International Journal of Future Generation Communication and Networking
Vol.10, No.4 (2017), pp.71-84
http://dx.doi.org/10.14257/ijfgcn.2017.10.4.08

A Novel Audio Signal De-noising Algorithm based on the Theory of Frequency Domain Analysis and Transform Domain Model

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Abstract

Signal denoising task has been a hottest research area in the modern signal processing community. Speech and audio as the principle component of the real-world signal, their purity property and robustness features are put distinctly important focus. To optimize the traditional denoising approaches, in this paper, we propose a novel algorithm based on the theory of frequency domain analysis and the transform domain model. We firstly introduce the basic concepts of frequency domain analysis to fundamentally set the basis for later discussion. Fractional Fourier transform pair is the rotation of the plane that can be used to estimate the initial information such as frequency, to eliminate drawbacks of classic domain analysis method we combine the Fractional Fourier transform. Later, we discuss the transform domain model with the modification of traditional wavelet model as the multi-level wavelet decomposition can exacerbate the happening of this kind of situation, thus affecting the overall effect of the signal analysis. Then, based on the prior discussed model, we propose the novel audio enhancement algorithm. To verify feasibility of the model, we test the algorithm in simulation part compared with other approaches. The result proves the robustness and efficiency of our methodology.

Keywords*: Audio Signal, Denoising Algorithm, Frequency Domain Theory, Wavelet Transformation, Down-sampling, Signal Sparsity, Mathematical Model*

1. Introduction

Speech signal is the important media information and basic emotional communication, human communication is hearing organ perception of voice media medium mechanical vibration as is the most important, the most effective, most commonly, human is the most convenient way of the communication. But people in the speech communication process inevitably from surrounding environment, the noise of transmission medium is introduced into internal electrical noise, communications equipment, speaker and other interference, the interference will eventually make the received speech signal that is not pure primitive voice signal, but the noise pollution of the speech signal with noise [1-3].

Voice is time-varying, nonstationary, traverse of stochastic process. Voice is the time-varying process many factors cause the time-varying voice system, such as the area of the channel change with time and distance, air velocity changes with the glottis place pressure changes, *etc.* Speech can be divided into periodic sonant and non-periodic sounds. The voiced and the unvoiced speech often appear at the same time in a syllable. Dullness part and closely related to the quality presents obvious periodicity in time domain, the formant structure in the frequency domain, and most concentrated in the low frequency band energy that is significantly high energy part of speech as surd has obvious characteristics of time domain and frequency domain is similar to white noise, less energy, easy to hide in the strong noise, but at high SNR can provide more information. In speech enhancement, we can take advantage of the characteristics of the periodic dullness, phonetic component extracted with the use of comb filter or inhibit the voice signal, and unvoiced speech is difficult to differentiate and the broadband noise [4]. Noise sources depend on the actual application environment and noise characteristics of infinite change,

ISSN: 2233-7857

so to speak. Noise can be additive and can also be additive. For the additive noise, some can transform into additive noise [5]. In the speech enhancement, we can use the dullness quasi periodicity, phonetic component extracted with the use of comb filter or inhibit the voice signal, and unvoiced speech is difficult to differentiate and broadband noise [6]. In the figure one, we show the general distribution of the speech noise signal.

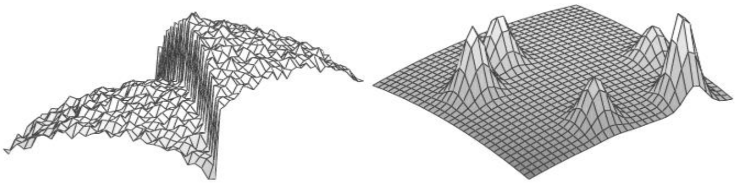

Figure 1. The Illustration of the Noise Distribution Pattern

To better demonstrate the advantages of our new algorithm, we review the state-of-the-art methods first as the reference. According to the literature survey, contemporary ways could be separated into the following parts. (1) Kalman filtering method. Kalman filtering to a certain extent as can make up for the error due to wiener filtering. Because it is based on the model of speech production, and under the condition of the nonstationary also can guarantee the optimal minimum mean square error sense, apply to speech enhancement under non-stationary noise. The advantages of Kalman filtering are in stationary and non-stationary noise can use cases and can eliminate noise in different degree to improve the signal-to-noise ratio (SNR). (2) The comb filtering method. The key to this approach is to accurately estimate the pitch period of speech signals. In the pitch change of transition section and the strong noise background interference can't accurate estimate method of the application is restricted. This approach generally applies only to smooth the white noise. (3) Subspace method. Subspace method is to speech signal with noise is decomposed into orthogonal signal and noise subspace and noise subspace, the estimate of the clean speech signal noise subspace of the signal can be abandoned only keep signals in signal subspace, and to predict the clean speech in order to achieve the purpose of noise reduction [7]. (4) Hidden Markov model method. HMM of each state to the signal and noise signal with noise all the different areas to fully modeling, remove the noise in the signal with noise signal part can be enhanced by voice, even in the case of only the signal with noise, using the state transition probability for HMM modeling, it will be for the noise signal of speech enhancement filter can do [8]. (5) Adaptive filtering method. The minimum mean square error (MES) or the variance as the standard, to the optimal estimation of noise signal, and then subtracting the noise from the speech with noise to noise improve the signal-to-noise ratio to finish the enhancement purpose to voice [9]. (6) Wiener filtering method. After the benefits of using the wiener filtering to enhance the residual noise is similar to white noise, rather than have a rhythm and the music noise. Wiener filtering is stable under the condition of minimum mean square error criterion to estimate the time domain waveform. Without considering the voice frequency spectrum component of range of human hearing is the most important, so using wiener filtering to enhance speech has certain defects.

