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An Analysis on Sparse based Speech Denoising Algorithms

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ABSTRACT—Speech enhancement aims to improve the speech quality and perceptual quality by using various techniques. Themost important part of speech enhancement is to enhance speech degraded by noise, and is useful for many applications. To enhance any speech input its noise components are to be removed using denoising algorithms. In this paper the dictionary learning based speech denoising is compared with other overlap group thresholding and wavelet translation-variant algorithms.Itis observed that the dictionary learning algorithm performed well when compared with other algorithms.
Keywords—Speech Denoising; Thresholding Algorithm; Sparse Representation; K-SVD Algorithm.

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I. INTRODUCTION

In numerous applications like mobile phones and speech recognition and tele-conferencing systems etc., speech enhancement plays a significant role. The speech signal quality and intelligibility are improved by using speech enhancement algorithms.Speech signals may contain noise component along with the required speech component and such components need to be suppressed using the enhancement algorithms.

The fundamental classes of speech enhancement algorithms for noise reduction are filtering based, spectral based, and model-based methods.Some of the Filtering Techniques are Spectral Subtraction Method, and Wiener Filtering. And Spectral Restoration techniques are Minimum Mean-Square-Error Spectral Amplitude Estimatorand Speech-Model-Based like vector-Taylor series-based methods [1]-[3].

The basic problem to be addressed in signal denoising is estimating the actual signal x from the noisy observation y.

$$y = x + n \quad (1)$$

Where n is additive whiteGaussiannoise.Recently, many algorithms have been developed for signal denoising. These algorithms use thresholding functions such as soft and hard thresholding and also various probability models like MAP and MMSE estimators. A general approach for thresholding function is

$$\tilde{x}* = \arg\min_x \{F(x) = (1/2)||y - x||_2^2 + \lambda R(x)\} \quad (2)$$

With penalty function defined as [4]

$$R(x) = \sum_{i\in x} \sum_{j\in J} |x(i+j)|^2 \quad (3)$$

Where x represents the signal itself and needs to be well modeled as sparse.

The main objective of this paper is to study and analyze various speech denoising algorithms recently addressed based on sparse representation of signals. The paper is organized as sections. Section II discusses sparse based denoising methods and section III describes about the implementation of algorithms with respect to section II, section IV provides the results of each algorithm and finally conclusions are given.

II. SPEECH DENOISING ALGORITHMS

In this section four denoising algorithms are discussed as below.

A. Overlapping group shrinkage/thresholding

This sectiondescribe over-lapping group shrinkage (OGS) algorithm [4],involving a group-sparsity promoting penalty functionsbased on the majorization-minimum of a costfunction that is convex. Here the approach is based on fully overlapping groups and this denoising algorithm is translation-invariant and it is observed that blocking artifacts are avoided.It is a simple iterative minimization algorithmthat monotonically reduces the cost function.

Assuminga group sparsity (clustering) property for the observed signal y, to perform translationinvariant denoising, the l2-normis added for each group to obtain the penalty function (3). The penalty function (3) is a convex andthe cost function F: C^N-> R in (2), i.e.,

$$F(x) = \frac{1}{2}||y - x||^2 + \lambda \left[\sum_{i\in x} \sum_{j\in J} |x(i+j)|^2\right]^{1/2} \quad (4)$$

The majorization-minimization method is adopted minimize the cost function.

B. **Group sparse with convex optimization**

Anon-convex regularization term is chosen such that the totalcost function is convex[5]. Therefore, in the standard convex formulationsparsity is more strongly promoted.

Albeit [6] defined the group-sparse denoising problemformulated as convex optimization problem in terms of a non-convex penalty function with parametric form. In this the cost function is monotonically reduced by using iterative algorithm.

C. **Wavelet Domain sparsity and total variation**

Thewavelet transform [6]denoted by W and the wavelet coefficients of signal x (1) as $w = Wx$. And thecoefficients indexedas $w_{j;k}$ where j and k are the scale and time indices,respectively.

In this work, the translationalinvariant wavelet transform (i.e.,undecimated), $W^TW=1$ is used and it satisfies Parseval. The total variation of x (1) is defined $TV(x):=\|Dx\|_1$ where D is the difference matrix of first order.

D. **Overcomplete Dictionary learning**

An over-complete dictionary is one in which the number of atoms is greater than thesignal dimensionality.Aprespecified or an adapting learning-based approach are used to realize this.

The prespecifieddictionaryapproach [7] the is based on a predefined mathematical function, likewavelet transform (DWT) or discrete cosine transform (DCT) etc.Dictionaries obtain from such functions are relatively easy toobtain and aresuitable for generic signals. Optimizing a dictionary is done by iterative algorithm with assumption of initial dictionary and modifiesit.

III. IMPLEMENTATION

In this section the methods discussed in section II are explained.

A. **Overlapping group shrinkage/thresholding [8]**

To minimize the cost function (2) the majorization and minimization method is used. Firstly the penalty function is majorized using the inequality statement and the elements of x are decoupled to get the modified majorize function r(i,x). The MM method produces the sequence x for which both converge producing the denoised signal. The algorithm steps are: Firstly input $y \in C^N$, $\lambda>0$,J is considered and the assigned or initialized the value to x and the iterate until the majorize function $r(i) = \sum_{j=J}\sum_{k\in J}\{|x(i-j+k)|^2\}^{1/2}$ and $x(i) = y(i)/(1+\lambda r(i))$ function converge.

