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DENOISING UNDERWATER ACOUSTIC SIGNAL BY EMPIRICAL MODE DECOMPOSITION AND DISCRETE WAVELET TRANSFORM

SRINIVASAPRABU.M[1], ARIVAZHAGAN [2]
[1.] *PG student, Cape Institute of Technology, email i.d –srinivasaprabu96@gmail.com,*
[2.] *Assistant professor, ECE Department, Cape Institute of Technology*

ABSTRACT

Noise reduction for underwater acoustic signals has attracted considerable attention over the last few decades. The wavelet soft thresholding (STH) has been considered one of the most effective noise reduction approaches, as it achieves near complete success in minimizing the mean-squarederror(MSR) and eliminating oscillations caused by noise. However, bands, which may cause distortion in high frequency bands. Few previous research effect have reported on the reduction of frequency distortions.TSF is advanced noise reduction algorithm which utilizes the signals time scale support region. It provides smooth reconstructions in both time and frequency spaces. In this paper, the noise reduction algorithm is implemented on two typical under water noise sources: the snapping shrimp sound and the rain fall sound. In addition, the denoised signal and the clean signal is also compared by using the TF distortion measurement. For a signal-to-noise ratio (SNR) from -10db to -20db, the noise reduction results obtained using TSF have an average of 42.1% distortion that STH for the snapping shrimp noise, and a 23.3% lower TF distortion for the rain fall noise.

Index terms- **Acoustic signal processing, noise, Timefrequency analysis, underwater acoustics, wavelet transforms.**

I.INTRODUCTION

Noise reduction continues to be an important aspect of underwater acoustic signal processing. A variety of methods have been investigated in the past decades,e.g., typical underwater noise sources include:ambient noise which is independent of the acoustic system(such as sound caused by wind, waves, rainfall, marine animal and human activities,etc).Self noise caused by the supporting platform of the acoustic system(such as radiated noise from ships and under water vehicles).All these noises may interfere with the expected signal and reduce the performance of underwater acoustic systems. For this noise types, self-noise caused can be reduced by carefully implementing the acoustic systems. This research addresses the reduction of underwater ambient noise. Traditionally, the noise reduction strategies are designed to minimizing the mean-squared error (MSE),such as the least-mean-square adaptive filter. Instead, the wavelet

thresholding have been designed to fulfil both the criteria, and they are among the most powerful tools for noise reduction.one of the major techniques is Donoho's soft-thresholding. which achieves near optimal performance in minimizing the MSE and provide a smooth reconstruction of denoised signals. STH has been adapted to many applications such as speech enhancement, ECG denoising and digital communication where the high frequency components are usually caused by noise. However, we have demonstrated that STH gives a preference for the lower frequency range and it's less applicable for a broadband noise. For many underwater ambient noise sources the spectrum extends from a few hertz to tens of kilohertz (such as the noise caused by snapping shrimp and rainfall).When STH is applies to signals exposed to these noise sources, the denoised signals exhibit over smoothing in the lower frequency range and significant highfrequency distortion. The effort of overly smoothed results using STH is also discussed for the application of image denoising. The noise filtering method developed in this work is an improvement of STH. The filtering is performed on the objective space of the wavelet transform,i.e.,the time-scale space ,thus its called the time-scale filter.It preserves the time and frequency patterns of the desired signal by estimating its TS support region and filtering the noisy signal throughout this region. The standard discrete wavelet transform used in STH is replaced by a frame-based wavelet analysis. The latter allows flexible choices of the translations and dilation parameters, which give higher TS resolutions then the standard DWT. Many underwater target detection and recognition systems are developed based on the joint time-frequency characteristics of the expected signals. Therefore,we also introduced a TF distortion measurement which quantifies the difference between the denoised signal and the original uncluttered signal in the joint TF space.

II.WAVELET THRESHOLDING

Let S[x] denote a discrete signal of size X.It is contaminated by on additive noise W[x].Thus the total noisy signal is expressed as *f*[x]=*s*[x]+*w*[x] For most noise reduction algorithms, the goal of denoising is to calculate an estimated Ŝ from the noise contaminated data f with a minimized MSE

$$E=\frac{1}{x}\sum_{x=0}^{x-1}(s^\wedge[x]-s[x])^2$$

Donoho pointed out that such estimator's exhibit considerable amount of noise-induced distortion such as blips and undesirable oscillations. Moreover, he introduced a smoothing criterion such the resulting Ŝ should be at least as smooth as S with a high probability. Donoho's wavelet thresholding method consists of three steps: decomposition, thresholding and reconstruction.

