

Research on Speech Enhancement based on Improved Wavelet Threshold Selection and Least Mean Square Error Adaptive Noise Cancellation

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Abstract:

Aiming at the problem of speech enhancement disturbed by high-frequency and broadband noise, a speech denoising algorithm based on improved wavelet threshold and least mean square (LMS) error adaptive noise cancellation is proposed. Firstly, LMS adaptive noise canceller is used to cancel some noise to obtain a speech signal with high signal-to-noise ratio, and then the wavelet analysis is used for denoising and reconstructing to obtain the denoised speech signals. Matlab simulation experiments show that the improved algorithm is superior than the single algorithm. The output signal-to-noise ratio, visual effect and root mean square error are greatly improved.

Keywords: Wavelet threshold; Least mean square; Adaptive noise cancellation; SNR.

I. INTRODUCTION

In common engineering application scenarios, the speech signal generation and sound transmission process will inevitably be interfered by the noise mixed into it, especially the broadband noise that completely overlaps with the speech signal both in frequency domain and time domain. After completing the speech endpoint detection, the key to ensure the accuracy of speech recognition results is to enhance the speech signal quality, suppress and process the noise, ameliorate the SNR, and improve the distinguishability of natural speech signal[1]. Therefore, based on the principles of various noise reduction algorithms, many comprehensive algorithms, including spectral subtraction[2-5], Wiener filtering[6], wavelet transform[7-9] and so on have been proposed[10]. And many research results have also been achieved[11]. But so far, there is no method that can eliminate the noise completely.

According to relevant research, the pure speech signal is usually considered as one-dimensional quasi-periodic signal, and the noise part which interfere in the transmission process can be regarded as additive Gaussian white noise, which is recorded as the formula $f(n) = s(n) + e(n)$, where $f(n)$ is the noisy speech signal, $s(n)$ is the pure speech signal part and $e(n)$ is the part of added Gaussian white noise. The noise part has no regularity and overlaps with the pure speech part in the time domain, so it is scarcely possible to distinguish in the time domain.

Usually in the frequency domain signal processing, Fourier transform is applied to the signal at first, then the signal is filtered by using the different characteristics of speech signal and noise signal in the frequency domain, and finally the signal is reconstructed in the time domain[12]. However, the filter parameters in the traditional frequency domain filter algorithm have been set at the beginning of design, and the filter parameters can't be adjusted adaptively with the characteristics of the signal in real time[13]. In addition, the traditional Fourier transform only has frequency resolution, does not have time resolution, and can not analyze the weak changes in the time domain, so it is difficult to achieve a good denoising effect.

Wavelet transform has good local characteristics in the frequency domain and the time domain, and has the unique advantage in decorrelation and multi-resolution, which is ideal for the non-stationary signals analysis[[14-17]. However, in the traditional wavelet transform method, the function of hard threshold is discontinuous at the threshold, which causes the reconstructed signal not smooth and easy to produce pseudo Gibbs phenomenon; On the other hand, the function of soft threshold is continuous at the threshold, but there is a fixed deviation in the denoising process, which is easy to reduce the strength of the reconstructed speech signal.

A new function of threshold is proposed in order to overcome the phenomenon that the reconstructed signal is not smooth and has fixed deviation caused by the discontinuity of the traditional function of threshold[18-21]. The new function of threshold is continuous at the threshold, and the reconstructed signal does not have fixed deviation. At the same time, before wavelet transform, LMS adaptive noise canceller is used to eliminate some noise part to acquire the speech signal of high SNR, and then wavelet analysis is used to denoise and reconstruct the signal, so as to obtain better denoising effect.

II. ADAPTIVE NOISE CANCELLATION ALGORITHM BASED ON MINIMUM MEAN SQUARE ERROR

The minimum mean square error (MMSE) algorithm, first proposed by Widrow and Hoff of Stanford University, used in the process of developing the antenna for general motors, is an improved algorithm of the "steepest descent" algorithm.

The idea of LMS algorithm is to minimize the MSE and the expected value of the square of the difference between the expected signal and the actual output of the filter, which is used as the criterion to modify the weight coefficient vector[11,22,23]. As a gradient steepest descent algorithm, LMS algorithm is very efficient compared with the traditional gradient descent algorithm because it does not need to calculate the corresponding correlation function or matrix operation[22].

