Empirical Mode Decomposition on T-Wave Alternans Detection

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***Abstract*—T-Wave Alternans (TWA) is a known marker for fatal cardiac arrhythmias which may lead to Sudden Cardiac Death (SCD). Its detection and estimation becomes a challenge under the presence of various types of noise including electrode movements and muscle artifacts. Various pre-processing techniques have been suggested by authors to counter for the issue of noise. One of the relatively new denoising techniques, Empirical Mode Decomposition (EMD) has also been used for extricating the trend of ST-T wave segments. In this paper, we have carried out a comparison of the effect of using EMD for denoising the ST-T complexes before applying the state of the art TWA analysis algorithms i.e. Spectral Method (SM), Correlation Method (CM), Modified Moving Average Method (MMAM) and Median Matched Filter (MMF) method. Application of EMD has noticeably improved detection and estimation accuracy. Application of EMD has improved detection performance of MMF by 50%. Estimator bias and Mean Square Error (MSE) are reduced by more than 30% for MMAM, SM and MMF with EMD. The improvement is most pronounced in MMF and is least in case of CM, while compared with results of directly applying the algorithms without denoising by EMD.**

***Index Terms*—empirical mode decomposition, T-wave alternans, detection and estimation, electrocardiography**

I. INTRODUCTION

Sudden Cardiac Death (SCD) is one of the threatening health related problems causing 40-50% of all cardiovascular deaths, which itself is a dominant cause of global mortality and is estimated to cause annually about 30% or 17 million deaths worldwide. In developing countries, it causes twice the deaths as caused by HIV, malaria and TB combined. The worldwide survival rate from sudden cardiac arrest is even lesser than 1%; it is nearly 5% in the USA [1]. T-Wave Alternans (TWA), also known as repolarization alternans, is considered among important markers for arrhythmia vulnerabilities leading to sudden cardiac death. TWA consist of a periodic alternation in the amplitude or shape of the ST-T complex in every alternate beat. TWA phenomenon is further elaborated in Fig. 1. In order to be considered as an index of increased risk of SCD, it is usually considered that TWA should be present at Heart Rate (HR) of 105±15 beats per minute (bpm). To obtain such HR, stress test is commonly applied but this result in ECG signals with poor SNR [2].

Manuscript received May 23, 2016; revised September 7, 2016.

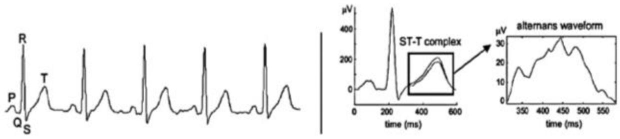


Figure 1. T-waves aligned in time and superimposed to highlight TWA phenomenon. Adapted from [3].

Owing to the presence of process noise, electrode movement and muscular activity, TWA analysis becomes a very challenging task. Furthermore, non-stationary nature of the cardiac signal and variations among beats make the scenario more complicated. Although there has been recent research in ECG denoising [4], TWA analysis remains challenging. In the last two decades, considerable number of TWA detection and estimation techniques have been proposed, generally classified in three broad categories: the Short-Term Fourier Transform (STFT) based techniques, methods based on counting of sign changes, and nonlinear filtering [2]. These techniques focus on pre-conditioning of the signal, its transformation, detection of the alternans, reconstruction of the signal and lastly estimation of the alternans. State of the art analysis algorithms include SM, MMAM, CM, MMF, complex Demodulation Method (CD) and Laplacian Likelihood Ratio Method (LLR).

TWA analysis techniques because of variety of noise types present, also need to cater for denoising before or even within the algorithms. An effort has been made by Manuel Blanco-Velasco *et al.* to use EMD for denoising of ST-T segment before applying SM, improving the detection performance by 2dB [5].

In this paper we have used EMD for denoising the ST-T segments before applying state of the art TWA analysis techniques, namely SM, CM, MMAM and MMF. We have carried out a comparison of the effect of EMD application on these algorithms. SNR and magnitude of induced TWA is varied to perform the Monte Carlo simulations in order to find out detection and estimation parameters for the comparison. In Section II we have discussed the materials and methods used, Section III

doi: 10.18178/joig.4.2.110-115

shows simulation results and in Section IV we have discussed the conclusion drawn from the work.

