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# Image Fusion using Empirical Mode Decomposition

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**Abstract**
Image fusion is used to produce a single fused image from a set of two or more than two input images. The fused image has enhanced information that is more useful, understandable and decipherable for human perception and, preferably, for machine learning and computer vision. Here we present a novel technique for image fusion, using Empirical Mode Decomposition (EMD). EMD is a non-parametric data-driven analysis tool that decomposes non-linear non-stationary signals into Intrinsic Mode Functions (IMFs). In this method, we decompose images, rather than signals, from different imaging modalities into their Intrinsic Mode Functions (IMFs).This process of image fusion is performed at the decomposition level and the fused IMFs are reconstructed to realize the resultant fused image. A scheme which emphasize features from both modalities by decreasing the mutual information between IMFs, so it increases visual content and information of resultant image. Here we describe that how this methods improves the visual information of input images, by comparing with other fusion techniques.
***Keywords**:* Data fusion, Empirical mode decomposition, Image fusion, intrinsic mode function.

## I. INTRODUCTION

Multisensor Image fusion is the process of combining relevant information from two or more images into a single image. The resulting image will be more informative than any of the input images. Multisensor data fusion has become a discipline which demands more general formal solutions to a number of application cases. Several situations in image processing require both high spatial and high spectral information in a single image. This is important in remote sensing. However, the instruments are not capable of providing such information either by design or because of observational constraints.

In this paper, we harness the potential of a relatively recent method for analyzing nonlinear and non-stationary datasets developed by Huang et al [1]. One is able to decompose any complicated data set into a finite set of IMFs that admit well-behaved Hilbert transforms. EMD is a sifting process that decomposes a signal or data into its IMFs and a residue based on the local frequency or oscillation information. The first IMF contains the highest local frequencies of oscillation or the highest local spatial scales, whereas the final IMF contains the lowest local frequencies of oscillation and the residue contains the trend of the signal/data. Like time-frequency distribution with EMD, acquiring the space spatial- frequency distribution of 2D data/image is possible with EMD. This decomposition method is data driven and hence highly effective. The decomposition is based on the local characteristic time scale of the data, and hence extendable to nonlinear and non-stationary processes. With the Hilbert transform, the IMFs allow representation of instantaneous frequencies as functions of time. The main conceptual benefits are the decomposition of parent signal into IMFs and the visualization of time-frequency characteristics. Although direct estimation of the horizontal and vertical frequencies of IMFs has been studied [2].

## II. EMD OVERVIEW

It is commonly known that Fourier transform is a useful method for stationary signal analysis, where as DWT is more suitable and useful for non-stationary signal analysis. In fact, the DWT is a windowed Fourier transform and a finite length of the DWT base may cause energy leakage. Once the wavelet base and decomposition level are determined, the signal obtained is within a certain frequency range that only depends on the sampling rate and has no relationship to the signal. Therefore, this method is not adaptive. Compared with the DWT, the EMD shows superior performance on data analysis and data filtering. It is a powerful tool for adaptive multiscale analysis of non-linear and non-stationary signals and data. These interesting characteristics of the EMD motivated the extension of this method to the area of image processing.

### 2.1 EMD Assumptions

The EMD theory was originally proposed for one dimensional data. It has been extended for two-dimensional data The IMFs of a signal/data obtained by EMD should have the following properties [1, 3, 4, 5].

(a) In the whole data set, the number of local extrema (maxima and minima together) and the number of zero crossings must be equal or differ by at most one.
(b) There should be only one mode of oscillation, that is, only one local maxima or local minima, between two successive zero crossings.
(c) At any point, the mean value of the upper and lower envelopes, defined by the local maxima and minima points, is zero or nearly zero.
(d) The IMFs are locally orthogonal among each other and as a set.

The definition and properties of the IMFs are slightly different from the IMFs. It is sufficient for IMFs to follow only the final two (c) and (d) properties given above [6, 7].

### 2.2 The Sifting Process

According to the definition of Intrinsic Mode Function, the decomposition method employ the envelopes defined by the local maxima and minima individually. The extrema are identified and all local maxima are connected by a thin plane spline orcubic spline to form the upper envelope. This process is repeated for the local minima and the lower envelope is constructed. While interpolating, care is taken that the upper and lower envelopes cover all the data between them. The point-wise mean of the envelopes is called m1, and is subtracted from the data a0 for the first component b1. For the first iteration, X(t) is the used as the data,

The envelope means may be different from true local mean and consequently some asymmetric waveforms may occur but they can be ignored as their effects in the final reconstruction are very minimal.

$$a0 = X(t)$$
$$b1 = a0 – m1$$

In the second sifting process, h1 is considered as the data where m11 is the mean of the b1 envelopes.

$$b11 = b1 – m11$$

The sifting process is continued k times till the first IMF, is obtained.

$$b1k = b1(k-1) – m1k$$

We designate c1 as the first IMF,

$$c1 = b1k$$

As per mathematical definitions, b1 should be considered as one of the IMF, as b1 should satisfy all the requirements of an IMF. But since we are interpolating the extrema with numerical schemes, overshoot and undershoot are bound to occur. These generate new maxima and minima, and distort the magnitude and phase of the existing extrema. These effects will not affect the process directly as it is the mean of these envelopes that pass on to the next stages of the algorithm and not the envelopes themselves. The formation of false extrema cannot be avoided easily and an interesting offshoot is that this procedure inherently recovers the proper modes lost in the initial examination and recovers low-amplitude riding waves on repeated sifting.