First, the algorithm filters the input signal, obtains the error signal between the expected output signal and the output signal. Then inputs the error signal into the adaptive filter to form a feedback loop. The algorithm process is as follows:

$$error(n) = d(n) - s(n) * w(n) \quad (1)$$

$$w(n+1) = w(n) + 2 * \lambda * error(n) * s(n) \quad (2)$$

Where error(n), d(n), s(n) and w(n) respectively represent the error between the filter signal and the expected output signal, the expected signal, the input signal and the filter weight factor. Equation (2) is the update formula of tap weight vector, where λ is the iteration step, and its value range is $0 < \lambda < 1/\lambda_{\max}$, λ_{\max} is the energy of the input signal, which is a number between 0 and 1.

In LMS algorithm, the steady-state error and the convergence speed of the filter are a pair of contradictions. The larger the step factor is, the faster the convergence speed of the filter will be, but the steady-state offset error will also increase; The smaller the step factor is, the slower the convergence speed of the filter will be, but the steady-state error will be reduced at the same time[24-26]. In order to overcome this contradiction, an adaptive algorithm with variable step size is proposed based on the fixed step size algorithm. When the error is large, the step size factor also takes a larger value, so as to obtain a faster convergence speed; When the convergence process is close to the steady state and the error is small, the step factor is also reduced to obtain a small steady-state error. In the LMS algorithm with fixed step size, the step size update formula based on sinusoidal function is introduced:

$$u(n) = a * (1 - (\sin(b * e^2(n)) / (b * e^2(n)))) \quad (3)$$

Parameter a is used to control the step size, and parameter B is used to adjust the parameter change rate. The change of u(n) should also obey the fixed step size λ Value requirement of, i. e. $0 < \lambda < 1$. This method has fast convergence speed in the initial stage of iteration and small steady-state error in steady-state.

Adaptive noise cancellation uses more reference noise as auxiliary input than other noise reduction algorithms, so the noise reduction effect is better. Especially when the auxiliary input noise is completely related to the noise in speech, it can completely cancel the noise in speech.

The principle of adaptive noise cancellation based on LMS algorithm is shown in Fig. 1. The main input is the pure signal s transmitted through the channel and the superimposed uncorrelated noise signal n_0 sent from the signal source, and the reference input is the noise n_1 related to the noise signal n_0 but independent of the pure signal s. In the process of adaptive filtering, the filter filters n_1 to produce a signal output y similar to n_0 . According to the correlation between the two input noises and the independence between the signal and noise, the output y of the reference input through the adaptive filter is subtracted from the signal d of the main input, and the error signal e is output. By continuously adjusting the tap coefficient of the FIR filter, the mean square error between the output signal y of the adaptive filter and the noise signal of the main input is minimized, and the difference e between d and y approaches the original pure signal s, The best case is $y = n_0$, then $e = s$.

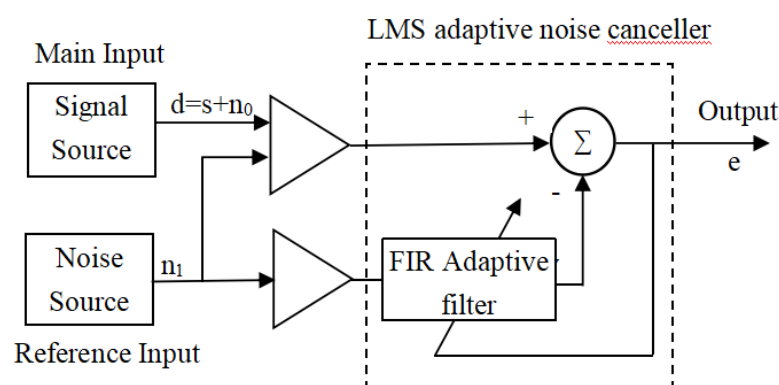


Fig. 1: Schematic diagram of LMS adaptive noise canceller

The steps of LMS algorithm, i. e. minimum mean square error algorithm[7,8], are as follows:

- (1) Filtering: $y(n) = W^T(n) s(n)$;
- (2) Error calculating: $error(n) = d(n) - y(n)$;
- (3) Weight update: $w(n+1) = w(n) + 2\mu error(n)s(n)$

Where: $s(n) = [s(n), s(n-1), \dots, s(N-N+1)]^T$, $W(n) = [W_0(n), W_1(n), \dots, W_{N-1}(n)]^T$, N is the length of FIR adaptive filter, μ is the step size.