B. Group sparse with convex optimization [9]

This method is derived from MM method but the penalty function is modified with prior assumptions. The cost function is defined

$$F(x) = (1/2)||y-x||_2^2 + \lambda\sum_{i\in Z}\emptyset(|x(i,k)|_2; a)\}$$

where ϕ is penalty function with a non-convex sparsity. The penalty function with respect to the value a sets the threshold towards the convergence of cost function. The algorithm steps involved in this method are: firstly the input is initializing with y and then iterate the steps until the function converges with the following equations

$$a(i) = \sum_{k=0}^{K-1}\{|x(i+j)\}^{2^{1/2}}$$

b(i)=ϕ(a(i))/a(i)

$$r(i) = \sum_{j=0}^{K-1} b(i-j)$$

$$x(i) = y(i)/(1+\lambda r(i))$$

The overlapping group thresholding with soft, absolute and atan methods.

C. **Wavelet denoising [10]**

TheWATV denoising method uses split augmented Lagrangian shrinkage algorithm and it also applies the convex way to reduce the cost function.The proposed formulation (4) requires parameters λj ,aj ,and β. Here using aj = 1/λj or slightly less (e.g.,0:95/λj) is used to maximally induce sparsity while keeping F cost function convex.

D. **Overcomplete Dictionary learning [11]**

Sparse representation is to express a given signal **y** ofn dimension as a linear combination of a small number of signalstaken from a dictionary also called the "resource" database.Elements of the dictionary are called atoms andthey are typically unit normfunctions.They are denoted as dictionary D andthe atoms as ϕ *k*, *k =1,2…, N*, where *N* is the size of the dictionary.The dictionary is overcomplete (*N >n)*when it spansthe signal space.TheK-means algorithm, called the K-SVD algorithm is used for dictionarylearning, has been proposed byAharon et al [11].

The objective function of KSVD algorithm is$\min(D,X)\{(||Y-DX|)|_F^2$ subject to ∀i, $||||xi||_2 \leq T_o$. X is the sparse matrix obtained from given D is the Dictionary and Y the signal using pursuit algorithm. Then using SVD decomposition update the dictionary and reduce the overall error and while this converges it yields a solution.

IV. RESULTS & DISCUSSION

This section discusses about the results obtained after denoising algorithms are applied on the noisy signal and the SNR of each method is also obtained.

A. **Original Signal and Noisy signal**

The plot of original signal and the noisy signal are shown in figure 1 & 2. The frequency plot and signal plot are also indicated in both the figures. The amount of noise added to the speech signal is 10dB.

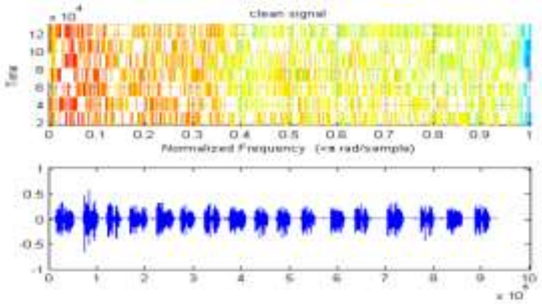


Figure -1

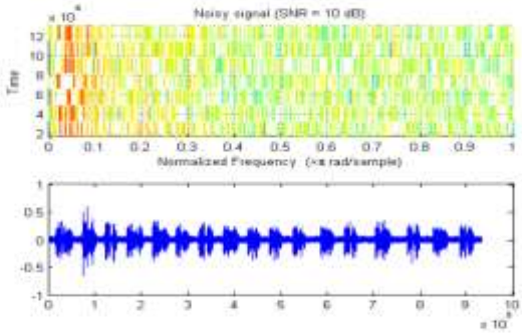


Figure -2

B. **Overlapping group shrinkage/thresholding**

The frequency plot and signal plot are of the different thresholding methods i.e. soft, block etc. are plotted in figure 3-7.