II. Materials and Methods

A. Pre-Processing of ECG

The pre-processing is performed to condition the ECG signal for further analysis. QRS detection and then segregation of ST-T complex are logical steps at this stage. The output of the pre-processing stage is an N x M matrix of ST-T segments $X=[x_0, \ldots, x_{M-1}]$, where $x_k=[x_k[0], \ldots, x_k[N-1]]^T$ represents an ST-T interval. *M* therefore, is the total number of beats and *N* is data samples in each ST-T segment [4].

B. Applying EMD on ST-T Segments

The EMD is based upon a fully data-driven mechanism that does not require any basis function in advance like in Fourier transform. Furthermore, it is relevant for analysis of natural signals, which are most often non-linear, non-stationary and stochastic processes [6]. It has been reported as a good tool for denoising and detrending purposes like in image processing and biomedical applications. EMD, without leaving time domain, decomposes a complex signal into its instantaneous frequency components, which are called Intrinsic Mode Functions (IMFs). The IMFs are simple oscillations which may be defined as [5]:

1. Difference between number of extrema and zero crossings should be zero or at the maximum one.

2. At any point the mean value (of envelopes which are defined by maxima and by minima of the function) should be zero (or approximately zero).

M ST-T segments, obtained after pre-processing, are applied with EMD algorithm in a sequential order. Steps for EMD algorithm for a single ST-T complex *x[n]* are as under ((Fig. 2):

1. Determine the maxima and minima of the complex.

2. Build upper envelope $e_u[n]$ using the maxima and lower envelope $e_l[n]$ using the minima by applying cubic spline interpolation.

3. Find mean envelope $m_{11}[n] = (e_u[n]+e_l[n])/2$.

4. Find first proto IMF as $h_{11}[n] = x[n] - m_{11}[n]$, which should ideally be first IMF but generally it contains multiple extrema between zero crossings. So, it is treated as data for next sifting iteration (step 1 to 4), which results $h_{12}[n] = h_{11}[n] - m12[n]$.

6. The sifting process is repeated till the proto IMF $h_{1k}[n]$ (with $h_{1(k-1)}[n]$ being treated as data) meets the criterion of IMF, thus first IMF is $c_1[n] = h_{1k}[n]$. This is based upon some stopping criterion. Most commonly used procedure is checking sum of differences (SD) i.e. normalized squared difference between successive iterations till it is smaller than already specified threshold.

$$SD_k = \frac{\sum_{n=0}^{N}(h_{k\text{-}1}[n]-h_k[n])^2}{\sum_{n=0}^{N} h_{k\text{-}1}{}^2[n]} \tag{1}$$

7. After SD criteria is met, $c_1[n]$ should contain the maximum frequency component of the complex i.e. first IMF. This is subtracted from the complex $r_1[n]=x[n]-c_1[n]$. Now $r_1[n]$ is treated as data and steps 1 to 6 are repeated on this new data set, to obtain further IMFs.

8. Process of separating IMFs is continued, till the time the residual r_j [n] remains either as a constant or as a monotonic function.

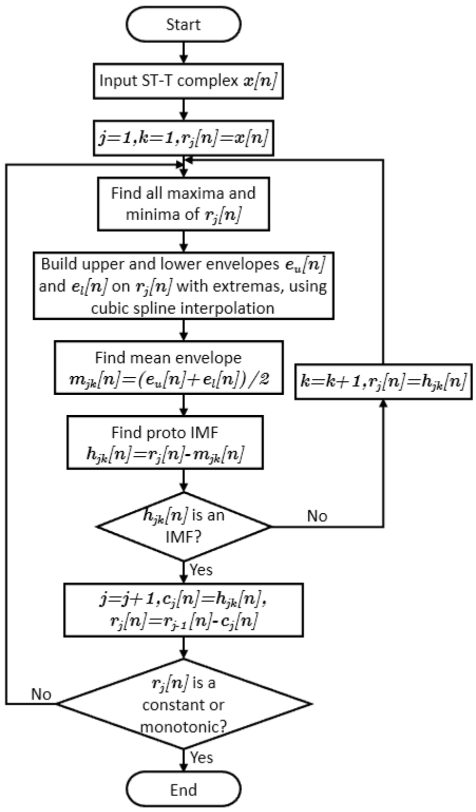


Figure 2. Flow chart of EMD algorithm.

