10.21611/qirt.2022.1016

QIRT'2022 16th Quantitative InfraRed Thermography Conference

Application of Hilbert-Huang Transform to Thermographic Data Analysis for Enhanced Nondestructive Testing of Materials

by Tung-Yu Hsiao*, Stefano Sfarra**, Yi Liu*** and Yuan Yao*†

* Department of Chemical Engineering, National Tsing Hua University, Hsinchu, 30013, Taiwan
** Department of Industrial and Information Engineering and Economics, University of L'Aquila, L'Aquila, I-67100, Italy
*** Institute of Process Equipment and Control Engineering, Zhejiang University of Technology, Hangzhou, 310023, China
† *Corresponding author: yyao@mx.nthu.edu.tw*

Abstract

In this work, the Hilbert-Huang transform (HHT) is utilized to improve the non-destructive testing based on thermographic data and enhance the defect detection of materials. In previous studies, HHT has been proven to be powerful for signal processing and analysis in 1D time series. Its generalization to 2D and 3D Euclidean space has also demonstrated the widespread utilizations of HHT. The authors performed experiments on a mosaic sample with defects deliberately introduced. By using the proposed method, we successfully extracted informative defect signals out of noisy raw thermographic data and provided accurate yet more intuitive testing results.

1. Introduction

Non-destructive testing (NDT) techniques have gained popularity for the assessment of high-value materials. Pulsed thermography (PT), an NDT technique, is favored for the sake of its convenience and rapid detection. However, the PT results are often contaminated by undesirable noises and measurement backgrounds which cover the defect information. To solve this problem, the Hilbert-Huang transform (HHT) has drawn our attention. With the integration of empirical mode decomposition (EMD) and Hilbert transform, HHT has demonstrated its capability to handle non-stationary and non-linear signals in the one-dimensional (1D) data processing. Herein, the authors proposed a generalized version of HHT to the 2D Euclidian space, which makes it suitable for thermographic data processing. The proposed HHT algorithm consists of two key elements: (1) the multi-dimensional ensemble empirical mode decomposition (MEEMD) and (2) the Riesz transform (RT). It is reasonable to use MEEMD to decompose raw thermographic data into a finite numbers of Intrinsic Mode Functions (IMFs) where each IMF represents features of different frequency mode. In doing this, the informative defect signals can be extracted by focusing on some specific IMFs. Moreover, RT allows us access to the critical local information for further feature extraction, which reveals the subtle defect signals. In general, HHT provides us a solution to enhance the resolution of PT results without compromising the convenience of the NDT method.

2. Methodologies

2.1. Multi-dimensional Ensemble Empirical Mode Decomposition (MEEMD)

MEEMD was developed to solve the problem of multi-dimensional data decomposition [1]. It inherits the powerfulness of EMD [2] in dealing with non-stationary and non-linear signals while adopting ensemble empirical mode decomposition (EEMD) as its basic tool to deal with intermittent signals. In EMD, a data series $x(t)$ is decomposed into a finite number of IMFs corresponding to different frequencies, together with a residue r with a monotonic trend.

$$x(t) = \sum_{i=1}^{n} IMF_n + r \tag{1}$$

The IMFs can be computed iteratively by a sifting process, which satisfy two requirements: (1) the upper and lower envelopes of the IMF are symmetry about zero and (2) the number of zero crossings and extremes are equal or differ at most by one. In EEMD, a "true" IMF is calculated as the average of the corresponding IMFs obtained from multiple EMD trials where different scales of white noise are added to the data in each trial. To process a two-dimensional signal, such as a thermal image, the MEEMD algorithm can be conducted by performing EEMD on each row of the image. In doing this, each row is decomposed into n IMFs and a residue. The ith IMFs from different rows are then combine to form a new image which denotes as $Image_i$. After the preliminary decomposition, $(n+1)$ IMF and residue images are obtained. Then, EEMD is conducted again on each column of each IMF image and the residue image. At the end of the process, there are totally $(n+1)^2$ sub-images generated. In the last step, these sub-images are combined into $(n+1)$ component images as:

$$C_i(a,b) = \sum_{k=i}^{n+1} SubImage_{i,k}(a,b) + \sum_{j=i+1}^{m=n+1} SubImage_{j,i}(a,b) \tag{2}$$

where C_i is the ith component image $(i = 1, 2, \ldots, n+1)$, $C_i(a,b)$ is the value of the (i,j) th pixel in image C_i, and $SubImage_{i,k}(a,b)$ represents the value of the (i,j) th pixel in $SubImage_{i,k}$.

