COMPLETE ENSEMBLE EMPIRICAL MODE DECOMPOSITION (CEEMD) FOR REAL-TIME SIGNAL DETRENDING IN IOT APPLICATIONS

M. T. Abduridha   A. S. Tolba   M. Z. Rashad

Computer Science Department,Faculty of Computers and Information,
Mansoura University, Egypt

Muayad.teto88@gmail.com   ast@astolba.com   Magdi_z2011@yahoo.com

Abstract: *The Internet of Things (IOT) is a promising area which will boost the world economy. The constituent components of the IOT are smart objects which generate actuation signals or receive sensory signals which are usually noisy, have trend or has small signal-to-noise ratio. Processing these signals for filtering, detrending and enhancing the signal-to-noise ratio is crucial for embedding intelligence in these smart objects. This research discovers the potential of CEEMD in preparing signals for further intelligent applications such as event detection or pattern recognition in smart objects. Algorithms are presented for signal filtering, detrending and event detection based on a combination of both CEEMD, the autocorrelation function and the learning vector quantization classifier.The performance of the proposed algorithms is compared for both CEEMD and the least squares fit approach. The CEEMD has shown promising results.*

Keywords: *Internet of Things, Real-time Signal Detrending, Empirical Mode Decomposition, Complete Ensemble Empirical Mode Decomposition, Signal Denoising, Thresholding, Event Detection, Learning Vector Quantization.*

1. Introduction

The weak and noisy signals produced by sensors impeded in smart objects of the IOT [15] and trend imposed on these signals as a result of the environmental changes are challenging the detection, prediction and event recognition algorithms which are essential part of smart objects. Trend is the low frequency part of a signal over which higher frequencies are carried and could be removed by filtering out the high frequency components from the signal.This research introduces a single algorithm for sensor signal denoising, detrending, and SNR enhancement in addition to extracting the signal discriminative features.In this paper a system that completely depends on CEEMD is implemented for real-time signal denoising, detrending, thresholding and event detection. Figure 1 shows the system layout.
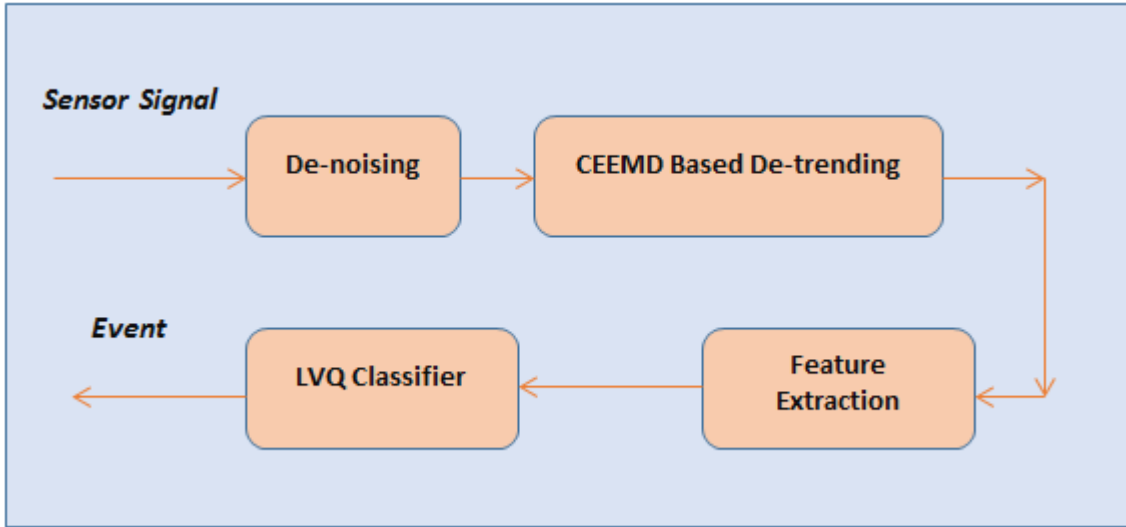
Figure 1: System Layout

2. Empirical Mode Decomposition (EMD)

The Empirical Mode Decomposition (EMD) is a recent signal decomposition approach which outperforms many signal processing approaches such as the Fourier Transform, Wavelet Transform. EMD decomposes a given signal into a set of Intrinsic Mode Functions (IMFs) using a sifting process according to the following algorithm [10-9].An EMD algorithm decomposes adaptively the signal $x(t)$ into intrinsic mode functions $c_i(t)$, $i = 1, 2, \ldots, n$ and into residue $r(t)$:

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

where n means the number of IMF functions. Residue $r(t)$ reflects the average trend of a signal $x(t)$ or a constant value.

1- Create upper envelope $E_u(t)$ by local maxima and lower envelope $E_l(t)$ by local minima of data $x(t)$.

2- Calculate the mean of upper and lower envelope.

$m_1(t) = E_{u1}(t) + E_{i1}(t) /2 \qquad (2)$

3- Subtract the mean from original data

$h_1(t) = x(t) - m_1(t) \qquad (3)$

4- Verify that $h_1(t)$ satisfies conditions for IMFs. Repeat steps 1 to 4 with $h_1(t)$, until it is an IMF.

5- Get first IMF (after k iterations)

$c_1(t) = h_{1(k-1)}(t) - m_{1k}(t) \qquad (4)$

6- Calculate first residue

$r_1(t) = x(t) - c_1(t). \qquad (5)$

7- Repeat whole algorithm with $r_1(t)$, $r_2(t)$, … until residue is monotonic function.

8- After *n* iterations *x*(*t*) is decomposed according to equation (1).

3. Complete Ensemble Empirical Mode Decomposition (CEEMD)

The major problems with EMD and end effects and mode mixing. The CEEMD version of EMD solves the two problems according to the following algorithm [17] by adding both negative and positive noise to the signal x(t) to be analyzed:
1- Select the number of EMDs used in the Complete Ensemble
2- Generate a Gaussian noise signal
3- Generate two signals by adding the sensor signal to the noise signal and subtracting the noise signal from the sensor signal
4- Apply the basic EMD to both signals separately to generate to separate sets of IMFs
5- Repeat steps 2 to 5 until the ensemble number of step 1 is reached
6- Calculate the ensemble means of the generate IMFs.

4. CEEMD based signal detrending

To remove trend from the sensor signal, all IMS are summed except the residue which represents the trend of the signal according to the following formula:

$$y(t) = \sum_{i=1}^{N-1} IMF_i \quad (6)$$

Where N is the number of IMFs resulting from the decomposition of the sensor signal.

5. CEEMD based signal denoising

Denoising of sensor signals is essential for accurate event detection. CEEMD is also used for signal denoising in addition to signal detrending. Table 1 shows the superior performance of CEEMD [5] compared to other recent techniques such as EMD DFA [8] [1]and morphological transforms [16].The major drawback is the high computational cost. IT results in lower Mean Square Error (MSE), lower Mean Absolute Error (MAE), higher Signal-to-Noise Ratio (SNR) and Peak Signal-to-Noise Ratio (PSNR).