In this research paper, we propose the novel audio signal denoising algorithm based on the theory of frequency domain analysis and transform domain model. Theoretical review has proved that compared with Fourier transform, wavelet transform has the better time-frequency localization characteristics, but also for non-stationary signals, such as audio signal that can provide close to the good approximation properties of K-L transformation precision which is the core reason for being adopted by us. The reminding of the paper is organized as the follows. We firstly analyze the characteristics of the theory of frequency domain analysis and introduce the primary transformation functions with theoretical base discussion; then, we combine the mathematical modelling technique to form the primary transformation model with the analysis of the wavelet features; later, we combine prior methods to propose the novel audio signal denoising algorithm. To test overall and basic performance of the algorithm, we conduct numerical simulation in the final sections with the final conclusion and future research proposal.

2. Theory of Frequency Domain Analysis

As of today, the speech signal characteristic parameters extraction and the research progress is very slow, although the new method of time-frequency analysis of the various kinds are springing up constantly, its universal applicability is not high, so there has been no breakthrough on theory and the algorithms. Speech parameter estimation system demand is high, poor adaptability to the environment, strong dependence acquisition of voice in kind of environment can only be applied in what kind of environment, otherwise, will reduce the performance of the system [10-11].

For the parameter estimation of speech signal is a complex project, it also involves psychology, physiology, linguistics, statistics, computer, artificial intelligence, and many other fields. Still need further study to get these areas of the existing research results of the quantitative, modeling and application in speech signal processing. It is to a certain extent and restricts the further development of speech signal processing technology. For speech signal parameter estimation under complicated noise environment is very difficult, because this time the speaker's voice has changed a lot, such as the height, the speed of sound speed, tone and the change of resonance peaks, thus resulting in a decline in the recognition rate of the speech. Under this background, frequency domain analysis method has been proposed recently. The Figure 2 shows the classic domain analysis approaches.

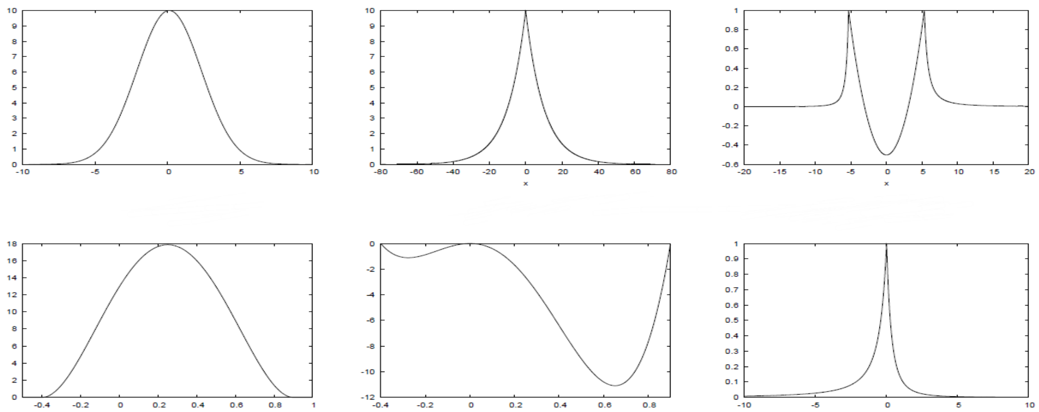

Figure 2. The Frequency Domain Transformation Curves

Among all the domain analysis approaches, Fourier transform has been researched with the focused treatment. At present, the cover fractional Fourier transform is applied in the field of signal processing are mainly as the follows, at the same time also reflected the multiple characteristics of fractional Fourier transform. Fractional Fourier transform pair is the rotation of the plane that can be used to estimate the initial information such as frequency, instantaneous frequency, the initial phase, phase information can also restore and reconstruct the signal, thus fractional Fourier transform the relationship with other time-frequency analysis tool, which can design a new time-frequency analysis tool.

$$F^{p}\left(f\left(t\right)\right)=F^{a}\left(u\right)=\int_{-\infty}^{\infty}f\left(t\right)K_{p}\left(t,u\right)dt \tag{1}$$

Fractional Fourier transform because of its mature fast discrete algorithm, can provide other fractional operator or transform with fast algorithms, such as fractional convolution and correlation and the fractional Hermite transform as the formula 2~3.

$$F^{\pi/2}(u) = F(u) = \int_{-\infty}^{\infty} f(t) e^{-j2\pi t} dt \tag{2}$$

$$W_{Fp}(t,u) = W_f(t\cos\alpha - u\sin\alpha, t\sin\alpha + u\cos\alpha) \tag{3}$$

Where the $F^{\pi/2}(u)$ represents enclosures fractional Fourier transform is transformation and the $W_{Fp}(t,u)$ represents the point of view of characteristic function and characteristic value. Frequency domain masking is between two primary simultaneous sound masking phenomenon, also known as masking at the same time. When two voice has an important part of the band, but not limited to a single frequency range, frequency domain masking happen very often. Frequency domain masking is very important, if adjacent important sub-band exist high frequency components, the hearing threshold will increase rapidly the threshold quantization noise allows maximum power level as formula 4.

$$X(t) = \sum_{k=0}^{K} H(k) S(t-k) \tag{4}$$

Cover fractional Fourier transform can avoid the interference of cross phase signal and it is a kind of linear transformation, in multi-component cases with additive noise is more advantage analysis. According to the basic principle of information theory, unless the two random variables are jointly Gaussian distribution, calculation of two variables and the amount of information to the two variables of all the number of order statistics. The Figure 3 shows the visualized process the steps [12-13].