III. WAVELET THRESHOLD DENOISING METHOD

3.1 Principle of Wavelet Threshold Denoising

The traditional Fourier analysis signal is only expanded in the frequency domain and does not contain any time-frequency information. Wavelet transform is a time-frequency analysis, which takes into account the frequency domain and time domain of the signal to obtain the frequency-time relationship of the signal. Better time resolution can be obtained in the high-frequency part of the signal and higher frequency resolution can be obtained in the low-frequency part of the signal. The characteristics of multi-resolution analysis have the ability to characterize the local information of the signal in time domain and frequency domain. It is a comprehensive signal analysis method, also known as “Mathematical microscope”, which has been widely used in signal processing.

In practical engineering applications, speech signals are generally low-frequency signals, while noise signals are high-frequency signals. This feature provides a theoretical basis for denoising by wavelet transform. After wavelet transform of noisy speech signal, the energy of speech signal is mainly concentrated on some large wavelet coefficients in the wavelet transform domain, while the noise energy is basically distributed in the whole wavelet domain, and the wavelet coefficient value of speech signal is usually higher than that of noise. Therefore, a threshold can be set to retain the signal above the threshold as useful (hard threshold method) or do the corresponding “shrinkage” processing (soft threshold method). The

denoised signal can be reconstructed by inverse wavelet transform of the retained wavelet coefficients, and the wavelet coefficients below the threshold are regarded as noise and filtered out. As shown in Fig. 2.

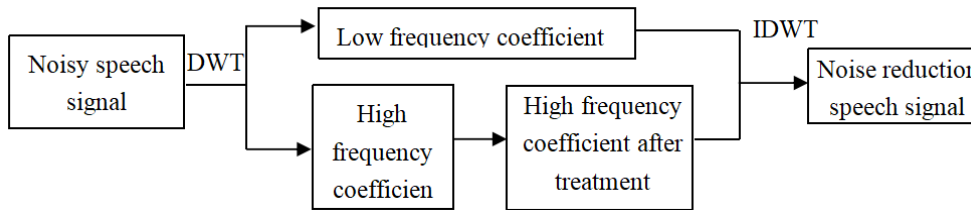


Fig. 2: noise reduction process of wavelet threshold

Taking the simplest Gaussian white noise model as an example, the 1-dimensional noisy speech signal model can be expressed as follows:

$$f(t) = s(t) + e(t) \tag{4}$$

Where $s(t)$ is the original pure speech signal, $e(t)$ is Gaussian white noise, which follows the normal distribution $N(0, \sigma^2)$

Discrete sampling is performed on the above signal $f(t)$ to obtain N-point discrete signal:

$$f(n) = s(n) + e(n), n=0, 1, 2, \dots, N-1 \tag{5}$$

The wavelet transform coefficient of noisy speech signal is:

$$W_f(j, k) = 2^{-j/2} \sum_{n=0}^{N-1} f(n) \psi(2^j n - k), \quad j, k \in Z \tag{6}$$

Among $\psi(n)$ as wavelet basis, it is difficult to obtain its analytical expression in general.

If the wavelet coefficients are recorded as $W_{j,k}$, the wavelet coefficients of the noisy speech signal are composed of two parts: the wavelet coefficients $W_{s(j,k)}$ corresponding to the original pure speech $s(n)$, which are recorded as $U_{j,k}$; The wavelet coefficient $w_{e(j,k)}$ corresponding to white noise $e(n)$ is recorded as $V_{j,k}$, then $W_{j,k} = U_{j,k} + V_{j,k}$.