Table 1: Comparison between different Denoising Methods

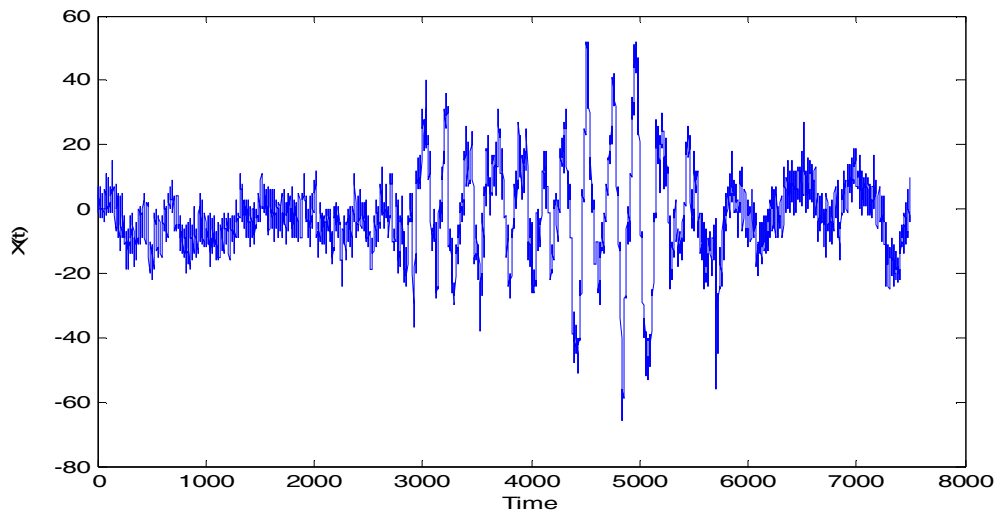| Method/Indicator	CEEMD	EMDDFA	Morphological Operators
Time	53.25 s	3.448 s	2.850 s
MSE	**12.638**	13.71	14.223
SNR	**11.814**	11.46	11.30
PSNR	**23.303**	22.95	22.79
Cross correlation	0.9666	0.9626	0.9802

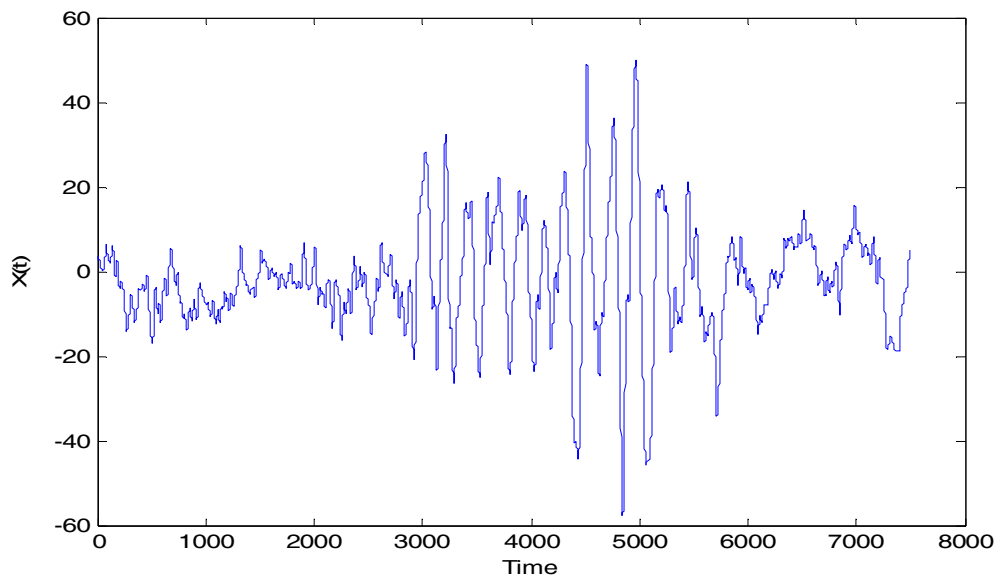Figure 2: Simulated Noisy Signal

Figure 3: CEEMD Denoised Signal

6. Experimental Set up and Results

In this paper a real time sensory signal capture system is built around the Arduino Ethernet microcontroller, which is used to capture a real-time signal from a light sensor. An Arduino Ethernet board is connected to a light sensor. A micro USB cable is used to interface the Arduino Ethernet microcontroller with the PC. Some of wires and resistors are used for connecting the light sensor to the Arduino on a Breadboard. The light signal is degenerated by a light sensor (Light Detecting Resistor (LDR)), whose resistance decreases with increasing light intensity. The experimental set up is shown in figure (4).
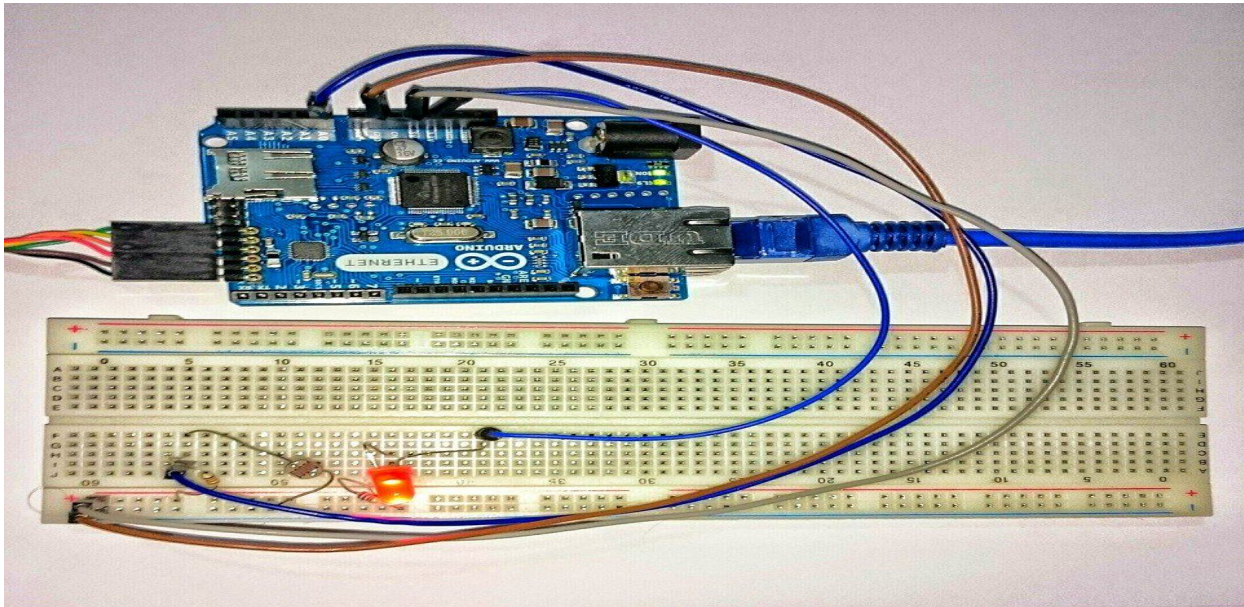
Figure.4. The Electronic Circuit

The control process is done through Arduino Ethernet [9-15] which contains a set of inputs (Analog Inputs) which can be used to read voltage (3.3-5V) restricted to the connected sensor. The sensor output signal captured in real time and then decomposed into a two sets of signals ,the first set with high frequency and called (IMF) in the sense that it is changing quickly and the second set with low frequency that is, they are slowly changing, we set a low frequency signal so that we remove the trend (hard light located in the work environment), which is a straight line by referring volatile variable (light coming from outside the work environment). Using complete ensemble empirical mode decomposition algorithm we remove this signal and as a result we will get the trend free signal.

