EMD clearly presents a novel and promising method of decomposing and extracting texture characteristics without the need of any parameters. 2. The BEMD may now be used for routine image processing tasks. Developing a blind method in this area might be a fascinating project in the future.

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