

# EMD BASED FILTERING (EMDF) OF LOW FREQUENCY NOISE FOR SPEECH ENHANCEMENT

Navin Chatlani and John J. Soraghan

**Abstract**— An Empirical Mode Decomposition based filtering (EMDF) approach is presented as a post-processing stage for speech enhancement. This method is particularly effective in low frequency noise environments. Unlike previous EMD based denoising methods, this approach does not make the assumption that the contaminating noise signal is fractional Gaussian Noise. An adaptive method is developed to select the IMF index for separating the noise components from the speech based on the second-order IMF statistics. The low frequency noise components are then separated by a partial reconstruction from the IMFs. It is shown that the proposed EMDF technique is able to suppress residual noise from speech signals that were enhanced by the conventional optimally-modified log-spectral amplitude approach which uses a minimum statistics based noise estimate. A comparative performance study is included that demonstrates the effectiveness of the EMDF system in various noise environments, such as car interior noise, military vehicle noise and babble noise. In particular, improvements up to 10 dB are obtained in car noise environments. Listening tests were performed that confirm the results.

**Index Terms**— Noise Estimation, Speech Enhancement, Empirical Mode Decomposition, Denoising.

## I. INTRODUCTION

A common problem encountered in speech enhancement systems is the removal of unwanted disturbances, i.e. noise from noisy speech signals. Adaptive noise cancellation is commonly performed when enhancing speech sequences using an available noise reference. Single-channel speech enhancement systems traditionally employ Voice Activity Detection (VAD) to estimate the statistics of the noise signal during silent segments. If the VAD approach is conservative, then it will attempt to reduce false alarms for silence detection, which results in less frequent noise power updates.

In highly non-stationary environments, the noise power must be tracked even during speech activity. Noise estimation

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techniques which operate in the short-time Fourier transform (STFT) domain are very popular, including newer noise estimation systems such as the Minimum Statistics (MS) [1] and the Improved Minima Controlled Recursive Averaging (IMCRA) [2]. These techniques estimate the noise spectrum based on the observation that the noisy signal power decays to values characteristic of the contaminating noise during speech pauses. The main challenge faced by these techniques is tracking the noise power during speech segments. This would result in poor estimates during long speech segments with few pauses. Speech enhancement systems such as the optimally-modified log-spectral amplitude (OMLSA) estimator [3] require a noise estimate to suppress noise and enhance the noisy speech.

Recently, new Empirical Mode Decomposition (EMD) based methods [4-6] for noise suppression and signal enhancement have been developed and include single-channel speech enhancement methods in stationary fractional Gaussian Noise (fGN) environments. We do not assume that the signal is contaminated with fGN and therefore the above denoising methods are not applicable. A novel post-processing technique for EMD based filtering of low frequency noise components is proposed for use in other types of noise environments. Our technique is inspired by the low-rank approximation typically used in subspace speech enhancement algorithms. Our method separates the speech from the noise by analysing the second order statistics of the Intrinsic Mode Functions (IMFs) formed from the EMD of the speech signals.

In [7], it was shown that in the presence of low frequency noise, the performance of IMCRA degrades due to poor tracking of the noise spectrum. This poses a problem in systems such as mobile devices in wind noise and speech recognition used in car interior noise environments. In [8], a high pass filter is used as pre-processing in a car's speech recognition system, where the cut-off frequency is varied between 200-400 Hz. The speech recognition performance was shown to be dependent on the cut-off frequency. Single-channel wind noise reduction is performed in [9], by using a VAD to detect wind-only frames and estimate the wind noise energy. A post-filter is subsequently designed to place nulls at the frequencies corresponding to the wind noise resonance. In [10], speech enhancement in car interior noise is achieved by using a speech analysis-synthesis approach, based on a harmonic noise model, as post-processing after a traditional log-spectral amplitude speech estimation system. This system is sensitive to accurate pitch estimation and voiced/unvoiced speech frame classification.

In this paper, a new EMD based filtering (EMDF) technique is described as a post-processor for noisy speech which is enhanced using an MS based noise estimate. This proposed technique has been designed to be particularly effective in low frequency noise environments. In EMDF, the speech is first decomposed into its IMFs using EMD. An adaptive method is developed to select the IMF index for separating the residual low frequency noise components from the speech estimate, based on the IMF statistics. The EMD based denoising of this speech estimate is performed, using our partial reconstruction method, to reduce these residual low frequency noise components.

The remainder of the paper is organised as follows. The background necessary to understand the EMD and a brief review of

EMD-based denoising techniques are presented in section II. In section III, the novel EMDF enhancement system is developed. In section IV, results obtained from testing and comparing the proposed EMDF method with basic OMLSA/IMCRA speech estimation are presented and discussed. These tests are performed in non-stationary and varying SNR car interior noise, babble noise and military vehicle noise conditions to show the improved performance of the EMDF system. The best overall quantitative improvements are obtained under car interior noisy conditions which are dominated by low frequency noise components. In this noise environment, segmental SNR improvements up to 10 dB are obtained using EMDF. The results of listening tests are also included to assess and compare EMDF to existing techniques. Conclusions are made in section V.

## II. EMPIRICAL MODE DECOMPOSITION

### A. Background

EMD [11, 12] is a non-linear technique for analyzing and representing non-stationary signals. EMD is data-driven and decomposes a time domain signal into a complete and finite set of adaptive basis functions which are defined as Intrinsic Mode Functions (IMFs). EMD does not use predefined basis functions. The IMFs formed by the EMD are oscillatory functions that have no DC component. Fig. 1 illustrates the main stages in the EMD algorithm. EMD examines the signal between two consecutive extrema (e.g. minima) and picks out the high frequency component that exists between these two points [12]. The remaining local, low frequency component can then be found. The motivation behind the EMD is to perform this procedure on the entire signal and then to iterate on the residual low frequency parts. This allows identification of the different oscillatory modes that exist in the signal. The IMFs found must be symmetric with respect to local zero-mean and have the same number of zero crossings and extrema, or differ at most by one. The IMF is considered as zero-mean based on some stopping criteria such as the standard deviation between consecutively sifted functions [11].