7.Performance evaluation of the CEEMD based method

To evaluate the performance of the proposed CEEMD algorithm , the Mean Square Error (MSE): MSE=$\sum_{n=1}^{N}(Z(t) - x(t))^{\wedge}2$,and the Peak Signal-to-Noise Ratio (PSNR) via PSNR=MSE/$\sum x(t)$ as are estimated.The table (2) compares the performance of the CEEMD with that of the well known least squares fit algorithm for a synthetic signal X(t).

Table 2 Performance comparison between the CEEMD and LSF detrending

	CEEMD	LSF
MSE	1.2926e+005	1.5436e+005
PSNR	7.068670 db	6.297807 db
SNR	0.157091 db	0.021998 db

8. Feature Extraction and Classification for Sensory Event Detection

To detect any abnormal event in a sensory signal (light or temperature), the detrended and denoised signal is used to extract a highly discriminative feature set which includes the following features:

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Skewness, Kurtosis and the sum of the ACF values for 10 lags are calculated according to the following formulas:

$$Kurtosis = \frac{\mu^4}{\sigma^4} \quad (7)$$

Where, μ^4 is the fourth moment about the mean μ of the ACF values and σ is the standard deviation of the ACF.

$$Skewness = \frac{1}{N} \sum_{i=1}^{N} (\frac{x_i - \mu}{\sigma})^3 \quad (8)$$

Where, N is the number of samples.

The Autocorrelation function $R(\tau)$ of the sensor signal x of N samples is calculated according to the following formula [14]:

$$R(\tau) = \frac{1}{N - \tau} \sum_{i=0}^{N-\tau-1} (x(i)x(i + \tau)) \quad (9)$$

9. Signal change event detection

To classify the sensor signal as normal or abnormal a Learning Vector Quantization Neural Network Classifier [12] is trained on a large set of normal and abnormal signals. The training is performed on feature vectors having the three features extracted from the ACF of the sensor signal: skewness, kurtosis and sum of ACF values (Table 3).

Table 3 Feature sets for Normal and Abnormal Light Signals

Feature / Status	**Normal**	**Abnormal**
Skewness of ACF	2.7085	0.3264
Kurtosis of ACF	8.6386	1.6439
Sum of the ACF values at 10 lags	0.4471	2.1903
Signal Status	Abnormal state	Normal state

The training set used by LVQ for detection of abnormal light change is extracted in real time as follows:

Skewness	Kurtosis	Sum of ACF	Target Class
2.5201	8.0281	1.0071	1
2.6390	8.4025	0.6441	1
2.7406	8.7436	0.6018	1
2.6942	8.6035	0.7762	1
-0.2253	1.7490	9.8001	2
-0.2296	1.7667	8.8142	2
0.1094	1.5752	3.9537	2
-0.1639	1.7462	9.5102	2

Where class 1 represents a normal light signal and class 2 represented a changed light signal due to an external interference.

10. Real-Time Experimental Results and Discussion

Experiment 1: Normal Light State

Figure 5-6, show a real-time light signal and its intrinsic mode functions. Figures 7 shows the results of signal detrending using both the CEEMD and LSF algorithms. The ACF of the detrended signal is shown in figure 8.
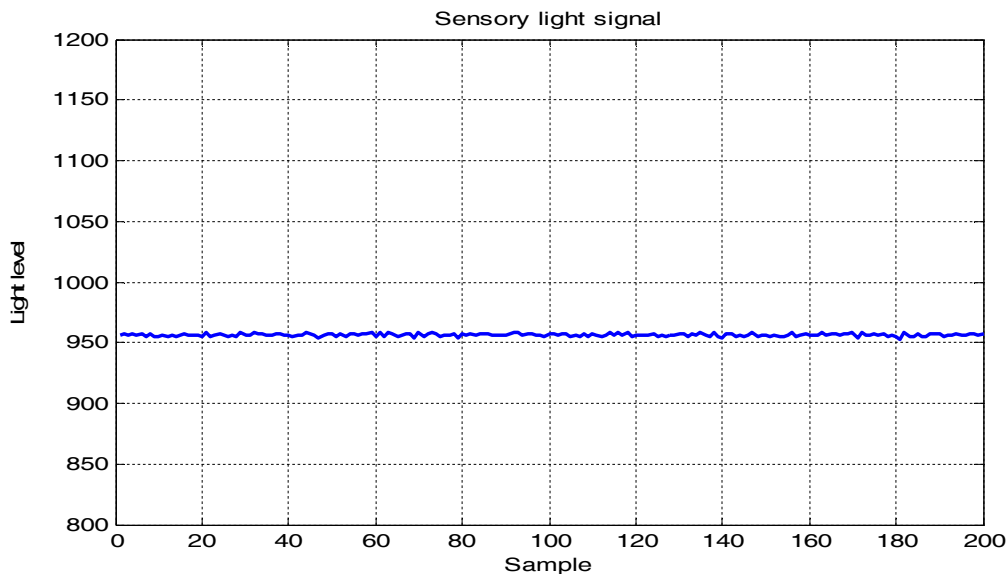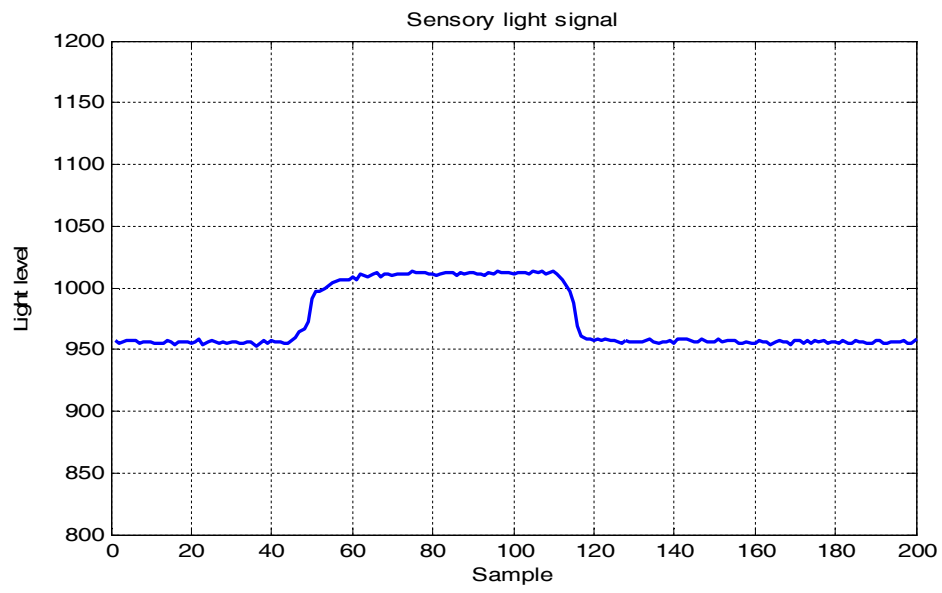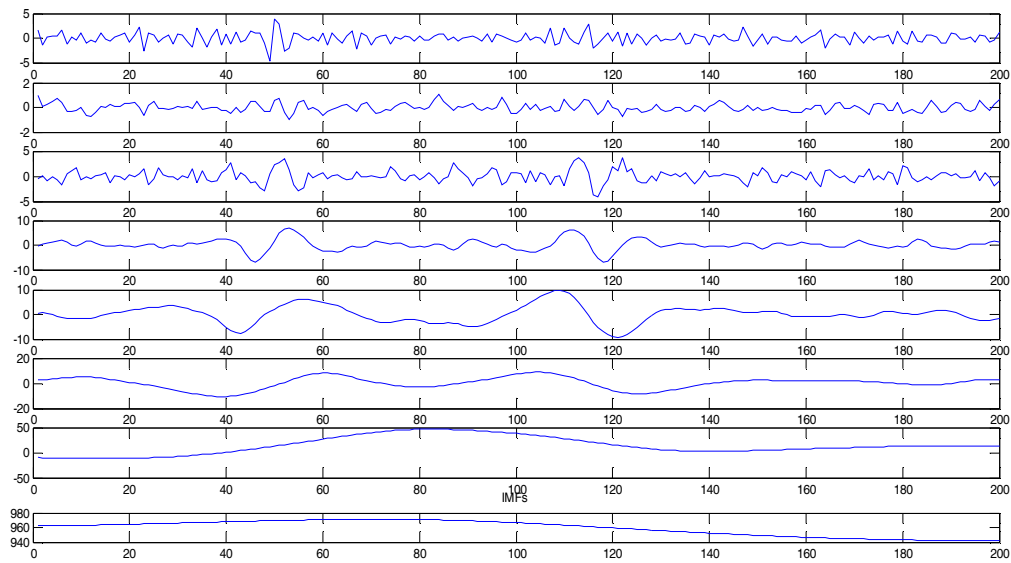