Given a family of wavelet functions {ψm,n}m,nεz and their corresponding scaling functions {ϕm.n}m,nεz, the wavelet

decomposition at level m can be written as

$$Am[n]=<f,\varphi_{m,n}>=\sum_{x=0}^{x-1}f[x].\,2^{-m/2}\varphi^*(x\text{-}2mn/2m)$$

Am[n] denote the mth level detail and approximation coefficients, respectively. The wavelet functions ψ(x) is implemented as a highpass filter, and the detail coefficients { Am[n]}mnεz are the results of lowpass filtering and they yield the smooth, low-frquency portion of f. To suppress the noiseintroduced terms, details coefficients are thresholded using either hard thresholding of soft thresholding, The standard hard thresholding is implemented with

$$T\delta,\text{hard }(K)=\begin{cases} K, & if\,|k|>\delta \\ 0, & if\,|k|>\delta \end{cases}$$

$$(K)=\begin{cases} sgn(k).(|k|-\delta), & if\,|k|>\delta \\ 0, & if\,|k|>\delta \end{cases}$$

and the standard soft thresholding is

Tδ,soft

STH is not suitable in reducing underwater acoustic noise,in cases where the noise spectrum does not necessarily occupy the lower frequency band to the expected signal.

III.TIME-SCALE FILTERING:

This section outlines a new noise reduction algorithm to estimate Ŝ by filtering the noisy signal through its DS support region. A frame-based wavelet analysis is applied to project the signal onto the DS space. The signal's DS support is calculated from the two dimensional envelope of the DS projection. The method of selecting on optimum threshold for the calculation of DS support is also introduced.

A. Frame-based wavelet analysis

The frame-based analysis is defined as follows

$$Wm[n]=<f,\psi m,n>$$
$$=\sum_{x=0}^{x-1}f[x].\,a_0^{-m/2}\psi^*(x-a0mb0n/a0m)$$

Where ψ(x) is the mother wavelet of the frame sequence and the constant a0 and b0 represent the dilation and translation parameter respectively. The coefficients {Wm[n]}m, n ε z correspond to the decomposition of f at time a0mb0n.Where a0-mŋ is the centre frequency of the spectrum of ψm,n. Thus the frame analysis decomposes a signal onto the two-dimensional space. B. Time-scale support region. Many underwater acoustic systems, especially the systems involving the detection and recognition of underwater objects, utilize TF characteristics of the received signals.

Therefore, preserving such characteristics is an important criterion in evaluating the noise reduction algorithms denoised for such signals.

It is of particular interest to examine the time and frequency ranges in which most of the energies are concentrated ,i.e., the Time-frequency(TF) support region. Here the defined support region is based on the frame decomposition so that the definition is consistent to the filtering technique. Note that the TS distribution provided by the frame-based wavelet analysis also yields a TF representation, where the frequency is replaced by the scale. C. Time-scale filter

We seek a filtering technique which maintain the signal's characteristics in its energy-concentrated area, i.e., the TS support region R. one of the options to implement such a filter is to reconstruct the signal directly using set of decomposition coefficients Wm[n].

To reduce the boundary oscillations, a smoothing procedure is applied on the indicator function I_R:

$\bar{I}_R(m,n)=(L_1L_2)^{-1}\sum_{p=-l1}^{l1} I_r(m+p,na_{o-p}+q)$

IV.COMPUTATIONAL RESULTS

The noise reduction performance of TSF has been tested on two types of underwater noise sources: snapping shrimp and rainfall. The noise reduction results obtained using TSF or compared with the results using STH. For a fixed input SNR, we compare the results in terms of smoothness, MSE, TF distortion and output SNRs in various frequency channels. Subsequently for a wide range of input SNRs (-10dB to 20dB), we compare the TF distortions given by the two methods.

TF distortions measures difference between TF distributions of the denoised signal Ŝ and the reference

$E_v=.\sum \; -=10\sum_{x\varepsilon=-01} |P\hat{S}(x,\xi)-Ps(x,\xi)|$

$/\sum_{xx-=01}\sum_{x\varepsilon=-01}$

$|Ps(\; , \;)|^2$

Where P denotes the TF representation defined by WVD Two types of SNRs are used in this computation: the average input SNR, and the SNRs in various frequency channels. The average input SNR is calculated using

$(\sum_{x=0}^{X-1} s[x].s*[x])^{1/2}$ ||s||=

$=20\log\frac{||s||}{||w||}$ S N

i

Since the noise sources considered here are colored, it is of practical interest to calculate the SNRs for different frequency bands. Let $h_k[x]$ denote the impulse response of bandpass filter with center frequency ξ_k,the filter output of a signal f[x] is given by