As a sample, an ST-T complex with 10dB noise, upper envelope build on its maxima, lower envelope build on its minima and mean envelope are shown in Fig. 3. This represents first iteration for extracting first IMF from the complex. When all IMFs are extracted, the original ST-T complex can be reconstructed by summing up the IMFs and residual signal:-

$$x[n] = \sum_{j=1}^{N-1} c_j[n] + r_n[n] \tag{2}$$

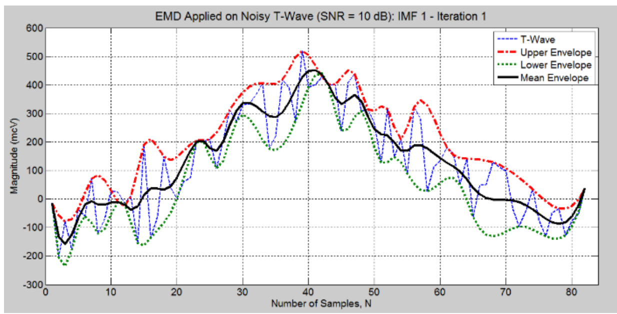


Figure 3. EMD applied on ST-T segment

The first IMF has maximum frequency component and so on. We can apply Hjorth descriptors to individual IMFs in order to calculate Spectral Purity Index (SPI) of each IMF. Basing upon SPI, we can discard the IMFs responsible for noise and reconstruct the noiseless ST-T complex by adding the remaining components [5].

C. *TWA Detection and Estimation Algorithms*

1) *SM*

SM is an advanced version of Energy Spectral Method, which was based upon measuring variation in T-wave energy among consecutive beats [7]. In SM, 128 digitized ECG beats are first aligned. Fluctuation between the beats is represented in terms of power spectrum, calculated differently for each sample point, obtained from all beats. Power spectra is calculated by squaring the magnitude of fast Fourier transform. Aggregate power spectra are calculated for QRS and ST-T complexes. Spectrum is a representation of the frequency at which beat-to-beat alteration occur. TWA, being a phenomenon among alternate beats, causes the peak of the power spectrum at 1/2 cycles per beat (cpb). This peak is compared with the spectral noise level, estimated from a predefined noise window, to decide about the presence of TWA or otherwise.

$$Valt_{SM} = \sqrt{alternans\ peak - \cancel{noise}} \tag{3}$$

where ~~noise~~ is the mean of the noise estimated from the noise window.

2) *MMAM*

MMAM is a time-domain methodology based upon noise cancellation through recursive averaging. This method does not provide detection statistics [8]. The technique continuously computes recursive running averages separately for even (*A*) and odd (*B)* beats as $Ak[n]$ and $B_k[n]$. The moving average controls the effect of the new beats through a variable, called update factor Δ. Update factor also minimizes the effect of impulsive artifacts. Studies have shown that rapid update factor equal to one-eighth makes the MMAM more sensitive to detect transients and important surges in TWA. The algorithm determines the average beats using the current average beat and the next incoming beat, respectively for even or odd groups. TWA is estimated as the absolute value of the maximum difference of any two computed averages of even and odd beats i.e.

$$Valt_{MMAM} = max\ (|B_k[n] - A_k[n]|) \tag{4}$$

3) *CM*

CM claims to detect TWA in seven heartbeats [9]. In CM, a median ST segment template x_m from 128 beats x_k is computed. Complete information of an ST-T segment is then represented by a single cross-correlation coefficient, known as Alternans Correlation Index (ACI), defined as:

$$ACI_k = \frac{\sum_{n=1}^{N} x_k[n] * x_m[n]}{\sum_{n=1}^{N} x_m^2[n]} \tag{5}$$

If continuous fluctuation is observed in ACI_k in at least seven consecutive beats, it is taken as an indication for presence of TWA.

4) *MMF*

Contrary to other schemes, which estimate the alternans amplitude directly, MMF technique is based upon estimating alternans energy within ST-T complexes [10]. In this methodology, even and odd T waves are separated as two groups. Difference between medians of both the groups is taken as a template. Finite Impulse Response (FIR) implementation of the classical energy detector maximizes SNR at the output, providing the required energy estimate. Generalized likelihood ratio decision statistic, is then used for TWA detection.

D. *Simulation Study*

To evaluate the effect of EMD on various TWA analysis algorithms, we propose the simulation study shown in Fig. 4. ST-T segments obtained from 128 beats of synthetic ECG are denoised using EMD and then four different TWA detection and estimation algorithms are considered for comparison.