Figure 5: Normal Light Signal
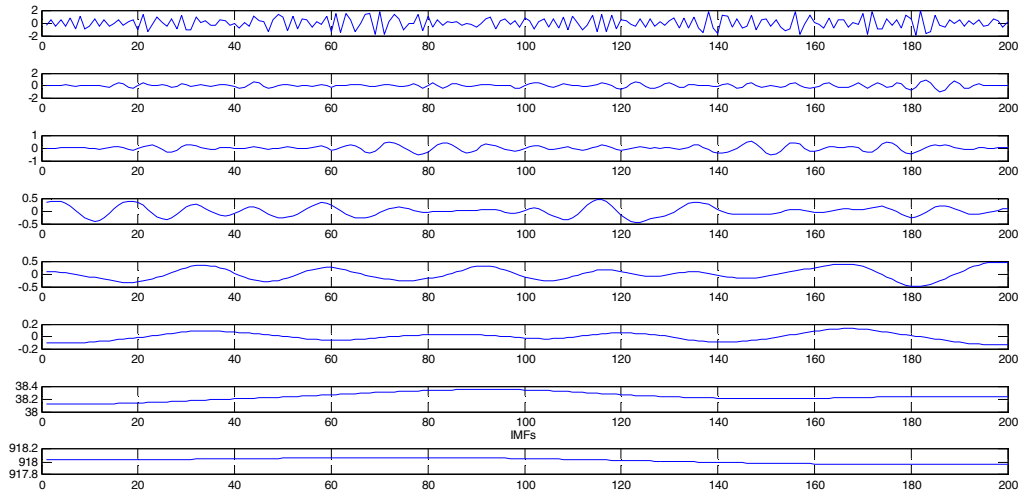
Figure 6: IMFs of the normal light signal
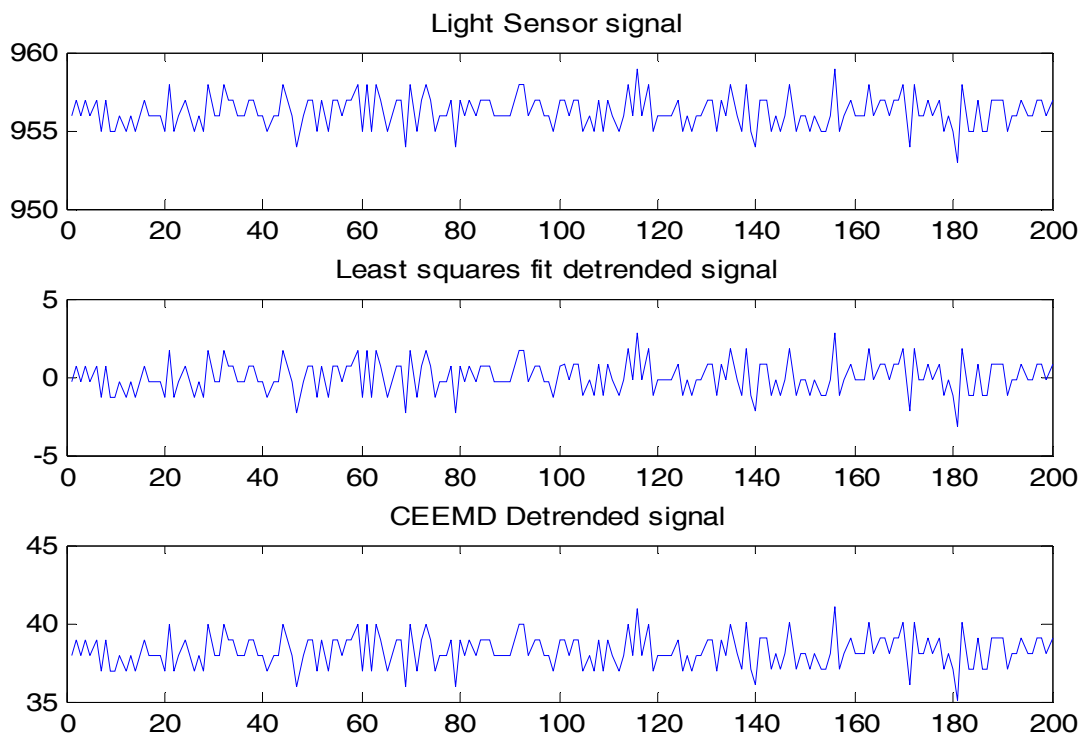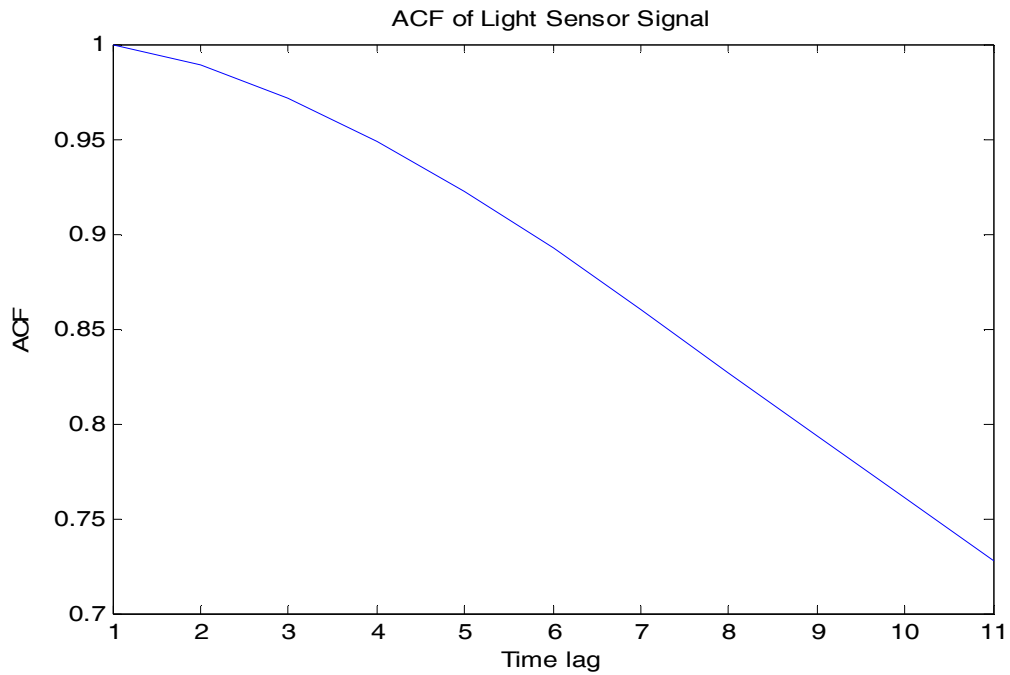