The basic steps of wavelet threshold denoising are:

(1) The appropriate wavelet basis is selected to decompose the noisy signal, and the low-frequency coefficients and high-frequency coefficients $W_{j,k}$ are obtained respectively;

(2) The selected threshold function is used to threshold the high-frequency coefficients of each layer to make the wavelet coefficients $\hat{W}_{j,k}$. The estimated value of K is as close as possible to $U_{j,k}$;

(3) The low-frequency coefficients of the first layer obtained by wavelet decomposition are compared with the processed high-frequency coefficients $\hat{W}_{j,k}$ is reconstructed to obtain the denoised signal.

In the process of wavelet threshold denoising, the denoising effect is related to the wavelet basis function, the number of decomposition layers, the threshold function and the threshold of each layer, and the selection of appropriate threshold function and threshold quantization is the most important, which directly affects the denoising effect.

3.2 Threshold Function Construction

How to combine the corresponding threshold to process the wavelet coefficients is also very important, which needs to select the appropriate threshold function for different noisy signals. The traditional threshold function is the hard and soft threshold function proposed by Donoho, and its expression is shown in equations (7) and (8):

$$\hat{w}_{j,k} = \begin{cases} w_{j,k}, & |w_{j,k}| \geq \lambda \\ 0, & |w_{j,k}| < \lambda \end{cases} \quad (7)$$

$$\hat{w}_{j,k} = \begin{cases} \text{sign}(w_{j,k})(|w_{j,k}| - \lambda), & |w_{j,k}| \geq \lambda \\ 0, & |w_{j,k}| < \lambda \end{cases} \quad (8)$$

Where: $\lambda = \sigma^2 \log L$, L is the signal length, σ is the noise variance, $\sigma = \text{median}(|w_{j,k}|)/0.6745$.

By analyzing the above two threshold functions, it can be seen that both soft and hard threshold denoising retain or compress the larger components in the wavelet coefficients, and set the smaller part of the wavelet coefficients to zero. The hard threshold function can well retain the useful part, but in practice, some useful speech signals may also exist in the wavelet coefficients less than the threshold. After processing with the hard threshold function, some useful signals may be filtered out, so the reconstructed signal may have some shocks and poor smoothness. Although the soft threshold improves the smoothness of the reconstructed signal, this method is easy to lose the useful signal part, which affects the degree of approaching the actual signal.

Due to some defects in both hard threshold function and soft threshold function, the denoising effect is not ideal. In order to obtain better denoising effect, researchers proposed an improved threshold function as shown in equation (9) on the basis of hard and soft threshold functions[6]:

$$\hat{w}_{j,k} = \begin{cases} \text{sign}(w_{j,k}) \left(|w_{j,k}|^\alpha - \lambda^\alpha \right)^{1/\alpha}, & |w_{j,k}| \geq \lambda \\ 0, & |w_{j,k}| < \lambda \end{cases} \quad (9)$$

Of which: $\alpha = 2j-1$, j is the number of decomposition layers.

Based on the above threshold function, this paper proposes a new threshold function:

$$\hat{w}_{j,k} = \begin{cases} \text{sign}(w_{j,k}) \left(|w_{j,k}|^2 - \lambda^2 \right)^{1/2}, & |w_{j,k}| \geq \lambda \\ \beta w_{j,k}, & |w_{j,k}| < \lambda \end{cases} \quad (10)$$

Where β is a normal number, and the threshold function can be flexibly adjusted. If $|W_{j,k}| > \lambda$, according to the threshold size, the threshold function can be selected between soft threshold and hard threshold. When $|W_{j,k}| < \lambda$, multiply $W_{j,k}$ by a smaller factor β , avoid the disadvantage of fixed deviation of soft threshold function, so as to obtain better denoising effect. At this time, most of the wavelet coefficients are noise β must be small enough. Experiments show that, $\beta \in (0.05, 0.15)$ will have better results, otherwise the noise cannot be eliminated.

The curves of different threshold functions are shown in Fig. 3. The hard threshold function is discontinuity at $\pm\lambda$, and ringing and pseudogibbs phenomena may occur during reconstruction; While the reconstructed speech signal has good smoothness at $\pm\lambda$ by the soft threshold function, but there is a constant deviation from the actual value and edge blur. The threshold function in reference[8] is almost close to the hard threshold function, and may also be prone to oscillation. The improved threshold function is not only in $\pm\lambda$ Continuous and $|w_{j,k}|$ with the increase of $|W_{j,k}|$ gradually approaches $|W_{j,k}|$ so there is no constant deviation problem.