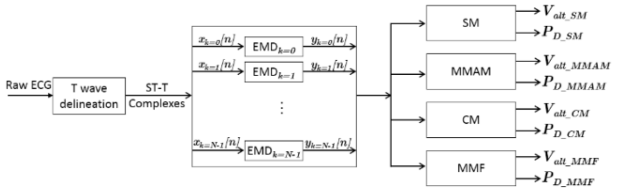


Figure 4. EMD applied on ST-T segment

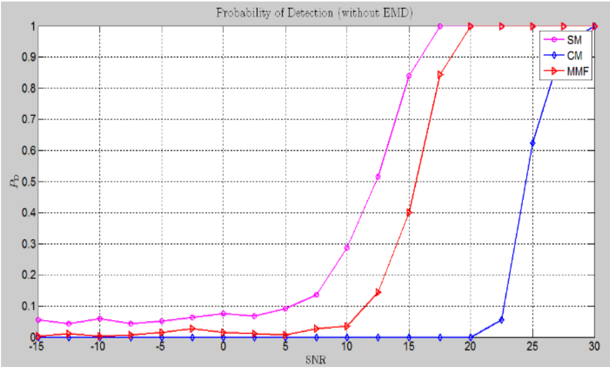
Background ECG signal is generated from heartbeat streams arbitrarily obtained from ECG signals of MIT-BIH Arrhythmia Database [11]. TWA of known magnitude is introduced by adding it in alternate beats. The performance of the scheme is evaluated with artificially generated Gaussian noise (with SNR varying from -15dB to 30dB). Simulations are also carried out by varying the induced alternans magnitude from 0 to l00 μV, while keeping the SNR constant. Monte Carlo simulation is performed to obtain the results.

III. RESULTS AND DISCUSSIONS

A. *Detection Performance*

1) *Varying SNR*

Results for varying Gaussian noise, while keeping the alternans magnitude of 10 μV, are presented in Fig. 5. SNR is varied from -15 to 30dB using artificially generated noise. Results both with and without EMD are shown. Impact of denoising with EMD is more pronounced with MMF than SM and CM in terms of improved probability of detection (P_D). In terms of percentage there is improvement in detection performance by 50.3%, 6.3% and 4.5% respectively for MMF, SM and CM. Another important aspect is that when these algorithms are used after preprocessing with EMD, detection performance of SM and MMF closely follow each other (Fig. 5(b)). Both algorithms taking a clear rise in P_D at SNR = 2.5dB and reaching P_D = 1 at SNR = 17.5dB.



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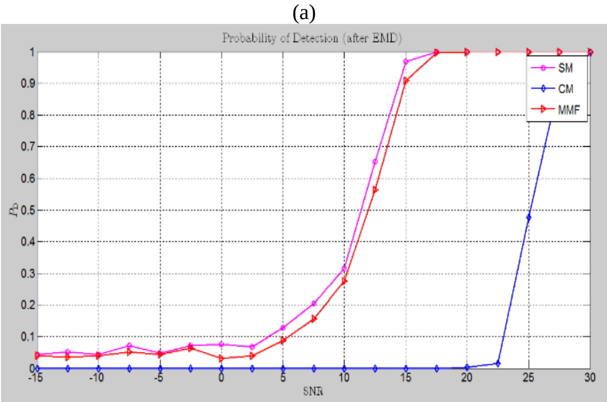


(b)

Figure 5. Detection results with varying SNR of Gaussian noise, keeping alternans amplitude fixed at 10 µV (a) without EMD (b) after EMD

2) *TWA magnitude*

Effect of denoising with EMD has nearly negligible impact on any of the procedures, when alternans magnitude is varied. Results are displayed in Table I.