Figure 7: Detrending by both LSF and CEEMD methods
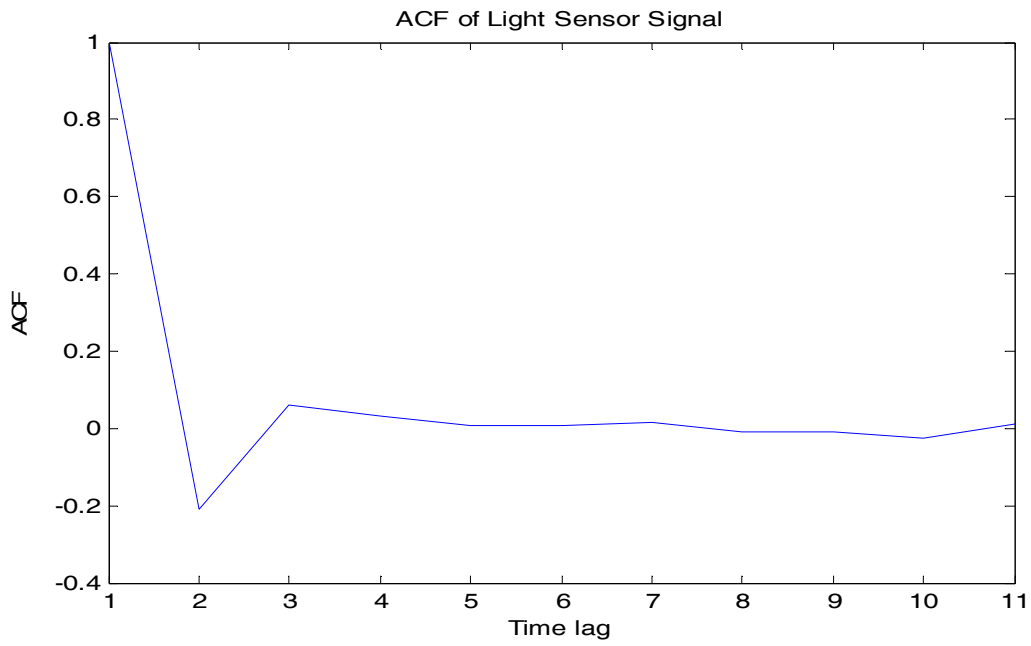
Figure 8: ACF of the detrended signal

Performance comparison of both LSF and CEEMD:

Table 5 Performance comparison between the CEEMD and LSF detrending of a Normal Temperature Signal

|	**CEEMD**	**LSF**
Time	10.203125 seconds	0.109375 seconds
MSE	842785.752087	914470.582030
SNR	0.354377 db	0.000005 db
PSNR	0.379200 db	0.024675 db
Skewness of ACF	2.562262	
Kurtosis of ACF	8.286071	
Sum of the ACF values at 10 lags	0.879909	
Signal Status/LVQ class	Normal state	