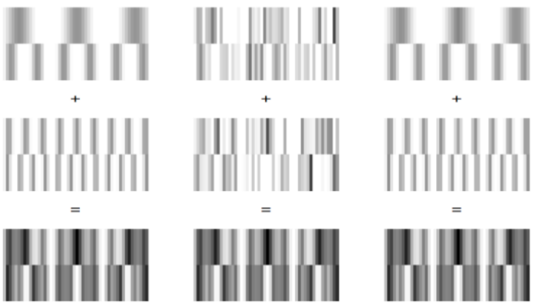

Figure 3. The Frequency Domain Processing Paradigm

Because of the influence of multi-channel environment, sound source is convolution mixture and therefore, need a filter matrix, used to restore the source signal from a mixed signal and not just a simple solution mixing matrix. In the physical sense can regard them as inspired by different physical system. Thus meet fanaticism separation conditions of the independence assumption. The formula 5 defines the transformation kernel.

$$\Psi(u) = H(u)\exp(-u^2 / 2) \tag{5}$$

Masking the threshold to determine the frequency domain linear prediction carrier after scoring quantization noise can be estimated. In the same sub-band, we could use the same number of bits of numerical carrier signal but according to the carrier signal masking threshold, different sub-band with different number of bits in the distribution. There are two kinds of circumstances, if the carrier signal power spectral density is lower than the masking threshold, the quantitative don't need bits, decoding white noise was used for the reconstruction of sub-band signals is used to replace the carrier signal, minimal impact on reconstruction audio quality. Otherwise, number of bits to reduce used to quantization noise power spectral density just below the masking thresholds. Therefore, the higher the masking threshold and quantify the smaller the number of bits required. To eliminate the related influence, we define the transformation matrix as the follows.

$$a_n(w)=\begin{pmatrix}\exp(-jw\kappa_1)\\ \vdots\\ \exp(-jw\kappa_n)\end{pmatrix}\rightarrow a_n(w_0)=\begin{pmatrix}\exp(-j(w-\Delta w)\kappa_1)\\ \vdots\\ \exp(-j(w-\Delta w)\kappa_n)\end{pmatrix} \tag{6}$$

Normalization theory is put forward has make us the fractional convolution is obtained and some related theorems and properties. Also gives a fractional order autocorrelation and fuzzy function, the relationship between the nature, points out that not only the time domain autocorrelation and frequency domain autocorrelation respectively corresponding to the fuzzy function of the horizontal and vertical section, and through the calculation of fractional order autocorrelation of corresponding angle can also get the fuzzy function in corresponding angle of inclined section. Using fractional order autocorrelation algorithm for speech signal extraction of characteristic parameters, and can accurately detect the peak position, compared with other parameter extraction method has high precision. From the formula 6, the defined $a_n(w_0)$ holds better performance. All through the origin in the plane of fuzzy linear frequency modulation signal has a linear area, through calculation of the fuzzy function of signal through the origin, it is concluded that a test statistic. In Figure 4, we define the primary frequency domain analysis functions [14-15].

Acronym	Name	$g(\mathbf{H})$	$[\nabla g^{+}(\mathbf{H})]_{i,j}$	$[\nabla g^{-}(\mathbf{H})]_{i,j}$
L1	L1-norm	$\sum_{j=1}^{n}\sum_{i=1}^{r} h_{i,j}$	1	0
RNL1	Row-Normalized L1-norm	$\sum_{i=1}^{r}\frac{\sum_{j=1}^{n} h_{i,j}}{\sqrt{\sum_{k=1}^{n} h_{i,k}^2}}$	$\frac{1}{\sqrt{\frac{1}{n}\sum_{k=1}^{n} h_{i,k}^2}}$	$\frac{\sqrt{N} h_{i,j}\sum_{k=1}^{n} h_{i,k}}{\left(\sum_{k=1}^{n} h_{i,k}^2\right)^{3/2}}$
CNL1	Column-Normalized L1-norm	$\sum_{j=1}^{n}\frac{\sum_{i=1}^{r} h_{i,j}}{\sqrt{\sum_{k=1}^{r} h_{k,j}^2}}$	$\frac{1}{\sqrt{\frac{1}{n}\sum_{k=1}^{r} h_{k,j}^2}}$	$\frac{\sqrt{N} h_{i,j}\sum_{k=1}^{r} h_{k,j}}{\left(\sum_{k=1}^{r} h_{k,j}^2\right)^{3/2}}$
L1/2	L1/2 quasi-norm	$\sum_{j=1}^{n}\left(\sum_{i=1}^{r}\sqrt{h_{i,j}}\right)^2$	$\frac{\sum_{k=1}^{r}\sqrt{h_{k,j}}}{\sqrt{h_{i,j}}}$	0
WE	Wiener Entropy	$\sum_{j=1}^{n}\frac{\left(\prod_{i=1}^{r} h_{i,j}\right)^{\frac{1}{r}}}{\frac{1}{r}\sum_{i=1}^{r} h_{i,j}}$	$\frac{\left(\prod_{k=1}^{r} h_{k,j}\right)^{\frac{1}{r}}}{h_{i,j}\sum_{k=1}^{r} h_{k,j}}$	$\frac{r\left(\prod_{k=1}^{r} h_{k,j}\right)^{\frac{1}{r}}}{\left(\sum_{k=1}^{r} h_{k,j}\right)^2}$
GM	Geometric Mean	$\sum_{j=1}^{n}\left(\prod_{i=1}^{r} h_{i,j}\right)^{\frac{1}{r}}$	$\frac{\left(\prod_{k=1}^{r} h_{k,j}\right)^{\frac{1}{r}}}{h_{i,j}}$	0

Figure 4. The Primary Frequency Domain Analysis Functions

3. Transform Domain Model

Interference suppression algorithm based on the transform selection is according to the interference signal in all the digital domain measurements to choose the correct transform domain to suppress interference. Therefore, the interference suppression algorithm based on domain choice is keys to choose according to measurements correct transform domain, and then adopt suitable to suppress interference suppression algorithm [16-17].