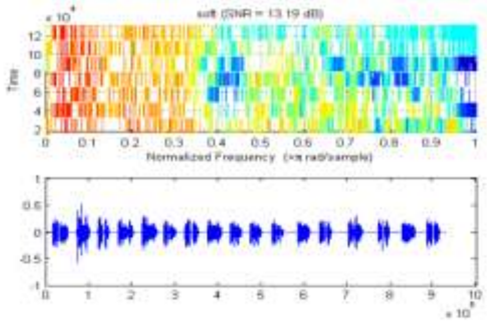


Figure -3

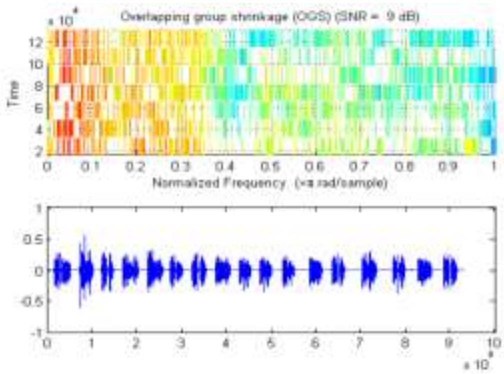


Figure -4

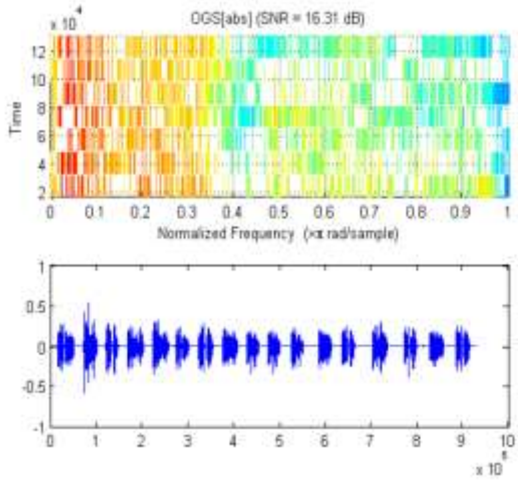


Figure -5

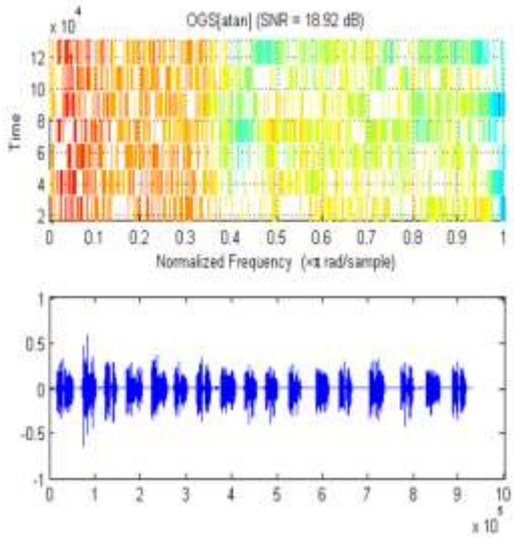


Figure -6

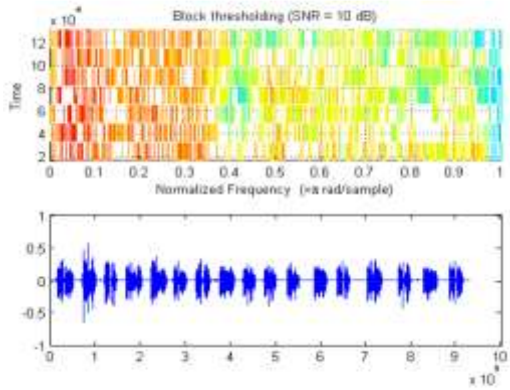
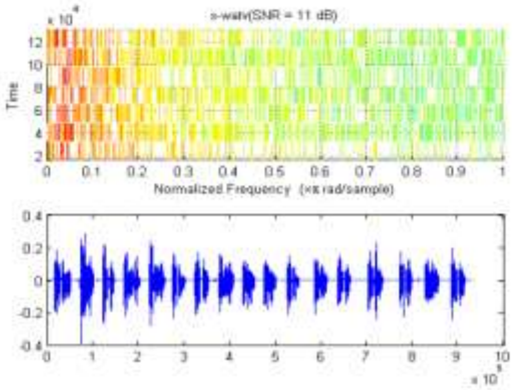


Figure-7

C. **Wavelet Translation invariant**

The frequency plot and denoised speech of wavelet translation invariant method is plotted in figure 8.



D. Sparse Dictionary learning

The frequency plot and denoised speech of dictionary learning method is plotted in figure 9.

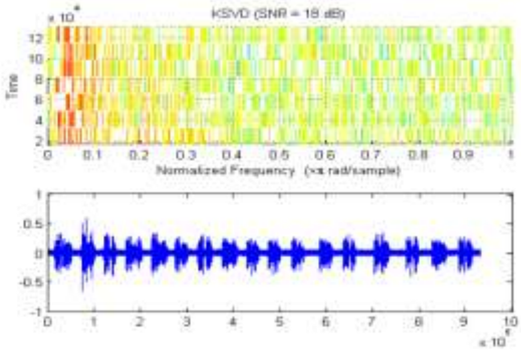


Figure-9

The SNR for each method is given in Table 1.

S. No.	Denoising Method	SNR dB
1.	Soft Thresholding	13
2.	Overlap Group Shrinkage (OGS)	9
3.	OGS absolute	16
4.	OGS atan	18
5.	Wavelet Translation variant	11
6.	KSVD	18

Table -1

V. CONCLUSION

In this paper, the problem of speech denoising is addressed by using thresholding techniques and dictionary learning algorithms. The SNR of these denoising algorithms arecompared as shown in Table 1 and it is found that the K-SVD dictionary learning algorithm is simple and an effective algorithm. The simulation results show that the performance of K-SVD algorithm is stable and has effectively separated the noise. This indicates that K-SVD is an alternative and novel method for denoising speech signal.

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