Frequency information is embedded in the IMFs. These data-adaptive basis functions give physical meaning to the underlying process. The signal reconstruction process is given in (1), which involves combining the  $N$  IMFs formed from the EMD and the residual  $r[n]$ :

$$x[n] = \sum_{j=1}^N IMF_j[n] + r[n] \quad (1)$$

### B. EMD-based Denoising

As detailed in [12], the IMFs formed from EMD are almost locally orthogonal. Furthermore, EMD does not correspond to pre-determined sub-band filtering. The frequency content of the IMFs varies from high frequency to low frequency as the IMF order

increases. In [12], the EMD of fGN was shown to result in a filter bank like structure with overlapping pass-bands for each IMF mode. The first IMF has a high-pass characteristic but also contains some lower energy, low frequency content. The higher order modes also have this overlapping band-pass characteristic [12].

EMD-based denoising [4] involves decomposing a noisy signal using EMD and performing a partial reconstruction with those IMFs composed of the desired signal. In [13], a study was carried out on the IMF statistics of fGN signals which resulted in an empirically observed noise model for noise-only situations. This noise-only model allows an estimation of the energy of the IMF modes. The noisy signal  $x[n]$  considered for denoising comprised the desired signal and fGN. For denoising, the energy of each IMF of the noisy signal is computed and compared to the noise-only model's IMF energy. The IMF order for which the computed IMF energy deviates from a predefined threshold is determined and denoted as  $M+1$ . The denoised signal  $x_D[n]$  is then obtained from the partial reconstruction of the IMFs:

$$x_D[n] = \sum_{m=M+1}^N I_m[n] + r[n] \quad (2)$$

This reconstructed signal corresponds to a slower-varying signal that was superimposed on the fGN signal which dominates the first  $M$  IMFs.

The case of a desired signal contaminated with fGN is special since the first few IMFs are predominantly composed of the noise signal and this led to successful speech denoising strategies such as in [5, 6, 14]. In [5], EMD-MMSE is performed by filtering the IMFs formed from the decomposition of speech contaminated with fGN. EMD-based thresholding methods were presented in [6] for signals contaminated with fGN. These proposed techniques followed successful wavelet thresholding methods. The EMD-MMSE and the EMD-based thresholding methods both estimate the noise statistics using the empirically observed noise model presented in [13]. In [14], enhancement is achieved for speech signals corrupted by fGN using an algorithm based on partial reconstruction of the higher order IMFs which are less affected by fGN. These techniques focus their enhancement efforts on the lower-order IMFs and therefore, for speech contaminated with additive fGN, it is expected that the high-frequency unvoiced components of the speech signal that exist in these IMFs will be filtered. In [15], an optimum gain function is estimated for each IMF to suppress musical noise that may be retained after single channel speech enhancement algorithms.

### III. EMD BASED FILTERING FOR SPEECH ENHANCEMENT

Single channel speech enhancement algorithms rely on accurate noise spectrum estimation and speech estimation. IMCRA [2] combines minimum statistics [1] with recursive averaging to perform noise spectrum estimation. The speech presence probability is estimated and incorporated into the noise estimation routine in IMCRA. In [2], it was shown that eliminating strong speech

segments from the second smoothing stage in IMCRA improves minima tracking and the estimation of the speech presence probability. In low frequency noise environments, such as in car interiors, there is poor noise estimation and tracking [7] in the noisy low frequency bins using IMCRA.

The new EMDF system for speech enhancement is illustrated in Fig. 2. Consider the model described by:

$$x[n] = s[n] + d[n] \quad (3)$$

where  $x[n]$  is the noisy speech signal,  $s[n]$  is the original noise-free speech, and  $d[n]$  is the noise source which is assumed to be independent of the speech. The STFT of (3) may be written as:

$$X(f, k) = S(f, k) + D(f, k) \quad (4)$$

for frequency bin  $f$  and time frame  $k$ . In Fig. 2, it can be seen that this new system first performs IMCRA to obtain the noise estimate  $\hat{\lambda}_d(f, k)$ . Speech enhancement is performed signal by minimizing the mean-square error of the log-spectral amplitude (LSA) [16] as follows:

$$E_{\min} \left[ \left\{ \log |S(f, k)| - \log |\hat{S}(f, k)| \right\}^2 \right] \quad (5)$$

where  $E[\cdot]$  is the expectation operator,  $|S(f, k)|$  is the speech amplitude component that exists in the noisy signal and  $|\hat{S}(f, k)|$  is the optimal speech estimate. The a priori SNR  $\hat{\xi}(f, k)$  is estimated using the modified, decision directed approach in [17]. The corresponding LSA gain function, denoted as  $G_{LSA}(f, k)$ , to be applied to  $|X(f, k)|$  is expressed in (6). The OMLSA estimator [3] incorporates speech presence uncertainty to produce the gain function  $G(f, k)$  given by:

$$G(f, k) = G_{LSA}(f, k)^{p(f, k)} G_{\min}^{1-p(f, k)} \quad (6)$$

where  $p(f, k)$  is the conditional speech presence probability which is estimated as in [2], and the threshold  $G_{\min}$  is based on a subjective criteria. The enhanced speech signal is then estimated as follows:

$$\hat{S}(f, k) = G(f, k) |X(f, k)| \exp(j\theta_x(f, k)) \quad (7)$$

where  $\hat{S}(f, k)$  is the OMLSA speech estimate,  $j = \sqrt{-1}$  and  $\theta_x(f, k)$  is the phase of the noisy speech.

The OMLSA/IMCRA enhancement stage from Fig. 2 produces the speech estimate  $\hat{s}[n]$  which contains residual noise components.  $N$  IMFs are formed from the EMD decomposition of  $\hat{s}[n]$ . The EMD based denoising of this speech estimate is then performed as a post-processing stage to reduce residual low frequency noise components after the OMLSA/IMCRA stage.