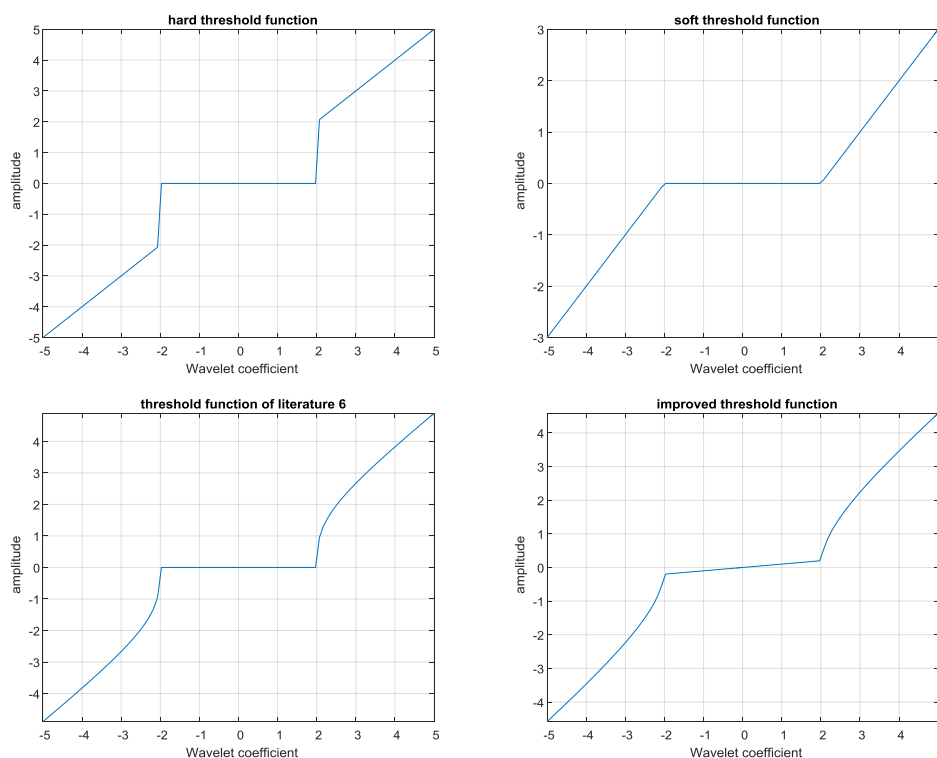


Fig. 3: Schematic diagram of different threshold functions

3.3 Selection of Wavelet Denoising Threshold

The selection of threshold in wavelet denoising threshold method directly affects the denoising effect. If the threshold estimation is too small, the reconstructed wavelet coefficients will contain too many noise components, and the noise in the signal can not be fully removed; if the threshold estimation is too large, some frequency components of the useful signal will also be filtered out, resulting in serious distortion of the reconstructed signal. At present, several common threshold selection rules mainly include unbiased likelihood estimation, fixed threshold estimation, heuristic threshold estimation and extreme value threshold estimation.

According to the characteristics of noise, donobo and Johnstone [9] proposed a general threshold.

$$\lambda = \sigma \sqrt{2 \log N} \quad (11)$$

While σ is the standard deviation of noise, $\sigma = \text{Medium}(|w_{j,k}|) / 0.6745$, n is the sampling length of the signal.

The threshold size obtained by this estimation method is related to the signal length. The actual speech signal often has long data samples, that is, n is relatively large. In this way, the threshold will be too large, which tends to set some edge wavelet coefficients to zero, affecting the denoising effect. According to the characteristics of wavelet decomposition, with the increase of wavelet decomposition level, the noise component in wavelet coefficients will be less and less, and the proportion of speech signal will be larger and larger. Therefore, the threshold needs to be reduced with the increase of wavelet decomposition scale. This paper adopts the improved threshold proposed in document [8]:

$$\lambda_j = \sigma \sqrt{2 \log N / \log(j+1)} \quad (12)$$

Based on the original calculation formula, this method introduces the decomposition scale J of the signal, so that the obtained threshold decreases gradually with the increase of the decomposition scale, which can effectively overcome the phenomenon that the wavelet coefficients may be “strangled” by the traditional general threshold.