2.2. Riesz transform

Felsberg & Sommer et al [3] proposed the Riesz transform in 2001 and considered it as a generalization of the Hilbert transform. The monogenic signal is a representation derived from the generalization of the 1D Hilbert transform to a higher dimensional signal space which is made possible via Riesz transform. The monogenic signal consists of real signal f and two odd parts f_{o1} and f_{o2} derived from the Riesz transform. The Riesz operator is defined as:

$$R[f(x,y)] \overset{FT}{\rightarrow} = \begin{cases} F_{o1} = \begin{cases} i\frac{\omega_x}{\|\omega\|}F(\omega), & \omega \neq 0 \\ 0, & \omega = 0 \end{cases} \\ F_{o2} = \begin{cases} i\frac{\omega_y}{\|\omega\|}F(\omega), & \omega \neq 0 \\ 0, & \omega = 0 \end{cases} \end{cases} \quad (3)$$

where $f(x,y)$ represents the image data, $R[\,.\,]$ is the Riesz operator, F_{o1} and F_{o2} are the frequency-domain representations of the odd parts of the monogenic signal, which are the Riesz transformed signals taken about the x and y axes, $\omega = [\omega_x, \omega_y]$ is a two-dimensional frequency. The Riesz transform of signal f can be further expressed in a three-element vector:

$$R(x,y) = [f(x,y), f_{o1}(x,y), f_{o2}(x,y)] \quad (4)$$

Projecting the vector onto a spherical coordinate, the signal's spatial phase is given by the angle ϕ which is the angle between the signal vector and f axis. According to this geometry relationship, phase can be easily expressed by an arctan function while spatial frequency is the first derivative of the spatial phase. By this means, the understanding of the spatial phase and spatial frequency becomes conceptually simpler. Here, the spatial phase is defined along the direction in which the signal has the maximum variation. The spatial phase distinguishes the signal response areas from no response areas in the thermogram, while minimum intensity in original data corresponds to the maximum phase value. The spatial frequency depicts the border between two areas. In this way, defect features with relatively low intensity can also be extracted. For a graphical illustration of phase and frequency, please refer to Figure 1.

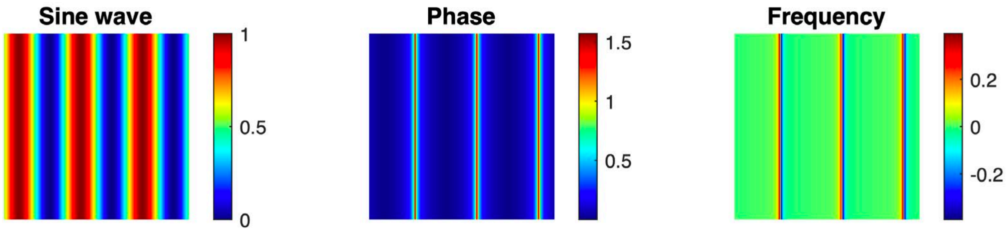

Fig. 1. *An illustrative example of phase and frequency extracted from a sinusoidal grating*

3. Results

Figure 2 shows the mosaic sample to be investigated. The proposed HHT-based thermography data analysis method was implemented to process the thermal image obtained from PT [4]. Using MEEMD, the image was decomposed into eight component images. According to the engineering understanding, it is known that the high-frequency images mainly contain noise, while the low-frequency images contain backgrounds. Therefore, only IMF4 (Figure 3) was used for further data processing. The subtle signal extrema of defects A, β, γ, which are difficult to identify in Figure 3, are captured by the RT's frequency spectrum (Figure 4). Our results demonstrate that HHT provides an efficient and intuitive way for thermographic data analysis.

Fig.2. *Mosaic sample*

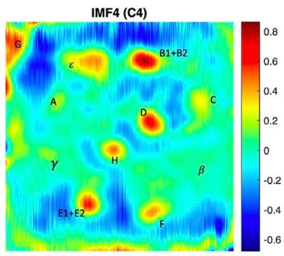

Fig.3. *IMF 4*

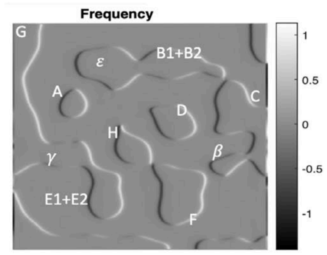

Fig.4. *Frequency spectrum of IMF4*

REFERENCES

[1] Wu Z., Huang N., Chen X. The multi-dimensional ensemble empirical mode decomposition method. Advances in Adaptive Data Analysis.1(3): pp. 339-372, 2009.

[2] Huang, N., Shen, Z., Long, S., Wu, M., Shih, H., Zheng, Q., Yen N.-C., Tung C. C., Liu, H. "The empirical mode decomposition and the Hilbert spectrum for nonlinear and non-stationary time series analysis", Proceedings of the Royal Society A: Mathematical, Physical and Engineering Sciences. 454: pp. 903-995, 1998.

[3] Felsberg, M., Sommer G. The monogenic signal. IEEE Transactions on Signal Processing, 49(12): pp. 3136-3144, 2001.

[4] Yao Y., Sfarra S., Ibarra-Castanedo C., You R., Maldague X. The multi-dimensional ensemble empirical mode decomposition (MEEMD): an advanced tool for thermographic diagnosis of mosaics. Journal of Thermal Analysis and Calorimetry, 128(3): pp. 1841-1858, 2017.