### A. System Analysis

As seen in Fig. 2, the EMD decomposes the speech estimate  $\hat{s}[n]$  into  $N$  IMFs. Consider the IMF variance plots shown in Fig. 3 for clean unvoiced and voiced speech components. The plots in Fig. 3 show the ensemble average of 900 random voiced and unvoiced utterances spoken by various males and females. These speech sequences were extracted from the TIMIT database. In these plots, the IMF order is denoted as  $m$  and the IMF variance is denoted as  $V[m]$  where:

$$V[m] = \frac{1}{L} \sum_{n=1}^L I_m^2[n], \quad m=1,2..N \quad (8)$$

where  $I_m[n]$  denotes the  $m^{\text{th}}$  IMF. Partial reconstruction of these speech signals is given by:

$$\hat{s}_D[n] = \sum_{m=1}^M I_m[n] \quad (9)$$

Fig. 3 shows that the IMF variance for clean speech signals significantly decreases after the fourth IMF, as the IMF order increases. The SNR is used to objectively evaluate the resynthesis error of  $\hat{s}_D[n]$  compared to the original speech components. The SNR of the partially reconstructed signals using (9) for clean unvoiced and voiced components spoken by a female, is given in Table 1(a) and Table 1(b) respectively. It can be seen that in both cases, signal reconstruction with the first 4 IMFs (i.e.  $M=4$  in (9)) is sufficient for good speech resynthesis. This is consistent with the low-rank approximation used in subspace algorithms [16, 17], which consider 9-15 dB SNR sufficient for reconstruction.

It was found experimentally that the IMF statistics for a speech signal contaminated with a low frequency noise has a peak IMF energy in a higher IMF order  $I_m[n]$ , where  $m>4$ . This is illustrated using an example of the IMF variance plot for a clean voiced speech female utterance  $s[n]$  contaminated with car interior noise  $d[n]$  at 0 dB SNR as shown in Fig. 4. The peak  $m_{p,1}$  and its associated trough  $m_{t,1}$  are highlighted. The IMF variance build-up,  $m_{b,i}$ , is defined as the IMF index deviation from the identified peak  $m_{p,i}$  to the previous trough  $m_{t,i}$  as given by:

$$m_{b,i} = m_{p,i} - m_{t,i} \quad (10)$$

Following (10), the variance build-up  $m_{b,1}$  in Fig. 4 is 3. Identification of this IMF variance build-up  $m_{b,i}$  is used to select the IMF order,  $M$ , to use in the speech reconstruction. The remaining IMFs from  $M+1$  to  $N$  are assumed to be dominated by the noise whereas in (2), these IMFs were used to reconstruct the desired signal which was contaminated by fGN. Therefore, in EMDF, the denoised signal  $\hat{s}_D[n]$  is obtained from the partial reconstruction in (9).

The IMF index  $M$  is determined by examining the trough  $m_{t,i}$  in  $V[m]$  prior to each identified peak  $m_{p,i}$ . Our method to select the IMF index  $M$  is shown in Fig. 5(a) and is described as follows:

1. Compute the variance  $V[m]$  of the  $m^{\text{th}}$  IMF from (8).

2. Identify the indices of the peaks,  $\mathbf{m}_p = \{m_{p,1}, m_{p,2} \dots\}$  in  $V[m]$  for  $m > 4$ .
3. If peaks have been identified, then find the indices of the troughs,  $\mathbf{m}_t = \{m_{t,1}, m_{t,2} \dots\}$  which correspond to the peaks in  $\mathbf{m}_p$ .
4. Compute the IMF variance build-up,  $\mathbf{m}_b = \{m_{b,1}, m_{b,2} \dots\}$  to those peaks using (10).
5. Determine the index,  $i$ , of the first occurrence of the largest build-up  $m_{b,i}$  in  $\mathbf{m}_b$ :

$$i = \text{index}(\max(\mathbf{m}_b)) \quad (11)$$

and select the corresponding peak  $m_{p,i}$  in  $\mathbf{m}_p$ .

6. The IMF index  $M$  is determined by:

$$M = m_{p,i} - m_{b,i} \quad (12)$$

As seen in the method for selecting  $M$  in Fig. 5(a) if no peaks are identified, then all IMFs  $I_m[n]$  are used in the partial reconstruction (i.e.  $M=N$ ) of the denoised speech  $\hat{s}_D[n]$  in (9). This is performed to reduce speech distortion effects. In Fig. 5(b), the IMF variance plot of the noisy speech used in Fig. 4 was used as an example to demonstrate the above algorithm for selecting  $M$ . The peak  $\mathbf{m}_p = \{m_{p,1}\} = \{7\}$  and the build-up  $\mathbf{m}_b = \{m_{b,1}\} = \{3\}$  are first computed. The value for  $M$  is then evaluated as in (12) from the algorithm above. In this example, the IMF index  $M$  is 4.

This method for the selection of  $M$  was used for filtering the residual low frequency noise from the speech estimate  $\hat{s}[n]$  to give  $\hat{s}_D[n]$  as in (9). This speech estimate  $\hat{s}_D[n]$  will be used to compare the performance of speech enhancement of the EMDF system in Fig. 2 with that obtained from the OMLSA/IMCRA system.

#### IV. PERFORMANCE EVALUATION

The performance of the EMDF technique for speech enhancement was tested on 192 speech utterances from 24 different speakers (16 male and 8 female) obtained from the core test set of the TIMIT database. The clean speech signals were corrupted with car interior noise, babble noise and military vehicle noise used for evaluating the speech enhancement systems. These non-stationary background noise sources were obtained from the Noisex-92 database. The EMDF system's performance was compared with the OMLSA/IMCRA algorithm at enhancing the noisy speech signals. A sampling frequency of 16 kHz was used. The signal was split up into frames of length 512 samples and a window overlap factor of 50%. The EMD-based denoising stage by partial reconstruction using (9) is applied to speech blocks of length 512 samples.

In order to assess the relative performance of the speech enhancers, the objective measures of segmental SNR (segSNR) and Weighted Spectral Slope (WSS) [18] improvements for the enhanced speech signals using the EMDF system, when compared to

the OMLSA/IMCRA system, is given in Table 2. It must be noted that negative values for the WSS improvement indicate better enhancement performance and a reduction in speech loss. These enhancement results were obtained under various SNR levels. The results show improvements in segmental SNR and WSS under all noise conditions with an improved quality of speech enhancement using the EMDF.

It can be seen that the best overall improvements are obtained under car interior noisy conditions which is dominated by low frequency noise components. EMDF achieves SNR improvements up to 10 dB in this noise environment, while still maintaining a low level of speech distortion, as characterized by the WSS improvement. Babble noise is composed of multiple talkers and has a similar spectral characteristic compared to the original clean speech utterances. Therefore, it is difficult to reduce the level of multi-talker babble from noisy speech signals. As shown in Table 2, EMDF also achieves increased noise suppression and reduced speech distortion in babble noise conditions. Military vehicle noise has a low pass characteristic. Under military noise conditions, SNR improvements up to 4 dB are achieved for noisy speech enhanced with EMDF, due to the improved suppression of the low frequency noise components.