TABLE I. DETECTION RESULTS WITH VARYING ALTERNANS MAGNITUDE KEEPING SNR = 20DB

Serial	TWA Added (µV)	P_D without EMD				P_D after EMD			
		SM	MMAM	CM	MMF	SM	MMAM	CM	MMF
1	0	0.06	1	0	0.04	0.48	1	0	0.04
2	10	1	1	0	1	1	1	0	1
3	20	1	1	0.76	1	1	1	0.71	1
4	30	1	1	1	1	1	1	1	1
5	40	1	1	1	1	1	1	1	1
6	50	1	1	1	1	1	1	1	1
7	60	1	1	1	1	1	1	1	1
8	70	1	1	1	1	1	1	1	1
9	80	1	1	1	1	1	1	1	1
10	90	1	1	1	1	1	1	1	1
11	100	1	1	1	1	1	1	1	1

B. *Estimation Accuracy*

1) *Performance parameters*

Comparison of performance accuracy is carried out in terms of estimator bias and MSE, which are defined as:

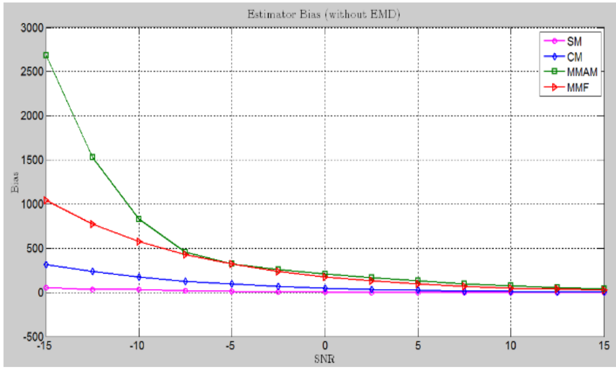
$$\text{Bias} = \frac{\sum_{i=0}^{n} \hat{V}_i - V}{n} \tag{6}$$

$$\text{MSE} = \frac{\sum_{i=0}^{n} (\hat{V}_i - V)^2}{n} \tag{7}$$

where n is total number of trials, V is alternans magnitude and $\hat{V}$ is estimated value in i^{th} trial.

2) *Varying SNR*

Results produced by varying SNR are represented in Fig. 6 and Fig. 7 for estimator bias and MSE respectively. Estimator bias is reduced by 59.7%, 42.7%, and 37.3% respectively in case of MMAM, SM and MMF; whereas it has increased 15% in case of CM when EMD is incorporated. MSE has decreased by 126.5%, 69.2%, 33.9% and 12.9% respectively for MMAM and MMF, SM and CM as an effect of pre-processing with EMD.



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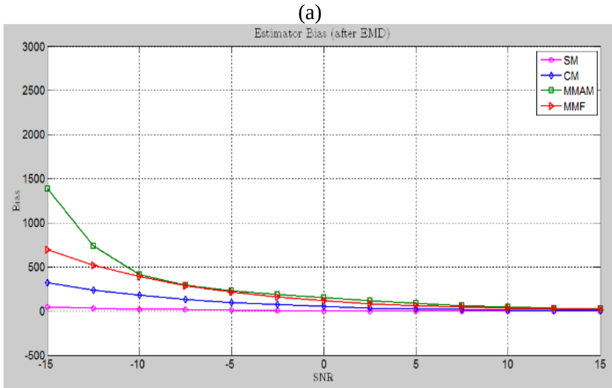
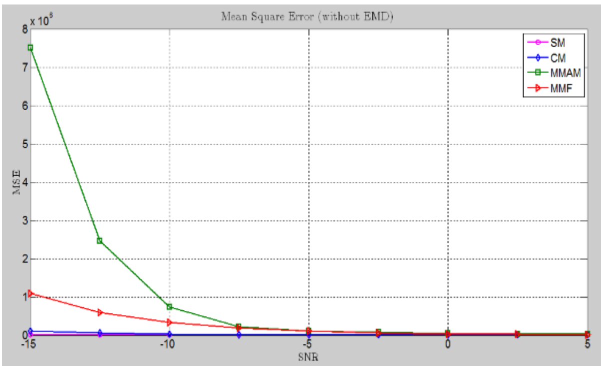


(b)

Figure 6. Estimator bias with varying SNR, with alternans magnitude fixed at 20 µV (a) without EMD (b) after EMD

3) *Varying TWA magnitude*

Results produced by varying alternans magnitude are represented in Table II (for estimator bias) and Fig. 8 (for MSE). Estimator bias has reduced significantly with EMD in case of MMF (140.9%), MMAM (76.6%) and SM (18.9%) but there is negligible effect on CM. Effect of EMD is nearly negligible on MSE in case of SM and CM, however it has reduced by 340.8% for MMF and 187% in case of MMAM.