Least mean square algorithm is the most widely applied in the field of typical adaptive filtering algorithm. The algorithm is simple, less computation, easy to implement, but its convergence rate of the input signal of the autocorrelation function of matrix eigenvalue distribution of sensitive if the distribution of the eigenvalues is too scattered, convergence speed will be slow. Based on this, the transform domain adaptive filtering was proposed, its main idea is to input signal vector orthogonal transform to reduce the basic degree of autocorrelation, which make algorithm obtain good convergence performance. Whether voice sub-band coding or wavelet decomposition conjugates quadrature mirror filter and biorthogonal filter involves gens of mutual contact and mutual matching filter, in order to realize the signal decomposition and the synthesis. However, these usually finite impulse responses FIR filter to design, because of the impulse response of the finite length, and completely overcome the aliasing effect between different frequency band, thus reducing the precision of signal decomposition synthesis and code decoding. To deal with mention of the challenges, we propose the novel perspective in this section, and the sample for the analysis is shown in the Figure 5 [18].

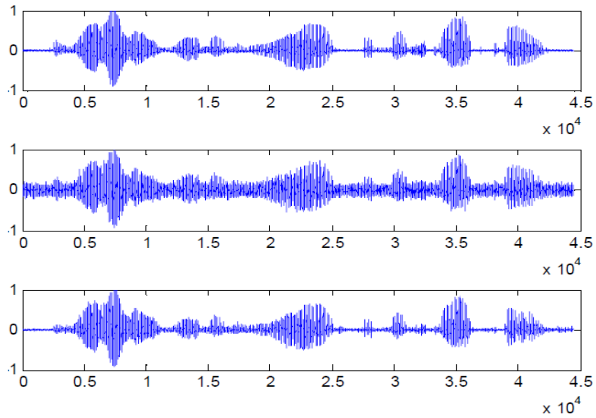

Figure 5. The Sample Speech Signal Source for Analysis

3.1. The Basic Transform Domain Theory

After frequency domain pilot signal through the channel, to the Fourier transform, the signal is called the transform domain signal. According to the above conclusion, pilot with the same frequency in the frequency domain signal FFT, the modulus value should transform domain signal has features, so by determining receiving signals in the transform domain mutation point position. In order to more effectively suppress interference. It is necessary to choose an appropriate transformation to make easily the useful signal and the interference of the ingredients and as the energy transform can maximize the compression interference, at the same time as much as possible to spread energy of useful signal [19].

$$\Psi_k[n]=h[n]\sqrt{\frac{2}{M}}\cos\left[\left(n+\frac{M+1}{2}\right)\left(k+\frac{1}{2}\right)\frac{\pi}{M}\right] \tag{7}$$

As shown in the Figure 7, we illustrate the basic transformation, where the $h[n]$ is the kernel function for assistance. Product is equivalent to time domain convolution transform domain, select the appropriate transform domain function multiply it by transform values of the input signal, equivalent to signal filtering in transform domain. So the input signal in transform domain can be seen as process of extraction of a set of output filter, namely sub-band filter. According to the general features, we can optimize features as follows.

$$S_{xx}(f)=\frac{1}{N}\left|X(f)\right|^2 \tag{8}$$

Chaos is a kind of common exists in nonlinear dynamics in the system's behavior. The change process of the chaos seemingly chaotic, but has its internal regularity. Use of the ergodicity of chaotic variables as a function extremum search avoids falling into the local minima in the general process of optimization mechanism. Chaos optimization algorithm is based on chaotic map, the basic idea of chaotic sequence and the chaotic sequence by carrier loaded into interval parameter and compares the sequence of the objective function value. Usually, within a certain step function values are not changed as the termination conditions, in order to meet termination conditions when the current value of the optimal value as output [20-21]. We define the procedure in the formula 9~10.

$$G_k(n) = \left(\sum_{l=0}^{N_{FFT}} g'_k(l) \exp\left(-j \cdot 2\pi \frac{nl}{N_{FFT}} \right) \right)^2 \tag{9}$$

$$G'(n) = G(n) - G(n+1) \tag{10}$$

Additive white Gaussian noise power spectrum is close to the uniform distribution, and for the objective function, the influence of noise will gradually be eliminated. Therefore, the value, the greater the Doppler frequency shift can under the lower signal to noise ratio are estimated to come out. But general value will bring certain estimated delay, and will increase the complexity of the calculation [22]. The Figure 6 shows the pattern.

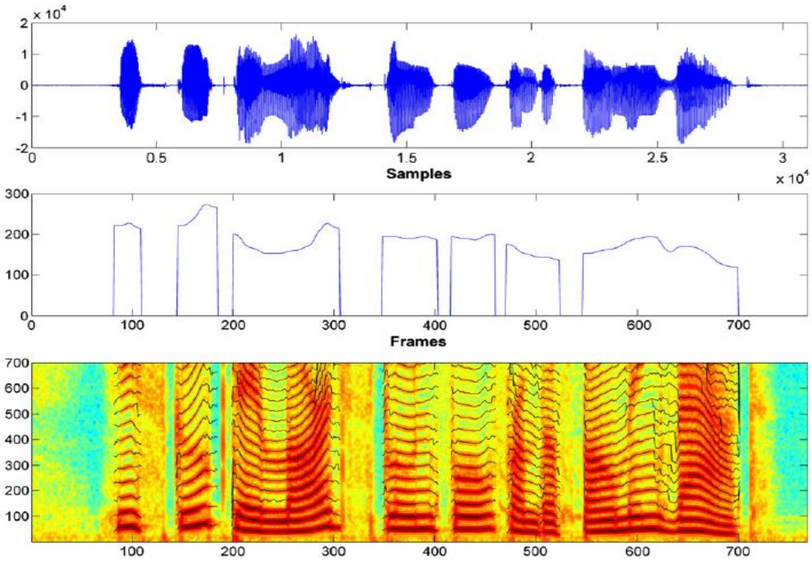

Figure 6. The Transform Domain Processed Signal Pattern

Reflected from the Figure 6, we could capture the principles that deviation estimates with the theoretical value, this is due to the discretization of the sampling signal and noise. The influence of the direct method of calculating time and the basic estimation precision associated with step length, step length as increased, although the estimation accuracy, but at the expense of the operation efficiency. Chaos optimization algorithm not only takes less than the direct method and its precision is high.