A ringing effect at the ends of the data array may occur, but even with these effects, the sifting process still extracts the essential scales from the dataset. The sifting process eliminates riding waves and makes the signal symmetrical.

### 2.3 Stopping Criteria

In sifting, uneven amplitudes of data will be smoothened, finest oscillatory are separated from data. If it is kept continuous too long the sifting process may destroys the physical meaning of the amplitude fluctuations. That means we get IMFs that are frequency modulated signals with constant amplitude. To retain the physical meanings of an IMF, in terms of amplitude and frequency modulation, a standard deviation based stopping criterion is used. The standard deviation, SD, computed from two consecutive sifting results, is used as one of the stopping criteria.
Sifting is stopped if SD falls below a threshold.The isolated intrinsic mode function, c1contains the finest scale of the signal and we separate c1 from the data.

$$a1 = a0 – c1$$

The new signal called the residue, a1, still holds lower frequency information. In the next iteration, the residue a1 is treated as the new data in place of a0 and subjected to the sifting process.

$$a(n) = a(n-1) – c(n)$$

The sifting through residuals can be stopped by any of the following stopping criteria; if the residue becomes too small to be of any practical importance, or when the residue becomes a monotonic function containing no more IMFs.

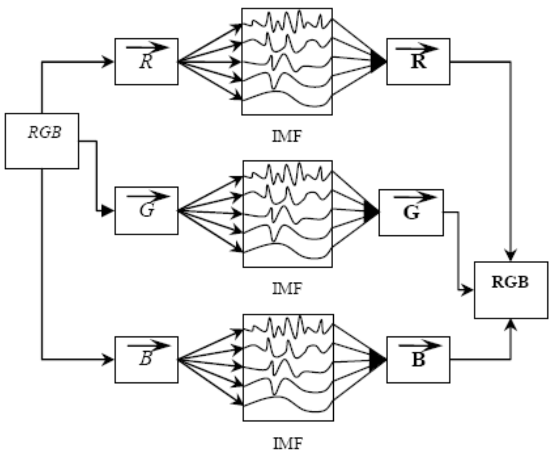


**Fig. 1:** Extension of one dimensional EMD to images via channel vectorization

### 2.4 Issues Related to EMD

The IMFs and the residue a(n) of an image together can be named as empirical mode components (EMCs). Except for the truncation error of the digital computer, the summation of all EMCs returns the original data/image. The decomposition of an image into EMCs is not a unique process. The number of EMCs and their characteristics depend on the extrema detection method, interpolation technique, and stopping criteria of the iterations for each IMF. There are an infinite number of EMC sets for each image [8].

The expected result of image fusion using Empirical Mode Fusion (EMD) is shown in figure 2.

## III. CONCLUSIONS

EMD is a potential image processing algorithm. To boost increased application of this algorithm for image processing applications, a fast, time efficient, and effective method is essential. Our fusion technique preserves information from both the input images. As input, we use registered visual and thermal images. Empirical mode decomposition is used to obtain the decomposed IMFs of the various channels of the visual and thermal image. Fusion is performed at the IMF level where a weighting scheme is used to emphasize features or, to discourage distracting features from one, or both, of the modalities by minimizing the mutual information between the IMFs. The output is a fused image containing enhanced visual and thermal information.

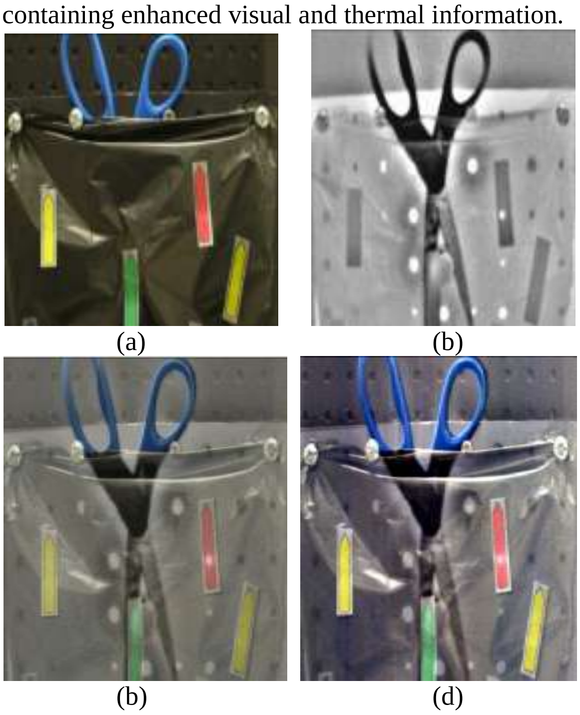


**Fig. 2:** Comparison, (a) the visual image, (b) the thermal image, (c) pixel-bypixel averaging, (d ) EMD fusion.

The proposed EMD can test for decomposing various images, and will give better result as expected, some of which have been reported in this paper. The simple change in the envelope estimation procedure provides a tremendous enhancement of the algorithm in terms of computation time and will play a very significant role in this area..

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