IV. APPLICATION OF LMS BASED ADAPTIVE FILTERING AND IMPROVED WAVELET DENOISING ALGORITHM IN SPEECH SIGNAL PROCESSING

4.1 Algorithm Flow

LMS adaptive filtering method and wavelet denoising method can effectively remove the noise in speech. Wavelet transform makes use of the time-frequency localization ability and the characteristic that the noise after wavelet decomposition is mainly concentrated in the high-frequency part to remove the noise. Although the low-frequency image noise after transformation is reduced, the low-frequency image noise is still a residual part of the noise. LMS adaptive filtering is to remove the low-frequency noise by filtering the noise frequency components in the frequency domain to obtain a better denoising effect.

This paper uses LMS based adaptive filtering and improved wavelet denoising algorithm. The high-frequency part uses wavelet transform to reduce noise, and the low-frequency part uses LMS adaptive filtering to remove residual noise, so that LMS filtering and wavelet transform can give full play to their advantages. The processing flow is shown in Fig. 4:

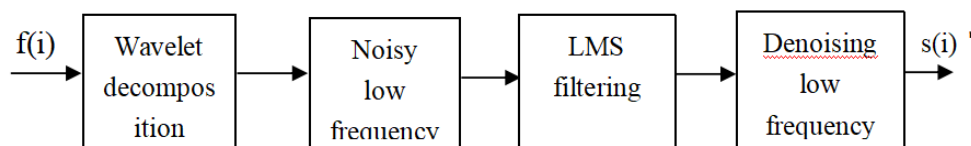


Fig. 4: noise reduction process based on LMS filtering and wavelet transform

(1) Select the appropriate wavelet base to decompose the noisy speech signal s in N layers.

(2) For each layer of high-frequency subband, the subband coefficients are processed by using the improved threshold function and threshold.

(2) LMS adaptive filtering is applied to the low-frequency part of speech after wavelet decomposition.

(4) Wavelet reconstruction. According to the low-frequency coefficients filtered by LMS and the high-frequency coefficients processed by wavelet analysis, the signal is reconstructed to obtain the denoised speech signal.

4.2 Evaluation Parameters

Different results will be obtained after denoising with different threshold functions. Two evaluation indexes, signal-to-noise ratio and root mean square error, need to be used to verify the denoising effect of these threshold functions. The expressions of signal-to-noise ratio SNR (dB) and mean square error function MSE are as follows:

$$SNR = 10 \times \lg \left(\frac{\sum_{i=1}^N (s(i) - \text{mean}(s))^2}{\sum_{i=1}^N n(i)^2} \right) \quad (13)$$

$$MSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (f(i) - s(i))^2} \quad (14)$$

Where s is the original voice signal, n is the noise signal, f is the processed voice signal, and N is the length of the voice signal.

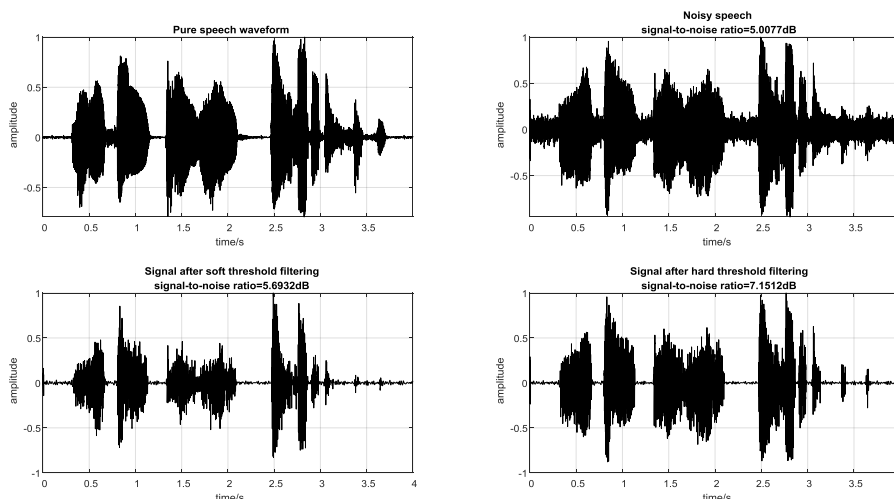
4.3 Simulation Analysis

In this paper, matlab2015b is used for simulation, and a pre-collected speech signal is used for denoising analysis. In the experiment, the speech signal with Gaussian white noise is decomposed into six layers using DB7 wavelet basis[27-28]. The algorithms used for comparison include hard threshold method, soft threshold method and this algorithm.