Experiment 2: Abnormal Light State

Figure 9: Abnormal light signal
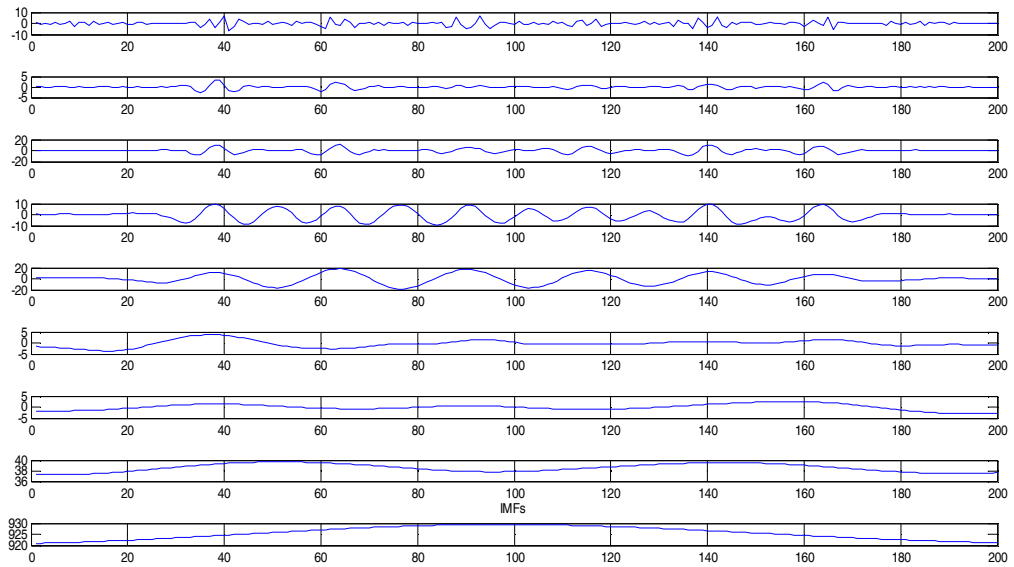

Figure 10: IMFs of an abnormal light signal
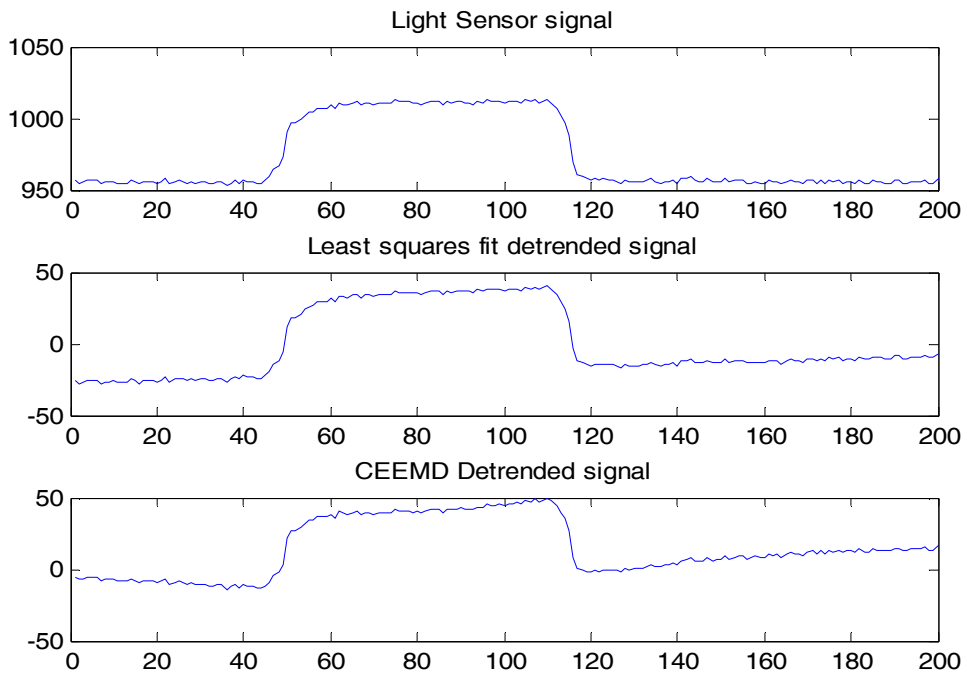
Figure 11: Dtrended signal by both LSF and CEEMD

Figure 12: ACF of the detrended signal

Performance Evaluation of both LSF and CEEMD:

Table 6 Performance comparison between the CEEMD and LSF detrending of an Abnormal Temperature Signal

	CEEMD	**LSF**
Time	10.281250 seconds	0.031250 seconds
MSE	926294.848920	966443.351835
SNR	0.132751 db	0.002717 db
PSNR	0.444696 db	0.260425 db
Skewness of ACF	0.269408	
Kurtosis of ACF	1.733650	
Sum of the ACF values at 10 lags	9.692990	
Signal Status / LVQ class	Abnormal state	

Experiment 3: Abnormal Light State
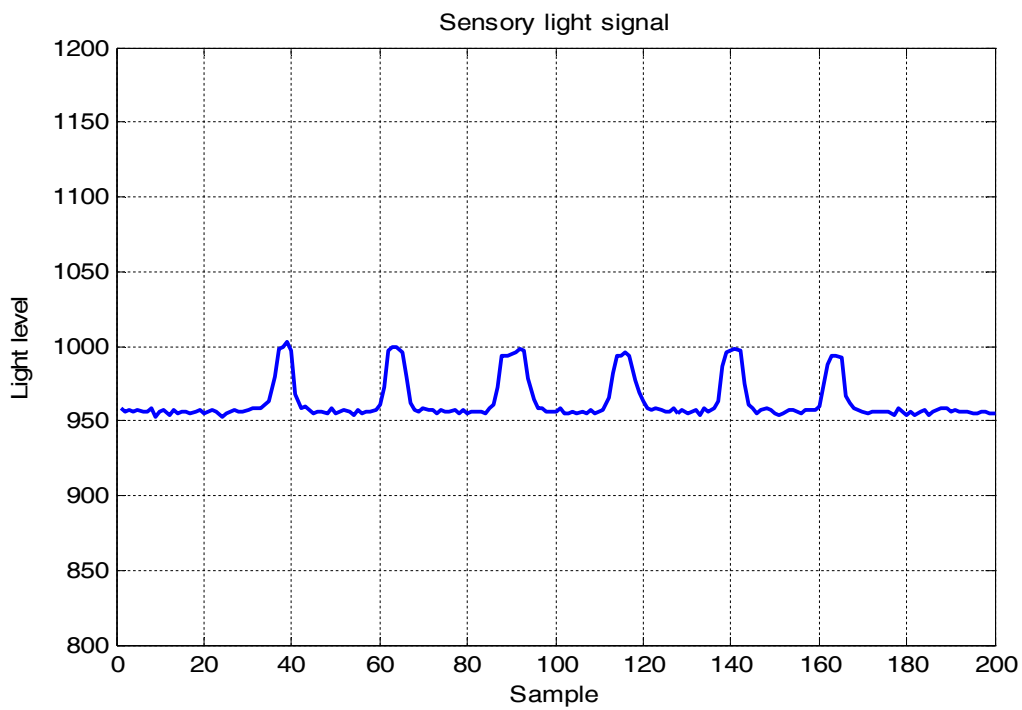
Figure 13: Abnormal light signal