The spectrogram for a clean male speech utterance is given in Fig. 6(a). This speech signal was contaminated with car interior noise at -10 dB SNR and its spectrogram is shown in Fig. 6(b). This noisy speech was enhanced using both techniques. The spectrograms for the enhanced speech using the OMLSA/IMCRA and the EMDF system are illustrated in Fig. 6(c) and Fig. 6(d) respectively. These plots demonstrate the improved noise suppression using EMDF. In Fig. 6(c) and in Fig. 6(d), the residual noise components during unvoiced speech activity and speech pauses are highlighted with open arrows on the spectrograms for speech enhanced by the OMLSA/IMCRA and the EMDF systems respectively. Comparison of these regions shows that these noise components are significantly attenuated using the EMDF technique. The areas highlighted with solid arrows in Fig. 6(c) and Fig. 6(d) show that EMDF retains more of the low frequency voiced speech components.

The effectiveness of EMDF is now demonstrated in the difficult enhancement scenario of multi-talker babble noise. The same male speech utterance from Fig. 6(a) was contaminated with babble noise at -2 dB, and its spectrogram is shown in Fig. 7(a). The spectrograms for the enhanced speech using the OMLSA/IMCRA and the EMDF system are given in Fig. 7(b) and Fig. 7(c) respectively. As before, these plots demonstrate the improved noise suppression using EMDF. The open arrows are once again used to highlight the areas where there is more attenuation of residual noise components during unvoiced speech and pauses, using EMDF. The solid arrows highlight that voiced speech components are retained at low frequencies when EMDF is applied.

It was shown in Fig. 5(a) that EMDF uses all IMFs in the partial reconstruction if no peaks are identified, for a reduction of speech distortion. Fig. 8 shows the percentage of segments for the speech utterances used in the tested data set, where the EMDF method selected all IMFs (i.e.  $M=N$ ) in the partial reconstruction, under car interior noise, babble noise and military vehicle noise environments. These results demonstrate that in these noise environments, this percentage decreases as the SNR decreases. This

corresponds to the increased noise suppression as the SNR decreases, as shown in Table 2. Fig. 8 shows that the percentage of segments where all IMFs were selected by EMDF in the partial reconstruction is higher in babble noise environments. This indicates that there is less noise suppression under babble noise conditions compared to the other tested noise types, as previously discussed in Table 2.

The presented results objectively quantify the effectiveness of the proposed EMDF post-filtering technique. Subjective listening tests were also performed to evaluate this proposed system. The EMDF system was subjectively compared against the OMLSA/IMCRA algorithm which had a high-pass filter (cut-off frequency  $f_c$  of 120 Hz) at its output. Three sets of 10 sentences from different male speakers were corrupted by car interior noise, babble noise and military vehicle noise, at three SNR levels (5 dB, 0 dB and -5 dB). These sentences were processed using the two techniques and 10 listeners were asked to rate the quality on:

1) The level of speech signal quality (SIG) where the five point scale is given by [5-very natural/no degradation, 4-fairly natural/little degradation, 3-somewhat natural/somewhat degraded, 2-fairly natural/fairly degraded, 1-very unnatural/very degraded].

2) The level of residual background noise (BAK) where the five point scale is given by [5-not noticeable, 4-somewhat noticeable, 3-noticeable but not intrusive, 2-fairly conspicuous/somewhat intrusive, 1-very conspicuous/very intrusive].

The presentation level of the stimuli was measured by an artificial ear (Bruel & Kjaer Artificial Ear Type UA 4153) connected to a sound level meter (Bruel & Kjaer Modular precision sound analyser) to ensure that the sound level did not exceed 75 dB SPL. K702 AKG premium class headphones were used in the listening tests. Prior to each listening test, training sentences were played for each listener to make them aware of the nature of the clean speech signals, the contaminating noises and the noisy speech signals. Listeners were given breaks to reduce fatigue since the total test time was approximately 55 minutes.

The results of the listening tests are shown in Fig. 9 where the label “EMDF” refers to our proposed system and the label “HPF” refers to the OMLSA/IMCRA system with the predefined high-pass filter at its output. In general, it can be seen that in the presented noise conditions in Fig. 9(a), Fig. 9(c), and Fig. 9(e), the speech signal quality of the HPF system is slightly better than EMDF. However, at -5 dB SNR, the speech signal quality of EMDF slightly exceeds that of HPF in car interior noise and military noise environments. In Fig. 9(b), Fig. 9(d), and Fig. 9(f), it can be seen that EMDF performs significantly better than HPF in terms of background residual noise suppression. These comparative listening tests show that EMDF achieves its best performance in the presence of military vehicle noise.

## V. CONCLUSION

A new EMDF technique as a post-processing stage for speech enhancement was presented. The basic IMCRA technique is

effective at updating the noise spectrum by applying recursive averaging. However, in noise environments with strong low frequency noise environments, IMCRA does not update the noise power accurately. The new EMDF method for speech enhancement performs denoising of the residual low frequency noise components after the OMLSA/IMCRA system. The performance of this technique was evaluated using speech contaminated with car interior noise, babble noise and military vehicle noise conditions. When compared to an OMLSA/IMCRA system, this method was shown to give improved performance at suppressing background noise under the presented noisy conditions.

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He currently holds the Texas Instruments Chair in signal processing within the Centre for excellence in Signal and Image Processing (CeSIP), University of Strathclyde. His main research interests are signal processing theories, algorithms, and architectures with applications to high resolution methods for radar, biomedical data processing, and video analytics for surveillance, 3D video and condition monitoring. He has published over 280 technical papers and has supervised over 35 PhD students to graduation. Professor Soraghan is a Member of the IEEE Signal Processing in Education Technical Committee, a Member of the IET and a Senior Member of the IEEE.