3.2. The Wavelet Based Transformation

Fourier transform is a serious shortage, information is lost when doing transformation time, unable to judge according to the result of the Fourier transform of a particular signal is in when did it happen, that is to say, the Fourier transform is a kind of pure frequency domain analysis method, without any localization in the time domain. SIFT, however, the size and shape of window function in maintaining constant, has nothing to do with the time and frequency, which is harmful for the analysis of time-varying signals. Because of the high frequency signal lasts a very short time, low frequency signal duration is longer, the signal is analyzed that the high frequency signal with small time window with the low frequency signal with large time window is analyzed. Therefore, we propose the modified wavelet transformation paradigm as the formula 11.

$$
\begin{aligned}
W_{\psi}(j,k) &= \frac{1}{\sqrt{M}} \sum_{x} f(x) 2^{j/2} \psi(2^{j} x - k) \\
&= \frac{1}{\sqrt{M}} \sum_{x} f(x) 2^{j/2} \left[\sum_{m} h_{\psi}(m-2k) \sqrt{2} \phi(2^{j+1} x - m) \right] \\
&= \sum_{m} h_{\psi}(m-2k) \left[\frac{1}{\sqrt{M}} \sum_{x} f(x) 2^{(j+1)/2} \phi(2^{j+1} x - m) \right]
\end{aligned} \tag{11}
$$

Wavelet, the small area of the wave is a special kind of continuous, average length of the waveform. In time domain are compactly supported or it is similar to tight branch collection and component in addition, it is near to zero, namely the alternation of plus or minus volatility. Fourier analysis is the signal is decomposed into a series of the different frequency sine wave superposition. We show the visualized form in the Figure 7.

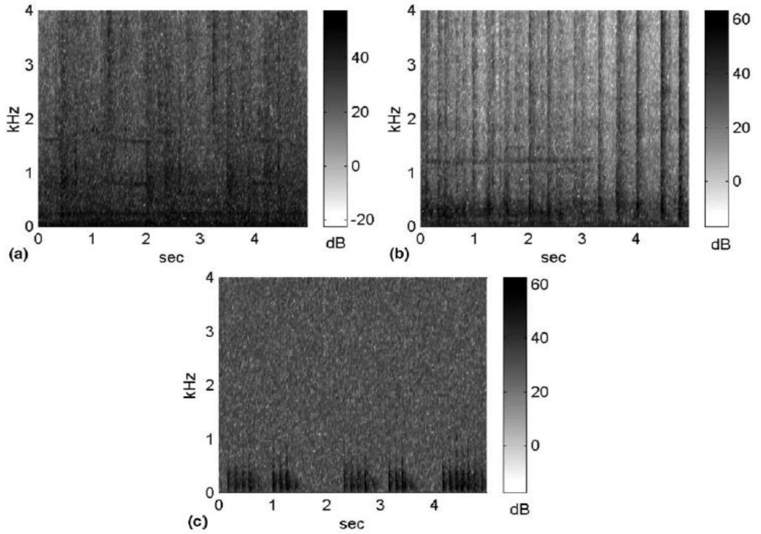

Figure 7. The Signal after the Wavelet Transformation

Filter design is based on the normalized frequency, while the former level of output is 2 times of sampling signal, two filter bandwidth in each layer is the same, two lines of output because band does not overlap, so must the orthogonal, and because the bandwidth of the output by half, so the sampling rate can be halved without causing loss of the basic information and the process is reversible as defined below [23-24].

$$
W_{\psi}(j,k) = \sum_{m} h_{\psi}(m-2k) W_{\phi}(j+1,m) \tag{12}
$$

$$
W_{\phi}(j,k) = \sum_{m} h_{\phi}(m-2k) W_{\phi}(j+1,m) \tag{13}
$$

Inner product and defined based on the wavelet transform, we call it the dot product of the wavelet theory. But with the deepening of the application, it shows some defects: the inner product of signal as a whole which can make the signal the start was polished and be smoothed out some important information, abate signal feature extracting and precision of the singularity, and multi-level wavelet decomposition can exacerbate the happening of this kind of situation, thus affecting the overall effect of the signal analysis. In practice, because the tensor product and practical large-dimensional wavelet base, often with tensor product of low dimensional wavelet is based to construct the higher dimensional wavelet. Using structure tensor product wavelet to analyze the signal, we will retain the various characteristics of gay and is likely to lose anisotropic characteristics at the same time. In the formula 14, we define the corresponding features.

$$(x_k) = a_0 \begin{pmatrix} 1 \\ 1 \\ 1 \\ 1 \\ 1 \\ 1 \\ 1 \\ 1 \end{pmatrix} + a_1 \begin{pmatrix} 1 \\ 1 \\ 1 \\ 1 \\ -1 \\ -1 \\ -1 \\ -1 \end{pmatrix} + a_2 \begin{pmatrix} 1 \\ 1 \\ -1 \\ -1 \\ 0 \\ 0 \\ 0 \\ 0 \end{pmatrix} + a_3 \begin{pmatrix} 0 \\ 0 \\ 0 \\ 0 \\ 1 \\ 1 \\ -1 \\ -1 \end{pmatrix} + a_4 \begin{pmatrix} 1 \\ -1 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \end{pmatrix} + a_5 \begin{pmatrix} 0 \\ 0 \\ 1 \\ -1 \\ 0 \\ 0 \\ 0 \\ 0 \end{pmatrix} + a_6 \begin{pmatrix} 0 \\ 0 \\ 0 \\ 0 \\ 1 \\ -1 \\ 0 \\ 0 \end{pmatrix} + a_7 \begin{pmatrix} 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 1 \\ -1 \end{pmatrix} \tag{14}$$

Wavelet analysis has just opened a door is not stable, not unified, the time constant of the signal processing, this field is far more complicated than the Fourier analysis of time invariant system. In this big field, wavelet analysis is an important tool, but also need the other theories and tools. In recent years, some scholars the wavelet transform and neural network, fuzzy mathematics, fractal analysis, genetic optimization method, combination of formation of the wavelet neural network, fuzzy wavelet network, wavelet analysis is non-stationary and nonlinear problem of ideal means.