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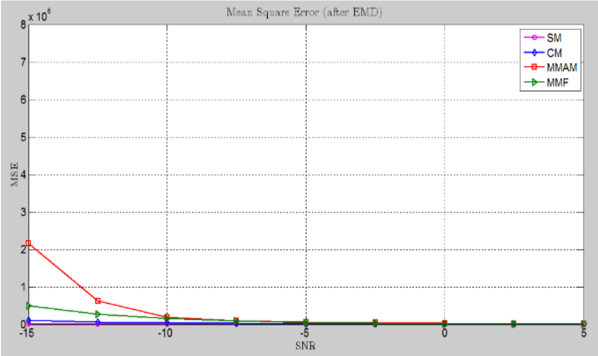
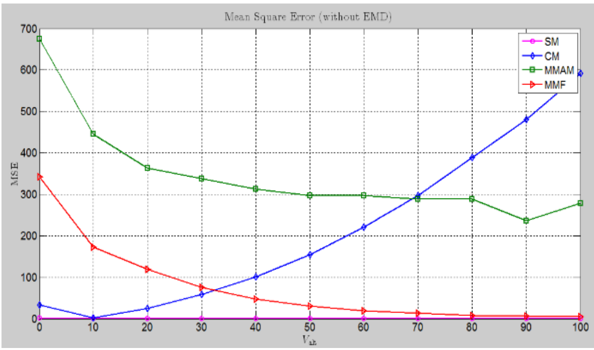


(b)

Figure 7. Mean square error with varying SNR, keeping alternans magnitude fixed at 20 μV, (a) without EMD (b) after EMD

TABLE II. ESTIMATOR BIAS WITH VARYING ALTERNANS MAGNITUDE, KEEPING SNR = 20DB

Serial	TWA Added (μV)	Estimator Bias without EMD				Estimator Bias after EMD			
		SM	MMAM	CM	MMF	SM	MMAM	CM	MMF
1	0	1.28	25.6	5.72	18.57	0.97	17.41	6.06	12.6
2	10	-0.12	20.3	-1.4	13.05	-0.1	12.52	-1.2	8.12
3	20	-0.09	19.3	-4.9	10.83	-0	10.85	-4.9	5.93
4	30	-0.12	17.1	-7.6	8.74	-0.2	9.71	-7.6	4.1
5	40	-0.2	17.2	-10	6.91	-0.2	9.47	-10	2.78
6	50	-0.27	16.8	-12	5.38	-0.3	9.3	-12	2.02
7	60	-0.29	15.8	-15	4.22	-0.3	8.75	-15	1.49
8	70	-0.35	15.6	-17	3.41	-0.3	8.92	-17	1.21
9	80	-0.37	15.4	-20	2.77	-0.4	7.96	-20	0.94
10	90	-0.43	15.5	-22	2.32	-0.4	8.5	-22	0.87
11	100	-0.52	14.9	-24	1.92	-0.6	7.9	-24	0.63



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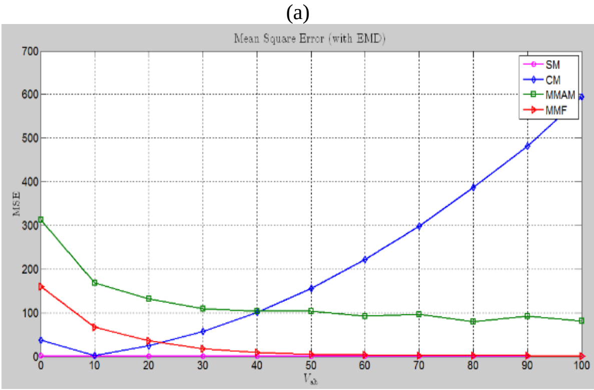

(b)

Figure 8. Mean square error with varying alternans magnitude, keeping SNR = 20dB, (a) without EMD (b) after EMD

IV. CONCLUSION

In this study conventional TWA system has been modified by incorporating EMD as a denoising tool after conditioning the ST-T complexes. Effect of utilizing EMD for denoising the complexes has been worked out with state of the art TWA detection and estimation algorithms. Application of EMD has significantly improved detection performance and estimation accuracy. However, it is observed that out of the four TWA analysis algorithms, effect of employing EMD is most pronounced in case of MMF but has minimal effect on performance of CM. To further improve the results, effective utilization of EMD for TWA analysis algorithms need to be studied. The EMD needs to be incorporated within the algorithms in order to find out the exact point / area, so that its application results in optimal performance.

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