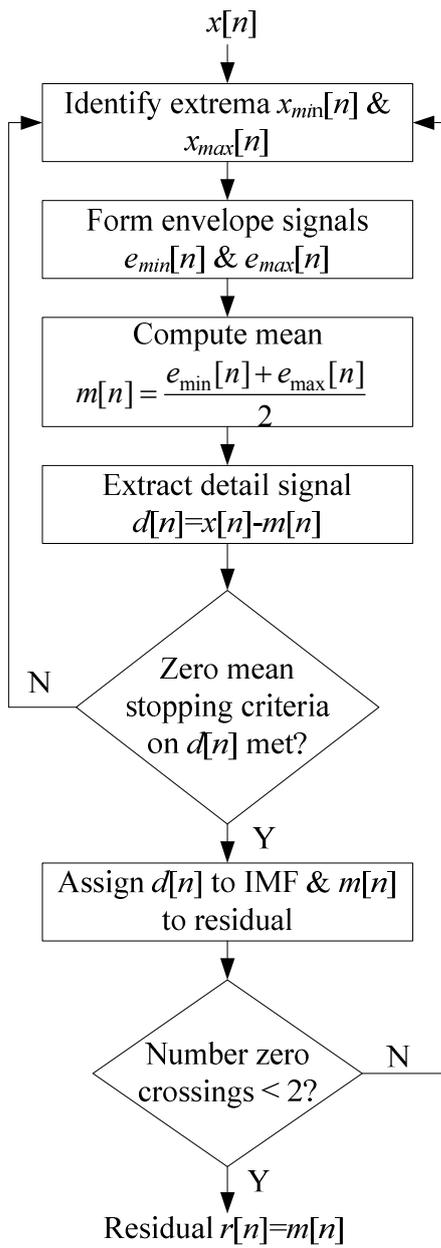


Fig. 1: EMD algorithm

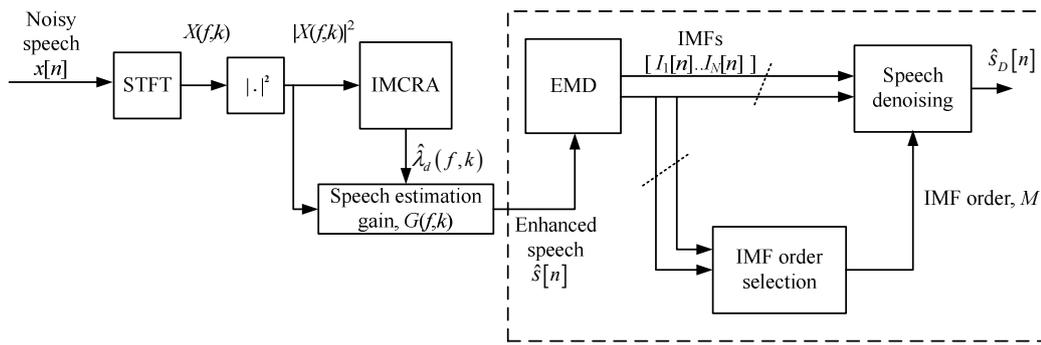


Fig. 2: Block diagram of the EMDF system for speech enhancement

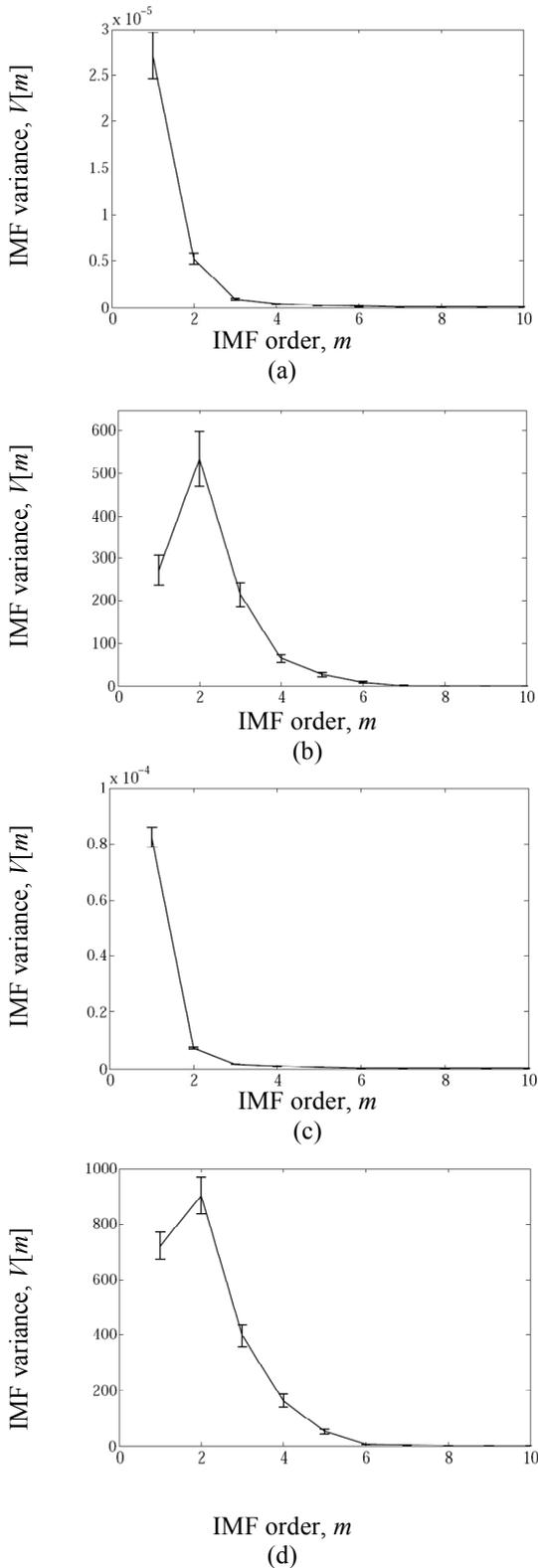


Fig. 3: Ensemble averaged IMF variance plots of (a) clean male unvoiced speech components (b) clean male voiced speech components (c) clean female unvoiced speech components and (d) clean female voiced speech components. In these plots, the error bars correspond to the standard error of the mean.