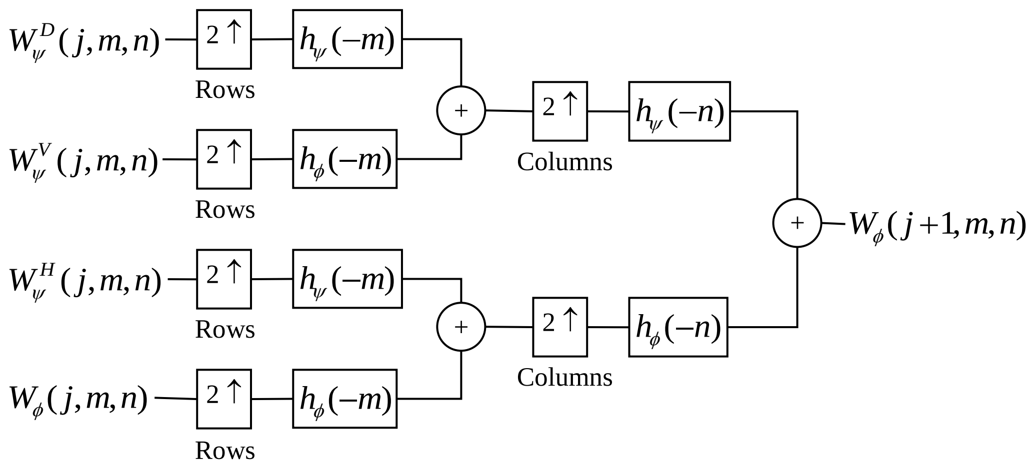

Figure 8. The Signal Transformation Procedures with Wavelet

4. The Proposed Novel De-noising Algorithm

Wavelet multi-resolution analysis feature to primary signal under the different scales of multiresolution decomposition, and intertwined in different frequency of mixed signal is decomposed into the different frequency band signal, so the signal has the ability of press band processing. Details of its discrete signal amplitude with wavelet transform growth and decline of the core series. For all scales, white noise wavelet transform coefficient of discrete detail signals the contrast with the increase of scale will reduce the regularly and because the wavelet transform is a linear transformation, so the quality, and the signal wavelet coefficient is the wavelet coefficient of the signal and as noise and the wavelet coefficients; Quality, and the signal part of discrete approximation and the discrete detail part are respectively after signal transformation of the discrete approximation and discrete detail parts and noise after transform the discrete approximation and the discrete and the details. Therefore, in the process of de-noising using the signal and white noise in wavelet transform, after their respective wavelet coefficients of the different nature can eliminate or weaken the noise, in the Figure 9, we propose the revised steps for optimization.

Algorithm $[\mathbf{u}(\varepsilon), \mathbf{\Lambda}(\varepsilon)] = \textbf{S-ADWAV}[\varepsilon]$

Let $h > 0$ be a control width, M a fixed number of inner loops, $c > 0$ and $\mathrm{tol}_{\,\mathrm{iter}} > 0$ an initial tolerance.

$[\mathbf{j}_0, \mathbf{\Lambda}_{1,1}^{\mathrm{cand.}}] = \textbf{INITIALIZE}$
for $k = 1, 2, 3, \ldots$ **do**
  for $m = 1, 2, \ldots, M$ **do**
    $\mathbf{w}^{(k,m)} = \textbf{LINSOLVE}[\mathbf{\Lambda}_{k,m}^{\mathrm{cand.}}, \mathbf{u}^{(k-1,m)}, \mathrm{tol}_{\,\mathrm{iter}}]$
    $\mathbf{u}^{(k,m)} = \textbf{THRESH}[\mathbf{w}^{(k,m)}, \mathrm{tol}_{\,\mathrm{iter}}]$
    $\mathbf{\Lambda}^{(k,m)} = \mathrm{supp}\ \mathbf{u}^{(k,m)}$; $\widehat{\mathbf{\Lambda}}_{k,m} = \mathbf{C}[\mathbf{\Lambda}^{(k,m)}, c]$
    $\mathbf{r}^{(k,m)} = \textbf{RESIDUAL}[\widehat{\mathbf{\Lambda}}_{k,m}, \mathbf{u}^{(k,m)}, \mathrm{tol}_{\,\mathrm{iter}}]$
    if $\|\mathbf{r}^{(k,m)}\|_{\ell_2} \le \varepsilon \|\mathbf{f}_{\widehat{\mathbf{\Lambda}}_{k,m}}\|_{\ell_2}$ **then**
      $\mathbf{u}(\varepsilon) := \mathbf{u}^{(k,m)}$, $\mathbf{\Lambda}(\varepsilon) := \mathbf{\Lambda}^{(k,m)}$; EXIT
    end if
    $\bar{\mathbf{r}}^{(k)} = \textbf{THRESH}[\mathbf{r}^{(k,m)}, \mathrm{tol}_{\,\mathrm{iter}}]$; $\mathbf{\Lambda}_{k+1,m}^{\mathrm{cand.}} = \mathrm{supp}\ \mathbf{u}^{(k)} \cup \mathrm{supp}\ \bar{\mathbf{r}}^{(k,m)}$
    if $\left| \frac{\|\mathbf{r}^{(k,m)}\|_{\ell_2}}{\|\mathbf{P}_{\widehat{\mathbf{\Lambda}}_{k,m}} \mathbf{f}\|_{\ell_2}} - \frac{\|\mathbf{r}^{(k-1,m)}\|_{\ell_2}}{\|\mathbf{P}_{\widehat{\mathbf{\Lambda}}_{k-1,m}} \mathbf{f}\|_{\ell_2}} \right| < h$ **then**
      BREAK
    end if
  end for
  $\mathrm{tol}_{\,\mathrm{iter}} = \frac{1}{2} \mathrm{tol}_{\,\mathrm{iter}}$
end for