$f(\xi_k,)[x]=\sum_{p=0}^{x-1} f[p]h_k[x-p]$

calculated using

$SN_i=20\log\frac{||s||}{||w||}$

$SNR_i(\xi_k)=20\log\frac{||s(\xi k)||}{||w(\xi k)||}$

$SNR_0(\xi_k)=20\log\frac{||s(\xi k)||}{||\hat{S}(\xi k)-w(\xi k)||}$

A.Snapping Shrimp Noise

The input and output SNRs around center frequency, ξ_k

The noise caused by large aggregation of snapping shrimp is a predominate source of underwater interference. The frequency range of snapping sound extends from a few hertz to 10 kHZ with variation depending on the species and geographical regions. It can be conveniently suppressed using a high pass filter.If the acoustical system is operated at a much higher frequency range then the snapping sound. However, it is a difficult for a linear time-invariant frequency-selective filter to suppress this noise when the centre frequency of the expected signal over laps with a snapping sound. We consider a signal that is commonly used in underwater target the recognition systems such as in the signal and consists of a lowe frequency part s1 and a signal higher frequency part 2 these are generated using the following Gabor function:

$S_i[x]=10.\cos(2\pi f_i x+\pi/6). \quad ^{-\pi^2}(x-\tau_i^2)$

Where f_i represents the central frequency, τ_i denotes the centroid of the waveform,and Δ_i is the root-mean-square duration of the signals.

B.RAINFALL SOUND

Sound resulting from raindrop impact on the ocean's surface is another major underwater ambient noise source. Rainfall sound recorded slightly below the ocean surface is used as the noise source for this study. TSF calculates the support region of the noise contaminated signals and tries to preserve the signal within this region. When there's limited noise at the higher frequency range, the support region R matches with that of the reference signal, hence the result is better. However, the TSF does not give perfect reconstruction at the higher frequency region either. This is a result of a smoothing filter applied on the estimated support region. The SNRs are calculated for six frequency channels range from 0.5 to 3 kHZ. with the input SNR varying from -52.6 to 8.7 dB,the average SNR gain obtained by TSF is 11.4 dB, and for STH it is 9.1 dB.

C.DISCUSSION

Other popular noise reduction methods such as the wiener filter and matched filter are restricted in their application because they require the noise to be stationary and the autocorrelation of noise to be known a priori.

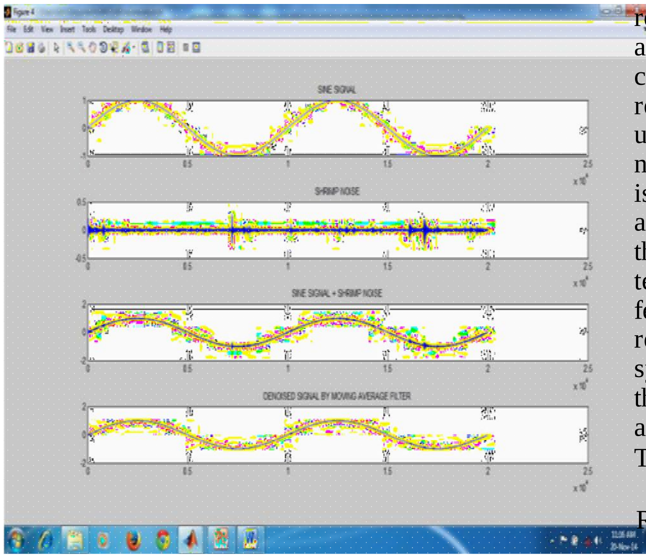

Fig 1. Noise Reduced By Moving Average

TSF has several unique advantages the expected signal from the noise in a wavelet frame-based TF space .It filters the signals through its TS support region to preserve its TF characteristics.

Moreover, it does not require a priori information regarding the noise statistics. Hence, TSF is a robust and convenient approach for cause in which the noise model is difficult to construct or the noise sources cannot be determined. TSF is to help analysing TF characteristics of active sonar signals obtained from underwater target recognition systems.

V.CONCLUSION

We have proposed a TSF specifically designed to recover narrowband acoustic signals from noisy underwater environment. The study were conducted for two underwater ambient noise souces:snapping shrimp and rainfall. TSF provided high quality reconstruction with significant improved SNR. The stochastic replay of channels recorded at sea proves to be a very useful way of designing and validating underwater acoustic communication systems. From a single measured impulse response, it is possible to independently evaluate the impact of various physical phenomena on the communication link with a good statistical significance level. It has been shown that the analysed underwater acoustic communication channels can be well modelled by trend stationary random processes. Before Denoising the signal the signal is decomposed using stochastic replay. Using stochastic replay various components such as noise, fading (small scale and large scale fading) components are separated and analyzed. After stochastic replay denoising technique is applied on equivalent underwater acoustic signal using two denoising schemes namely EMD and DWT. The technique based on EMD is totally independent of any previous basis functions, it acts according to the given data. The DWT approach though a bit multifarious but better than other classical techniques because it takes into account the sharp features of signal while decomposing as well as reconstructing the signal. The results are obtained using synthetic signals. The noise level comparison of the three signals shows the compression of noise level after application of Denoising
Technique

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