The first group of experiments did not use LMS adaptive filtering, but only wavelet decomposition denoising. Gaussian noise with different intensity is added to the original speech, and soft threshold, hard threshold and adaptive filtering algorithm are used to denoise the original speech ($\beta=0, 0.05, 0.1, 0.15, 0.2$) respectively, as shown in Table I. Fig. 5 shows that the standard deviation of noise is 5dB, and the soft threshold, hard threshold and adaptive filtering algorithm in this paper are used for denoising ($\beta=0, 0.05, 0.1, 0.15, 0.2$) respectively.

TABLE I. Adaptive threshold denoising algorithm based on signal-to-noise ratio

Noise variance	Soft threshold denoising	Hard threshold denoising	Adaptive threshold denoising (β)				
			0	0.05	0.1	0.15	0.2
-10	-0.0532	-0.0246	-0.0422	-0.0388	-0.0355	-0.0321	-0.0288
-5	0.3339	0.9860	0.6631	0.7077	0.7515	0.7946	0.8368
0	3.3706	4.4578	4.5010	4.7777	5.0433	5.2932	5.5220
5	5.6932	7.1512	7.0087	7.2091	7.3964	7.5671	7.7172



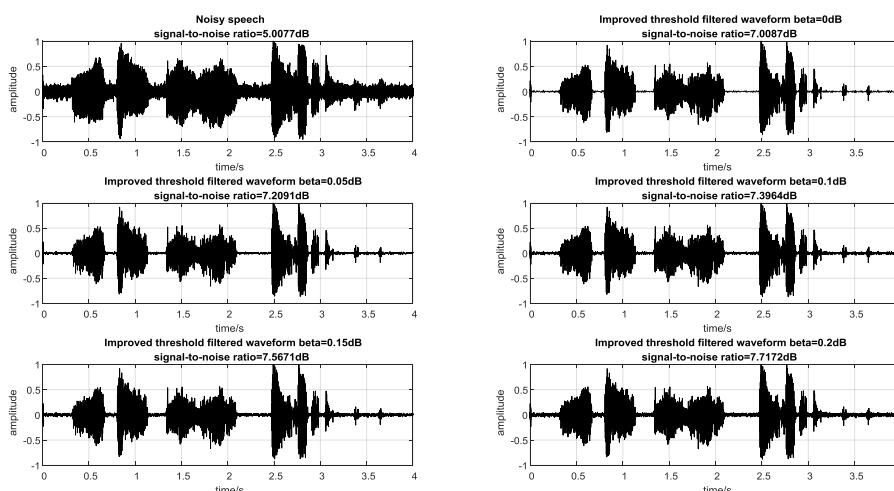


Fig. 5: Noise standard deviation is 5dB, soft threshold, hard threshold and adaptive threshold wavelet denoising effect

It is found from Fig. 5 that although both soft threshold and hard threshold filtering can remove Gaussian noise better, the denoising effect of the improved adaptive threshold function in this paper is better than that of other methods.

The second group of experiments uses wavelet decomposition denoising based on LMS adaptive filtering algorithm. Gaussian noise with different intensity is added to the original speech, and soft threshold, hard threshold and LMS adaptive filtering algorithm are used to denoise the original speech ($\beta=0, 0.05, 0.1, 0.15, 0.2$) respectively, as shown in Table II. Fig. 6 shows the noise with a standard deviation of 5dB, which is denoised by using soft threshold, hard threshold and LMS adaptive filtering algorithm in this paper ($\beta=0, 0.05, 0.1, 0.15, 0.2$) respectively.