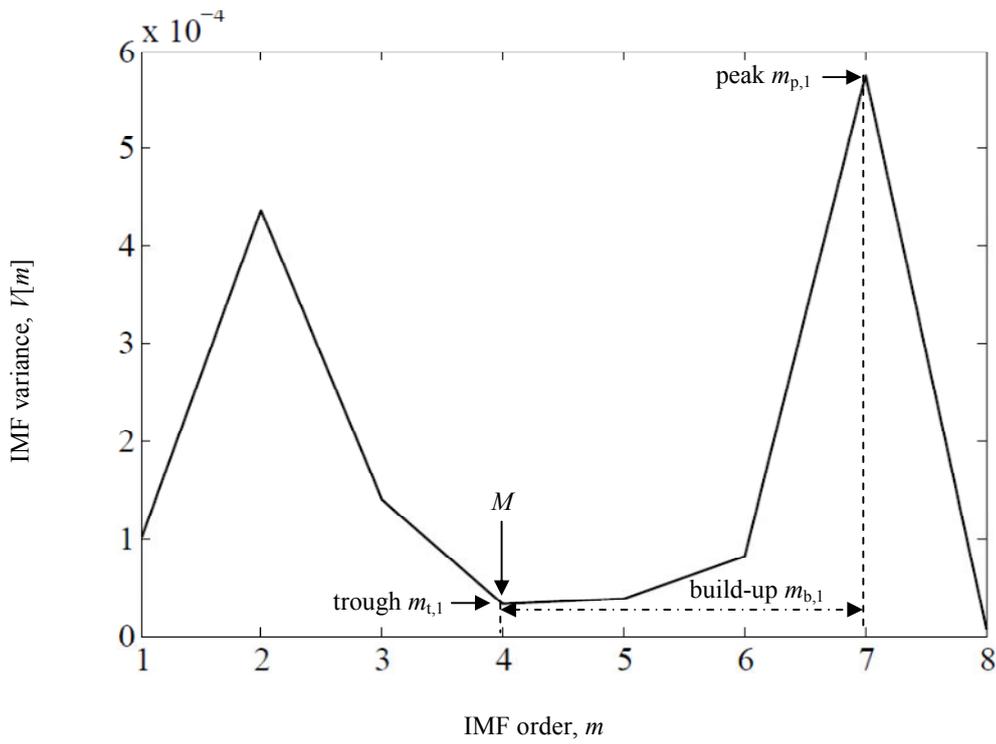
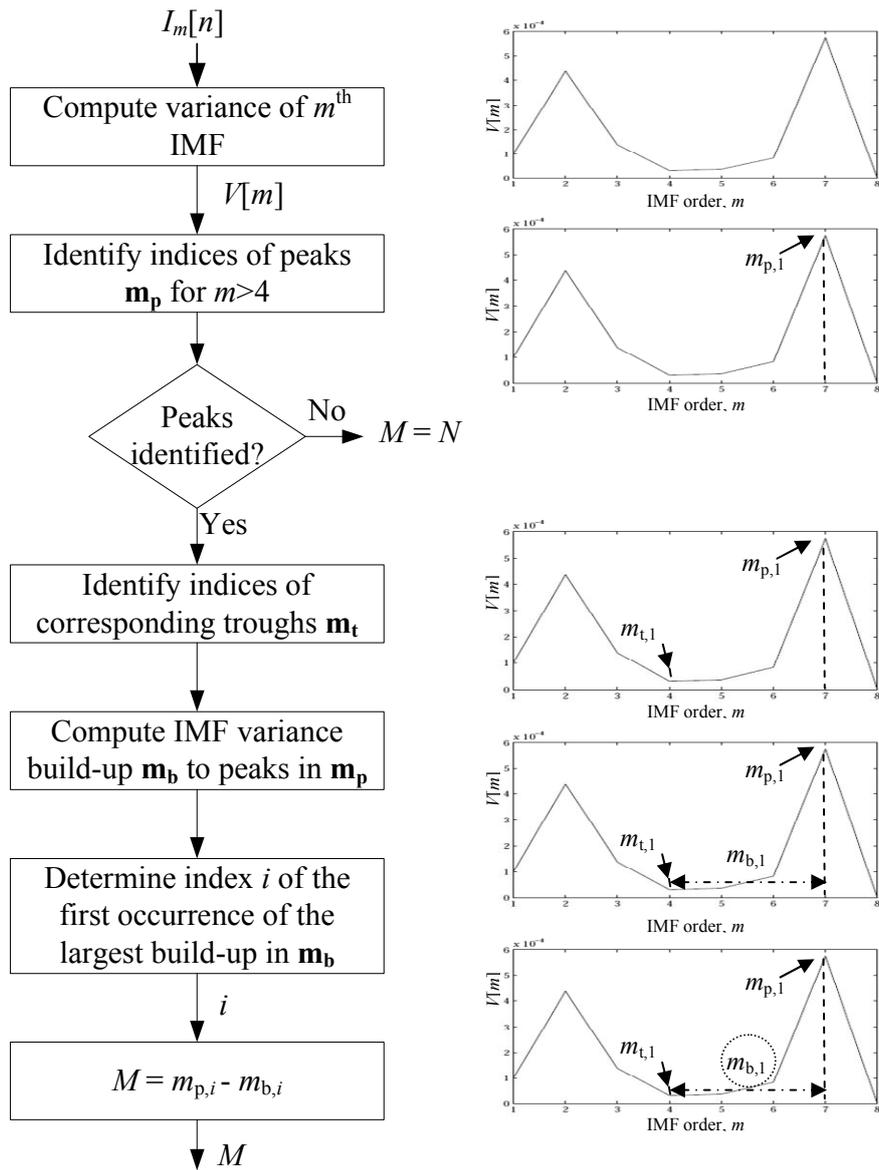


Fig. 4: IMF variance plot of clean speech contaminated with car interior noise at 0 dB SNR



(a) Method for selection of IMF order  $M$  used in the EMDF. (b) Illustrative stages of the method on the noisy female voiced speech utterance used to produce the IMF variance plot in Fig. 4.

