

## DOCTORAL THESIS

### EMD/BEMD improvements and their applications in texture and signal analysis

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# Abstract

The combination of the well-known Hilbert spectral analysis (HAS) and the recently developed Empirical Mode Decomposition (EMD) designated as the Hilbert-Huang Transform (HHT) by Huang in 1998, represents a paradigm shift of data analysis methodology. The HHT is designed specifically for analyzing nonlinear and nonstationary data. The key part of HHT is EMD with which any complicated data set can be decomposed into a finite and often small number of Intrinsic Mode Functions (IMFs). For two dimension, bidimensional IMFs (BIMFs) is decomposed by use of bidimensional EMD (BEMD). However, the HHT has some limitations in signal processing and image processing. This thesis addresses the problems of using HHT for signal and image processing.

To reduce end effect in EMD, we propose a boundary extend method for EMD. A linear prediction based method combined with boundary extrema points information is employed to extend the signal, which reduces the end effect in EMD sifting process. It is a simple and effective method.

In the EMD decomposition, interpolation method is another key point to get ideal components. The envelope mean in EMD is computed from the upper and lower envelopes by cubic spline interpolation, which has overshooting problem and is time-consuming. Based on the linear interpolation (straight line) method, we propose using the extrema points information to get the mean envelope, which is Extrema Mean Empirical Mode Decomposition (EMEMD). The mean envelope taken by EMEMD is smoother than EMD and the undershooting and overshooting problems in cubic spline are reduced compared with EMD. EMEMD also reduces the computation complex. Experimental results show the IMFs of EMEMD present more and clearer time-frequency information than EMD. Hilbert spectral of EMEMD is also clearer and more meaningful than EMD. Furthermore, based on the procedure of EMEMD method, a fast method to detect the frequency change location information of the piecewise stationary signal is also proposed, which is Extrema Points Empirical Mode Decomposition (EPEMD).

Later, two applications based on the improved EMD/BEMD methods are proposed. One application is texture classification in image processing. A saddle points added BEMD is developed to supply multi-scale components (BIMFs) and Riesz transform is used to get the frequency domain characters of these BIMFs. Based on local descriptor Local Binary Pattern (LBP), two new features (based on BIMFs and based on Monogenic-BIMFs signals) are developed. In these new multi-scale components and frequency domain components, the LBP descriptor can achieve better performance than in original image. Experimental results show the texture images recognition rate based on our methods are better than other texture features methods. Another application is signal forecasting in one dimensional time series. EMEMD combined with Local Linear Wavelet Neural Network (LLWNN) for signal forecasting is proposed. The architecture is a decomposition-trend detection-forecasting-ensemble methodology. The EMEMD based decomposition forecasting method decomposed the time series into its basic components, and more accurate forecasts are obtained.

In short, the main contributions of this thesis are summarized as following:

1. A boundary extension method is developed for one dimensional EMD. This extension method is based on linear prediction and end points adjusting. This extension method can reduce the end effect in EMD.
2. A saddle points added BEMD is developed to analysis and classify the texture images. This new BEMD detected more high oscillation in BIMFs and contributed for texture analysis.
3. A new texture analysis and classification method is proposed, which is based on BEMD (no/with saddle points), LBP and Riesz transform. The texture features based on BIMFs and BIMFs' frequency domain 2D monogenic phase are developed. The performances and comparisons on the Brodatz, KTH-TIPS2a, CUREt and Outex databases are reported.
4. An improved EMD method, EMEMD, is proposed to overcome the shortcoming in interpolation. EMEMD can provide more meaningful IMFs and it is also a fast decomposition method. The decomposition result and analysis in simulation temperature signal compare with Fourier transform, Wavelet transform are reported.
5. A forecasting methodology based on EMEMD and LLWNN is proposed. The archi-

ecture is a decomposition-trend detection-forecasting-ensemble methodology. The predicted results of Hong Kong Hang Seng Index and Global Land-Ocean Temperature Index are reported.

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# Table of Contents

|   |     |
|---|-----|
| Declaration   | i   |
| Abstract  | ii  |
| Acknowledgements  | v   |
| Table of Contents   | vi  |
| List of Tables  | x   |
| List of Figures   | xii |
| Chapter 1 Introduction  | 1   |
| 1.1 Background . . . . .                                      | 1   |
| 1.2 Introduction to time-frequency analysis methods . . . . . | 2   |
| 1.2.1 Fourier transform . . . . .                             | 2   |
| 1.2.2 Wavelet transform . . . . .                             | 3   |
| 1.2.3 Wigner-Ville distribution . . . . .                     | 6   |
| 1.2.4 Conclusion . . . . .                                    | 7   |
| 1.3 Introduction to Hilbert-Huang transform (HHT) . . . . .   | 7   |
| 1.3.1 One dimensional empirical mode decomposition . . . . .  | 8   |
| 1.3.2 Two dimensional empirical mode decomposition . . . . .  | 10  |
| 1.4 Contributions of the thesis . . . . .                     | 12  |
| Chapter 2 Review of Hilbert-Huang transform                   | 13  |
| 2.1 Hilbert-Huang transform . . . . .                         | 14  |
| 2.1.1 Empirical mode decomposition (EMD) . . . . .            | 14  |