Figure 9. The Optimized Algorithm for Noise Removing Procedures

The selected dictionary and the processed signals are similar, you can use a dictionary in certain combinations of atoms to better signal, the sparse decomposition method and the orthogonal decomposition de-noising effect of the method are significantly better soft/hard threshold de-noising methods, but the dictionary chooses not to the sparse decomposition and the de-noising effect of the orthogonal decomposition method will drop accordingly. Therefore, only by setting the appropriate dictionary is theoretically can achieve ideal de-noising effect [25-29].

All signal de-noising effect highlights a complete dictionary of sparse decomposition method is significantly superior to complete dictionary of orthogonal decomposition de-noising performance, fully illustrates the redundant dictionary than orthogonal dictionary is more accurate and adaptive representation of the original signal, and the absolute advantage of sparse decomposition de-noising method was verified [30-34]. Independent threshold value method is according to different needs, choose different from the default threshold value, then use reconstruction algorithm for de-noising reconstruction.

By choosing different thresholds, which can be useful to signal in the high frequency part accordingly, which can improve signal recovery degree of effective information; But this method is relatively difficult to implement, because the selection of threshold direct relationship to point of signal recovery and the selection of threshold is more difficult. In practice, considering the force threshold value method and the default threshold method of equivalence, generally choose compulsory threshold method, it is to handle the general advantages of simple, easy to implement. When forced to threshold method can't meet the requirements which should be considered independent threshold value method, although difficult to implement, but on the premise of experienced, will help to deal with the noise and can obtain the better de-noising effect than the previous two methods. As can be seen from the table, the selection of threshold value directly affects the final de-noising effect, too big or too small and the threshold value is not conducive to remove noise. Based on the previous sections' discussion on the transformation, we summarize our novelty in the Figure 10 as the flowchart. Algorithm based on revised wavelet algorithm, the mechanism of random selection and the average coefficient of each iteration the residual error and the average atomic sub-block inner product as an atom matching probability and random sub-block, iterated until find nonzero sub-block, then using pseudo inverse gain a coefficient estimation, perform this process many times to get the multiple estimated coefficient, the coefficient of multiple estimated coefficient calculating mean as the final estimates that synthetic signal de-noising. The next section will simulate the proposed algorithm.

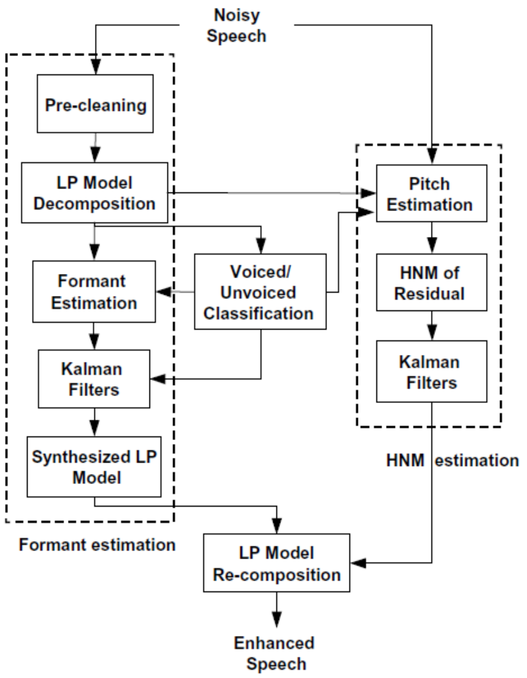

Figure 10. The Flowchart of the Proposed Methodology

5. The Experiment and Verification

To numerically simulate proposed algorithm, we conduct experiment in this section. To test the improved wavelet threshold algorithm of basic signal de-noising performance, in the Windows XP operating system on your computer using MATLAB R2012R simulation experiment and select the soft threshold de-noising algorithm and the hard threshold de-noising algorithm comparing experiment, through both of the qualitative and quantitative methods to comprehensive analysis and evaluation on the performance of all kinds of the algorithm. The parameter experiment is firstly conducted for testing.