Figure 14: IMFs of an abnormal light signal
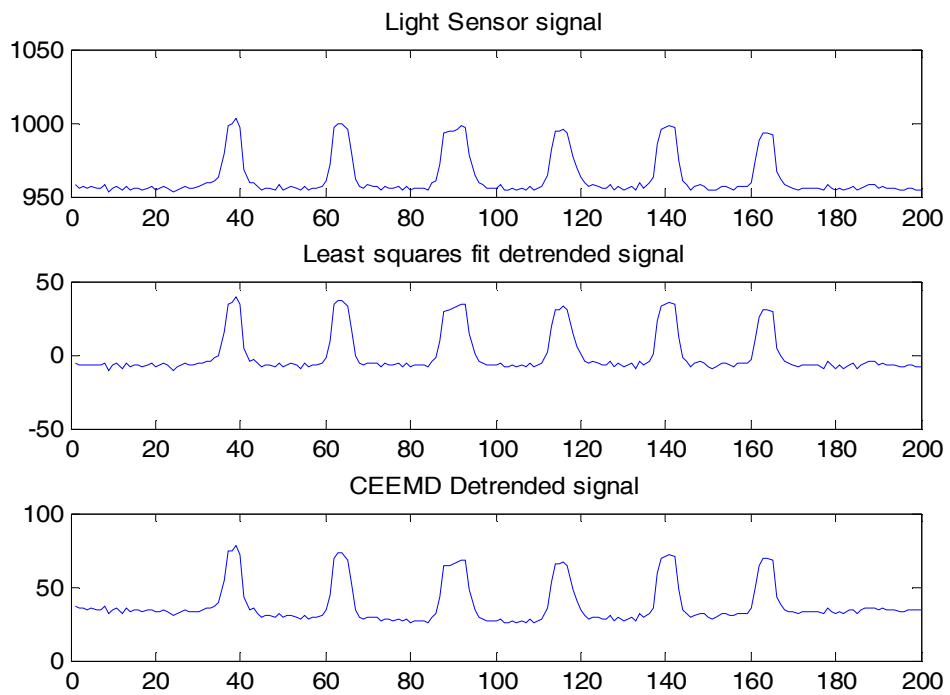
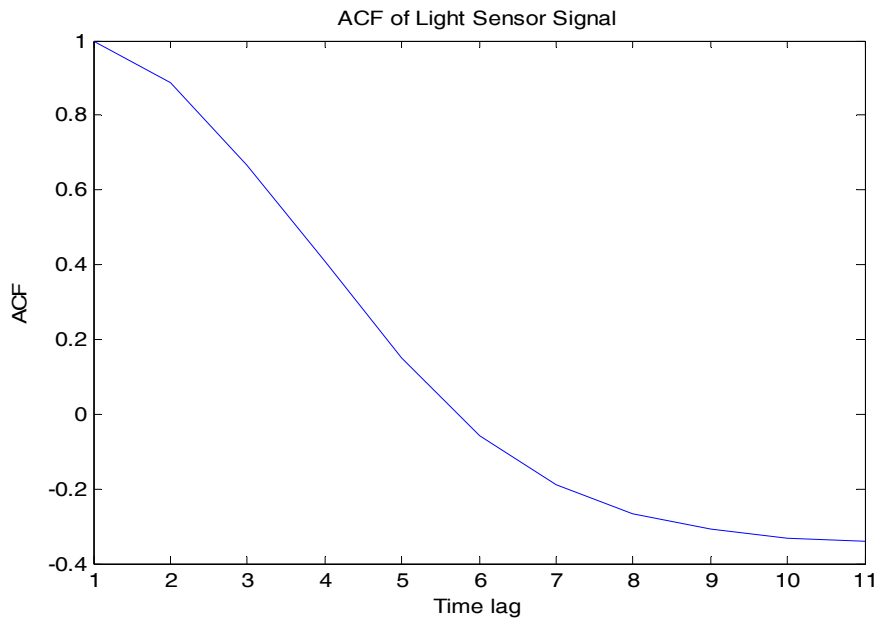Figure 15: Dtrended signal by both LSF and CEEMD

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Figure 16: ACF of the CEEMD detrended signal

Tables 5-6 show that the CEEMD detrending approach results in better performance than thee LSF approach.

Experiment 4: Simplified Signal Thresholding Based on Detrending

To detect events in a cluttered signal or in a signal with a trend it seems impossible without removing the trend. This section shows how trend removal could simplify the thresholding of a given signal. Figure 17 shows a pulse overlaid on an exponentially decaying trend signal.
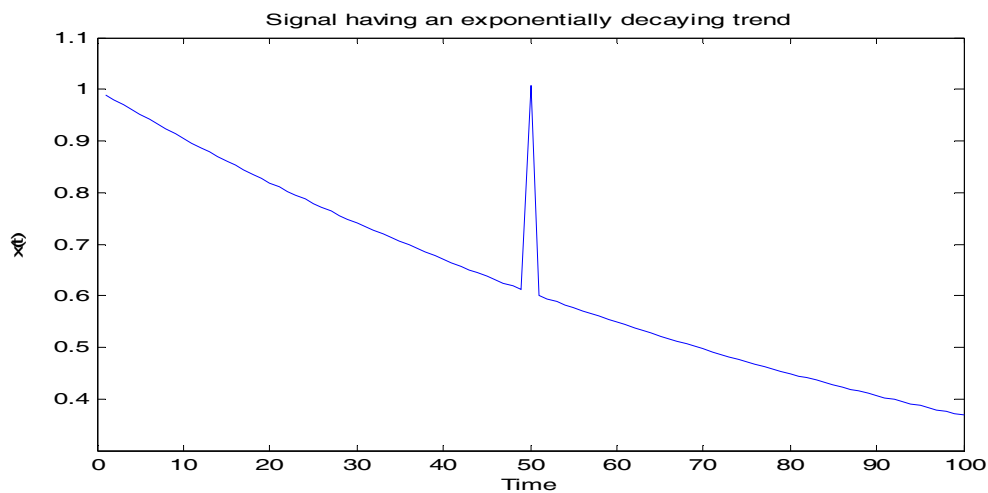

Figure 17: A pulse overlaid on an exponentially decaying trend signal

Separation of the pulse event after detrending using the CEEMD leads to excellent results as could be realized from figures 22 compared to thresholding of the original signal as shown in figure 18.
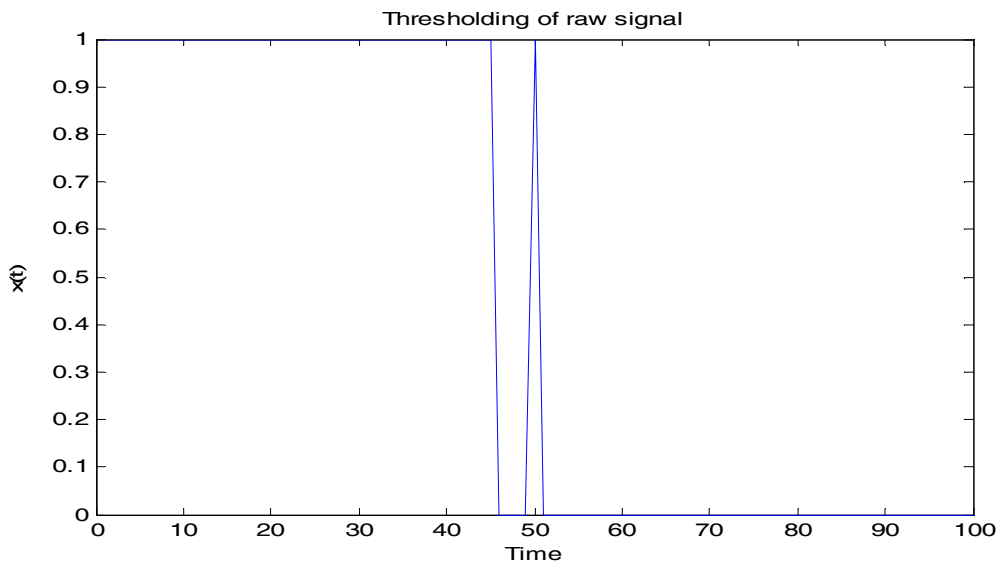
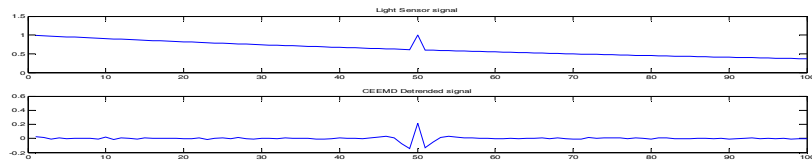Figure 18: Thresholding using the raw signal based on 3.5*standard deviation