TABLE II. SNR of soft threshold, hard threshold and denoising based on LMS adaptive filtering algorithm

Noise variance	Soft threshold denoising	Hard threshold denoising	Adaptive threshold denoising (β)				
			0	0.05	0.1	0.15	0.2
-10	-3.4039	0.1772	-0.6332	-0.3928	-0.3910	-0.6289	-0.8892
-5	1.0799	2.5011	2.1095	2.3679	2.4887	2.4676	2.3193
0	3.7851	5.4135	5.0606	5.3813	5.6147	5.7237	5.7105
5	6.1267	7.5811	7.4514	7.7710	8.0875	8.3375	8.5069

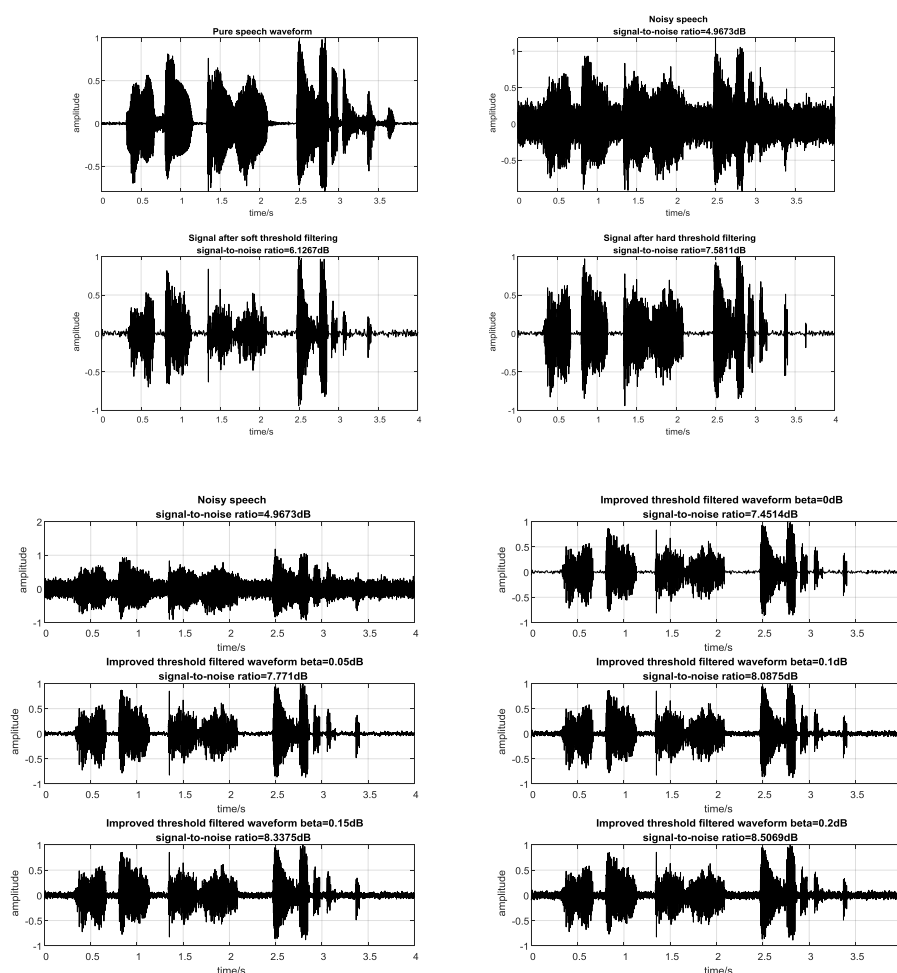


Fig. 6: Noise standard deviation is 5dB, soft threshold, hard threshold and adaptive threshold wavelet denoising effect based on LMS

It is found from Fig. 6 that the soft threshold and hard threshold filtering method after adaptive filtering based on LMS can better remove Gaussian noise, and the denoising effect is better by using the adaptive threshold function based on LMS improved in this paper.

V. CONCLUSION

Based on LMS adaptive filtering algorithm, variable step size adaptive algorithm can obtain faster convergence speed and smaller steady-state error. Compared with the traditional soft and hard threshold function, the improved threshold function is not only continuous at the threshold, but also does not have the problem of constant deviation [29]. The simulation results show that the processed speech signal does not have the “music noise” caused by the traditional spectral subtraction preprocessing, and has obvious noise reduction effect in the subjective auditory perception, and the signal-to-noise ratio and root mean square error are also greatly improved.

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