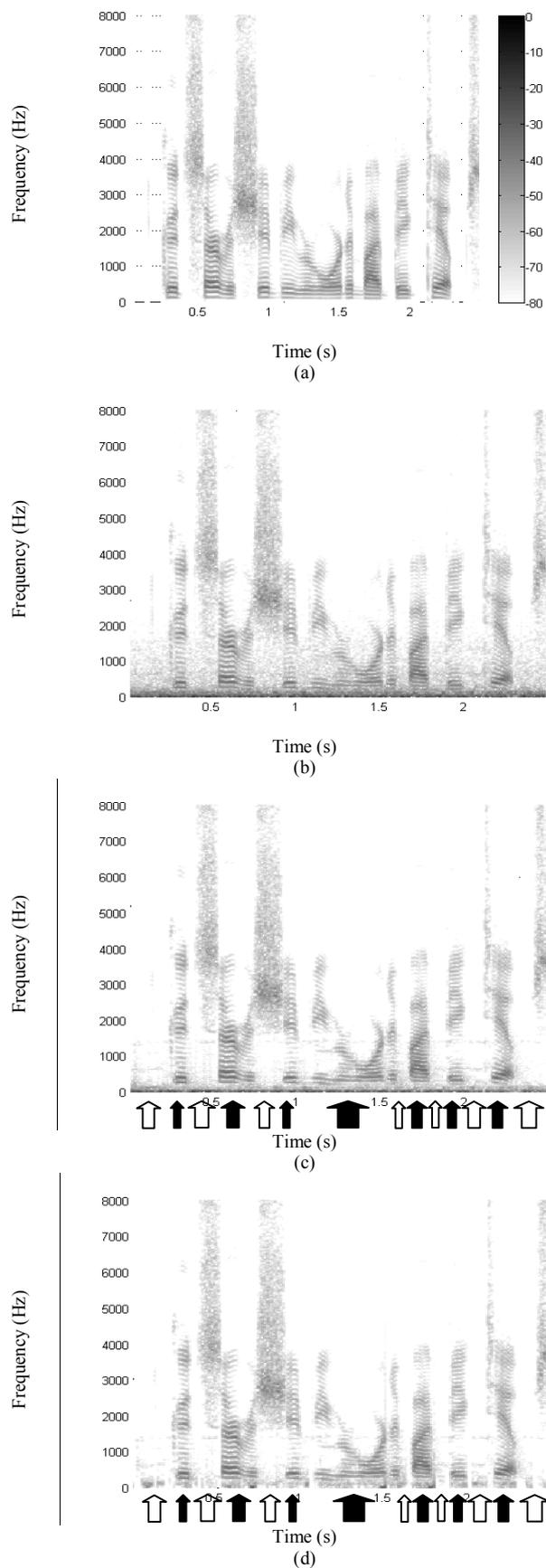


Fig. 6: Comparison of the spectrograms for speech enhanced by both methods in car interior noise at -10 dB. (a) Original clean speech (b) Noisy speech (c) Speech enhanced by OMLSA/IMCRA (d) Speech enhanced by EMDF

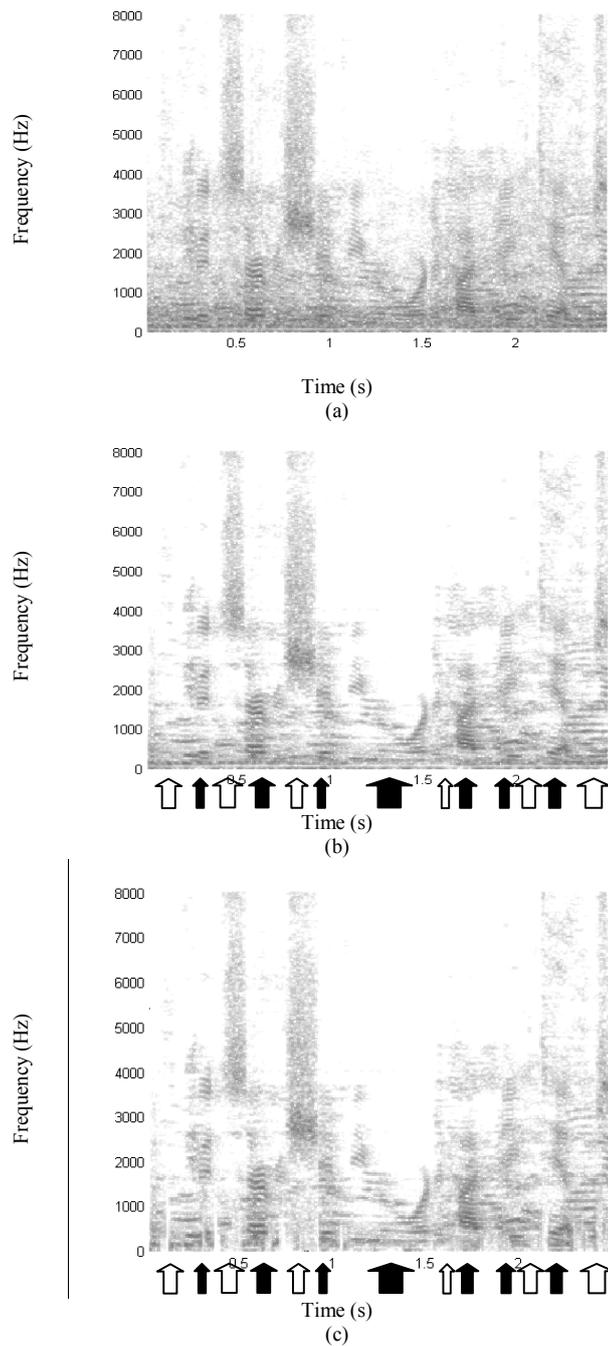


Fig. 7: Comparison of the spectrograms for speech enhanced by both methods in multi-talker babble noise at -2 dB. (a) Noisy speech (b) Speech enhanced by OMLSA/IMCRA (c) Speech enhanced by EMDF

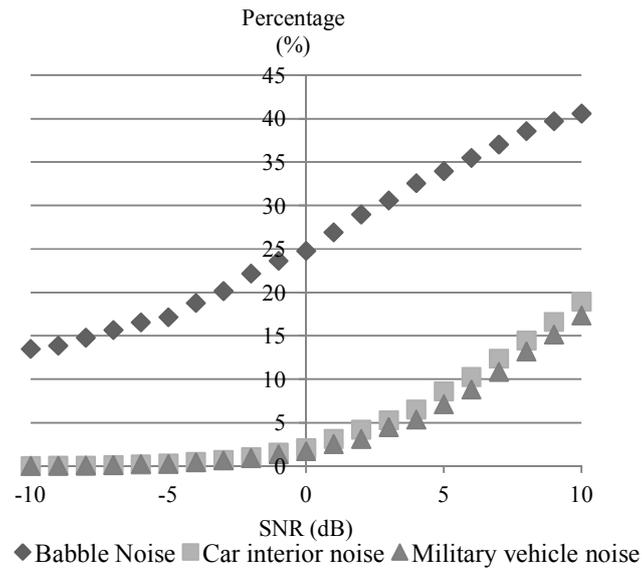


Fig. 8: Percentage of segments where all IMFs (i.e.  $M=N$ ) were selected by EMDF to be used in the partial reconstruction, in car interior noise, babble noise and military vehicle noise