|           |  |    |
|-----------|--|----|
| 2.1.2     | Hilbert spectral analysis . . . . .  | 19 |
| 2.2       | Bidimensional empirical mode decomposition and two dimensional Hilbert transform . . . . .         | 21 |
| 2.3       | Conclusion . . . . .   | 23 |
| Chapter 3 | Boundary extension methods in EMD  | 25 |
| 3.1       | Boundary extension problem in EMD . . . . .  | 25 |
| 3.1.1     | The principle of end effect . . . . .  | 25 |
| 3.1.2     | Analysis of available extension methods in EMD . . . . .   | 26 |
| 3.2       | One dimensional extension based on linear prediction and end points adjusting . . . . .            | 28 |
| 3.3       | Conclusion . . . . .   | 40 |
| Chapter 4 | Texture classification based on saddle points added BEMD, Riesz transform and Local Binary Pattern | 41 |
| 4.1       | Introduction . . . . .   | 41 |
| 4.2       | Local Binary Pattern (LBP) . . . . .   | 43 |
| 4.3       | Texture descriptor based on BEMD and LBP . . . . .   | 45 |
| 4.4       | LBP histograms of BIMFs by saddle points added BEMD . . . . .                                      | 48 |
| 4.5       | VBEMD-LBP and VSBEMDLBP features classification experiments and discussion . . . . .               | 53 |
| 4.5.1     | Databases and dissimilarity measurement . . . . .  | 53 |
| 4.5.2     | Parameters selection and feature combination selection in experiments . . . . .                    | 56 |
| 4.5.3     | Classification result on texture database . . . . .  | 58 |
| 4.5.4     | Discussion . . . . .   | 65 |
| 4.6       | Texture descriptor based on Monogenic-BIMFs and LBP for rotation invariant . . . . .               | 67 |
| 4.6.1     | Riesz transform . . . . .  | 67 |
| 4.6.2     | LBP histograms of BIMFs-monogenic signal . . . . .   | 69 |
| 4.7       | MonoSadBIMFs-LBP feature classification experiments and discussion . . . . .                       | 73 |
| 4.7.1     | Feature combination selection in experiments . . . . .   | 74 |

|           |   |     |
|-----------|---|-----|
| 4.7.2     | Classification result . . . . .   | 76  |
| 4.7.3     | Discussion . . . . .  | 82  |
| 4.8       | Conclusion . . . . .  | 84  |
| Chapter 5 | Extrema Mean Empirical Mode Decomposition (EMEMD)                                   | 85  |
| 5.1       | Interpolation methods in EMD . . . . .  | 85  |
| 5.1.1     | Interpolation methods . . . . .   | 86  |
| 5.1.2     | Piecewise linear interpolation (straight line method) . . . . .                     | 88  |
| 5.1.3     | Spline interpolation . . . . .  | 88  |
| 5.1.4     | Monotone piecewise Hermite interpolation . . . . .                                  | 90  |
| 5.2       | Extrema Mean Empirical Mode Decomposition (EMEMD) decomposition<br>method . . . . . | 92  |
| 5.3       | Simulation experiments . . . . .  | 96  |
| 5.3.1     | Decomposition result analysis . . . . .   | 97  |
| 5.3.2     | Computational complexity analysis . . . . .   | 107 |
| 5.4       | Simulation temperature signal decomposition analysis . . . . .                      | 109 |
| 5.5       | Extrema Points Empirical Mode Decomposition (EPEMD) . . . . .                       | 119 |
| 5.5.1     | EPEMD decomposition method . . . . .  | 120 |
| 5.5.2     | EPEMD decomposition of simulation signal . . . . .                                  | 123 |
| 5.6       | Conclusion . . . . .  | 126 |
| Chapter 6 | Signal forecasting based on EMEMD and LLWNN   | 127 |
| 6.1       | Signal forecasting methods . . . . .  | 127 |
| 6.2       | Neural network approaches for forecasting . . . . .                                 | 129 |
| 6.2.1     | Artificial Neural Network (ANN) . . . . .   | 129 |
| 6.2.2     | Local Linear Wavelet Neural Network (LLWNN) . . . . .                               | 131 |
| 6.3       | Forecasting methodology based on IMFs and LLWNN . . . . .                           | 133 |
| 6.4       | Experiments . . . . .   | 136 |
| 6.4.1     | The datasets and accuracy measures . . . . .  | 136 |
| 6.4.2     | PSO based training method for LLWNN . . . . .                                       | 138 |
| 6.4.3     | Experimental results . . . . .  | 140 |
| 6.5       | Conclusion . . . . .  | 145 |



|                  |                          |     |
|------------------|--------------------------|-----|
| Chapter 7        | Summary and future works | 146 |
| 7.1              | Summary . . . . .        | 146 |
| 7.2              | Future works . . . . .   | 147 |
| Curriculum Vitae |                          | 161 |