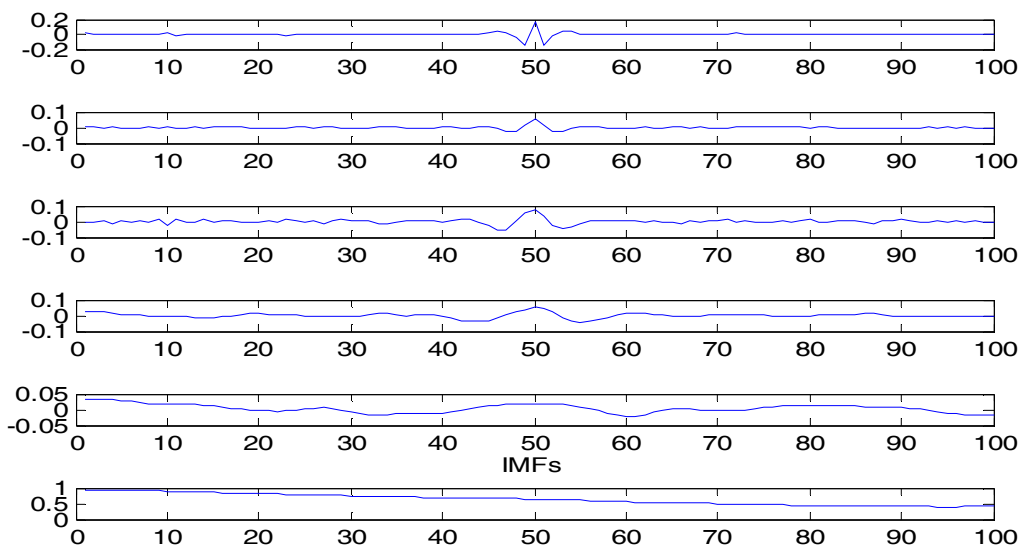Figure 19: CEEMD Detrended Signal

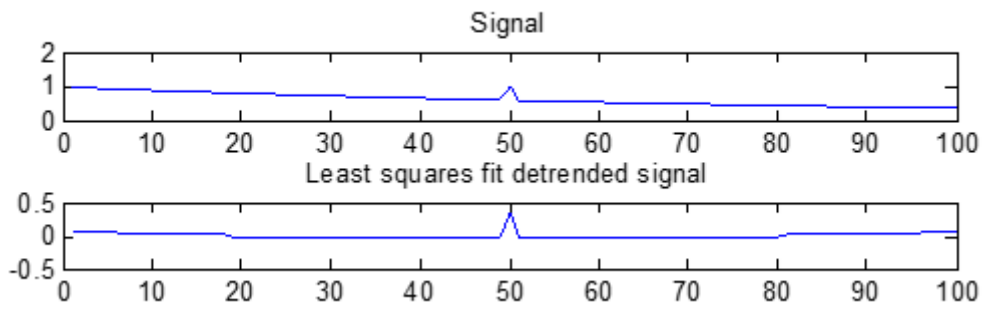Figure 20: IMFs of the original signal
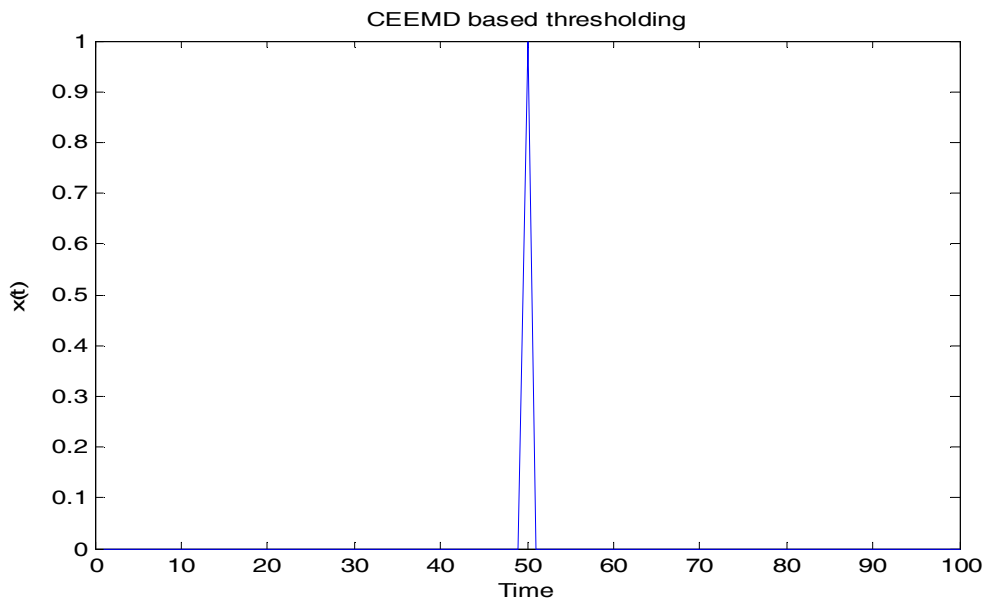
Figure 21: LSF Detrended Signal

Figure 22: Thresholded Signal after trend removal using CEEMD

11. Conclusions

The Complete Ensemble Empirical Mode Decompositiom (CEEMD) is considered a means of non-stationary and non-linear signals analysis. This paper discusses the application of CEEMD to real-time trend removal in light signals. The rationale is that (CEEMD) method completely depends on the data that solves the mixed mode problem of EMD. The trend is described through a set of low-frequency Intrinsic Mode Functions (IMFs). The CEEMD trend removal was shown to perform well. The test results of both CEEMD based detrending and the well known least squares fit method indicate the superiority of the CEEMD detrending method. Statistical features extracted from the autocorrelation function have been used effectively to detect abnormal events using an LVQ classifier.

Acknowledgements

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