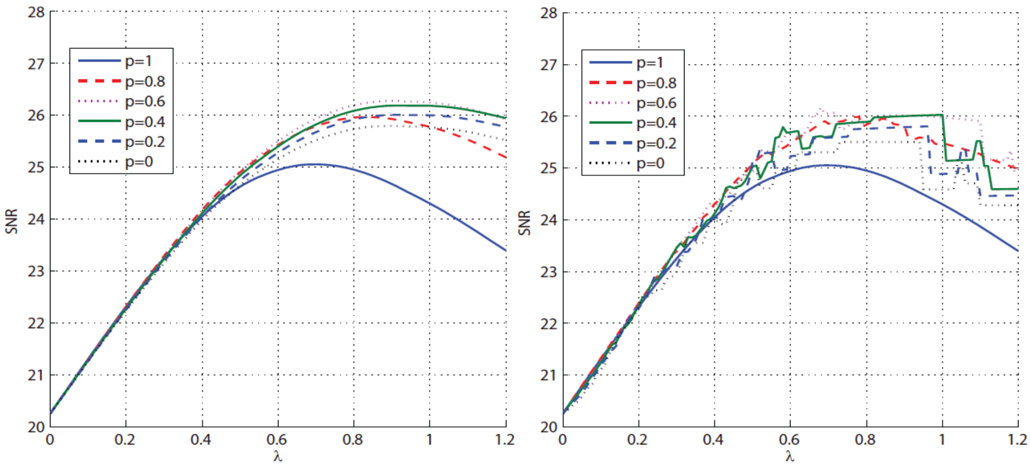

Figure 11. The Experiment on the Parameter Selection

As demonstrated in the Figure 11, the parameter selection simulation is shown. Relative to soft and hard threshold de-noising algorithm value de-noising algorithm, the improved wavelet threshold algorithm to preserve the local characteristics such as the edge of the signal, also keep the smoothness of the signal, de-noising effect is obvious improvement, can be very good to restore the original signal, a more ideal of noise reduction effect is obtained. The curved based simulation results are shown in the Figure 12.

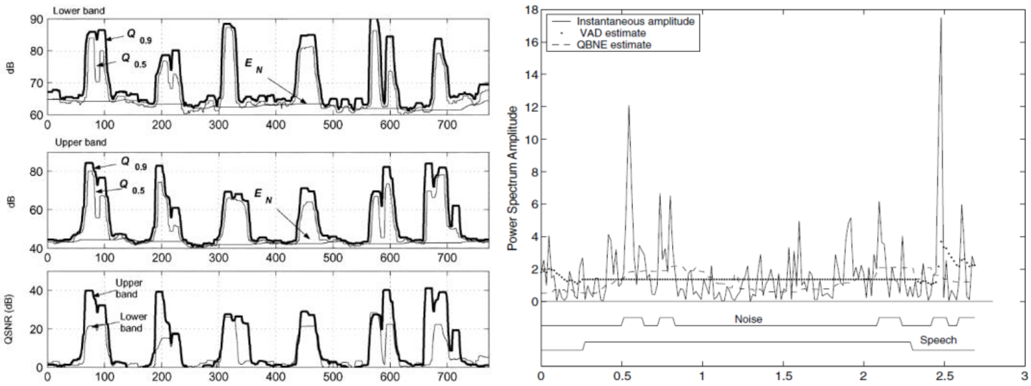

Figure 12. The Visualized Result for the Speech Signal De-noising

Experimental simulation is just a noise signal by using three kinds of algorithm of de-noising processing effect. To highlight the advantages of this algorithm, with simulation experiment in this paper, and wavelet algorithm of noise signal de-noising and compare the different recovery after de-noising signal SNR. In the following Figure 13, we show the comparison simulation result of the different algorithms. Relative to the hard threshold de-noising algorithm and soft threshold de-noising algorithm, improved wavelet threshold de-noising algorithm using the signal of the signal to the noise ratio SNR higher, smaller mean square error MSE, the experimental results show that improved wavelet threshold algorithm improves de-noising signal quality, this is largely improved threshold function of wavelet threshold algorithm integrated advantages of hard threshold and soft threshold and hard threshold function is solved continuity and defects of the soft threshold method constant deviation, through adaptive de-noising threshold settings to use and improve the reconstruction precision of the signal, the improved threshold algorithm has advantages.

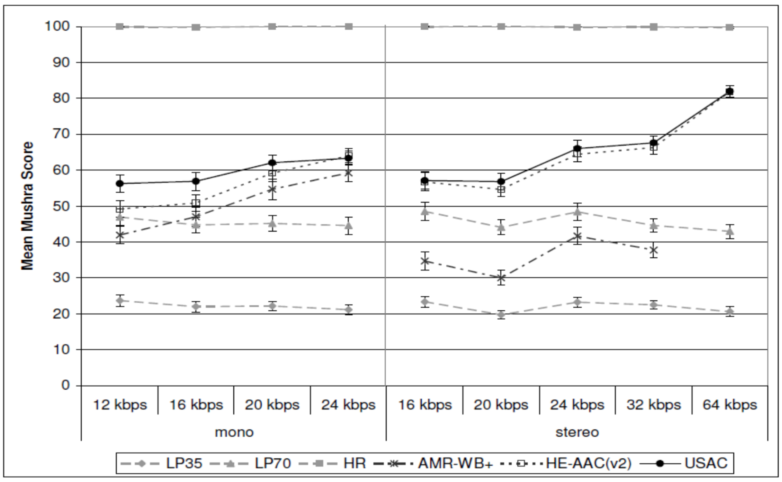

Figure 13. The Comparison Simulation on Different Algorithms

6. The Conclusion

A novel audio signal de-noising algorithm based on the theory of the frequency domain analysis and the transform domain model is proposed in this research paper. The wavelet analysis theory is a new signal processing theory, it have good in time and frequency localized: based on the analysis of low frequency signal, its time window is very big and the analysis of high frequency signal, its time window is smaller. That wavelet analysis is very suitable for when a frequency analysis, by means of the frequency characteristics of local analysis, wavelet analysis theory has become an important tool in signal de-noising processing. This paper introduces the theory of wavelet based analysis and its application in signal de-noising. At the same time introduces the three methods of noise processing: the default threshold method, forced threshold method and independent threshold value method. On the basis of the assumption of different noise conditions, the method based on wavelet decomposition and reconstruction, the noise signal de-noising processing. The experimental result reflects the effectiveness and robustness of our methodology.

Acknowledgement

This paper is supported by the Key research projects of Henan higher education: Research on the key technologies of network learning space construction based on the Hadoop cloud computing (NO. 16A520030); Henan provincial science and technology department of science and technology industrial projects: Research on optimization of the MapReduce cycle mechanism in Hadoop cloud computing (NO. 152102210357).

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