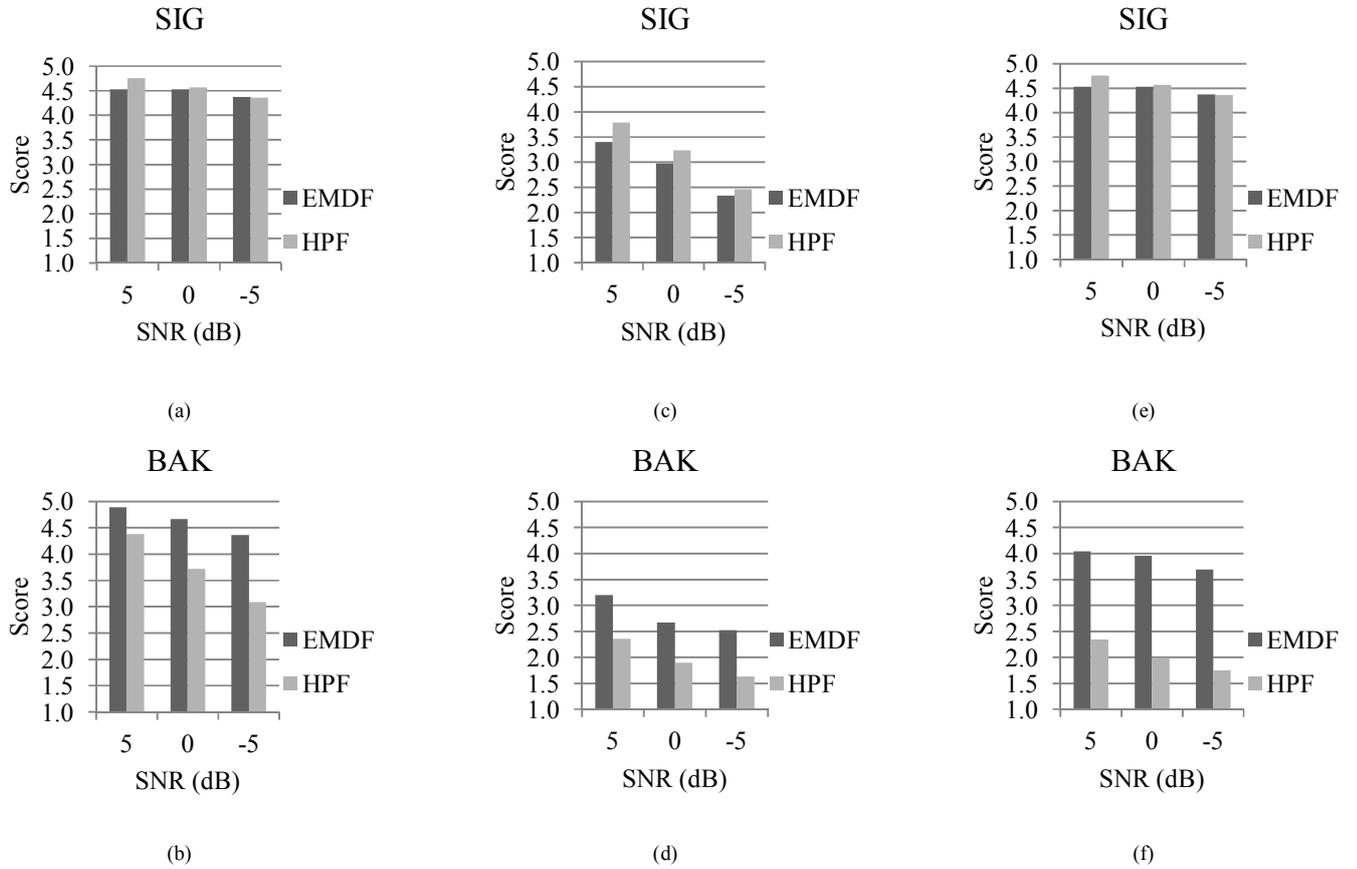


Fig. 9: Mean scores for SIG and BAK scales for the two methods evaluated in (a)-(b) car interior noise (c)-(d) babble noise and (e)-(f) military vehicle noise

TABLE 1:  
SNR of partially reconstructed signals using  $j$  IMFs for (a) clean unvoiced speech segment spoken by a female and  
(b) clean voiced speech segment spoken by a female

IMF order, $j$	SNR (dB) of $x_D[n]$	IMF order, $j$	SNR (dB) of $x_D[n]$
1	10.2	1	1
2	15.8	2	5.9
3	19.4	3	11.9
4	22.5	4	17.2
5	27	5	18.7
6	29.8	6	20.1
7	33.6	7	20.6
8	321.4	8	319.8

(a)

(b)

TABLE 2:  
Segmental SNR (dB) and WSS improvements obtained when comparing the EMDF system to the OMLSA/IMCRA for various noise types and SNR levels

Input SNR (dB)	Car interior noise		Babble noise		Military vehicle noise	
	segSNR	WSS	segSNR	WSS	segSNR	WSS
10	3.6	-17.6	0.3	-7.2	2.3	-21.1
8	4.8	-23.1	0.5	-9.5	2.7	-27
6	5.8	-28.7	0.6	-11.7	3.1	-32.9
4	6.9	-34.6	0.7	-14	3.4	-38.4
2	7.8	-39.9	0.8	-16.7	3.8	-43.6
0	8.5	-45.1	0.9	-19.3	4	-48.3
-2	9.2	-49.5	1	-22.1	4.3	-52.5
-4	9.7	-53.4	1	-24.5	4.5	-56.4
-6	10.1	-56.7	1	-26.6	4.6	-59.6
-8	10.5	-60	1	-28.5	4.7	-62.6
-10	10.7	-62.8	1	-30.4	4.7	-65.5