

# Wavelet denoising of Dolphin Whistle Sounds and Separation using FastICA

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Abstract: -Underwater environment contains number of sound sources with noise. The bio-acoustic sound includes marine mammal sounds which is nothing but dolphin echolocation clicks, dolphin whistles, snapping shrimp sounds which dominate ambient noise above 2MHz. Dolphin sounds have frequency up to 0.25KHz. When these bio-acoustic sounds are being recorded using hydrophones for the processing the recordings contain ambient noise with the signal having area of interest. So for clear understanding the characteristics of required signal it is necessary to separate required signal from the other sound sources. While processing these sounds the main signal having are of interest is only focused and all other sounds are treated as noise. For denoising of signals wavelet denoising is used, and to separate other sources FastICA can be used. Fast-ICA separates mixture of two signals without having any information about original signals.

Keywords- Bio-acoustic sounds, ambient noise, FastICA, Wavelet Denoising

#### I) INTRODUCTION

Bio-acoustic sounds are sounds that include sounds of different marine mammals i.e. dolphins, snapping shrimps, fish species, ambient noise.

Dolphins are the most intelligent mammals among all marine mammals. Dolphins produce two types of sounds, Whistles and echolocation clicks. In which whistles are used for the communication and echolocation clicks are used to investigate the dolphin's environment. By using echolocation clicks dolphins determine size, shape of object which comes under his environment. The frequency of echolocation clicks is about 0.2-220 KHz. The frequency of whistles is 5-15 KHz, which can peakup to 20-35 KHz.

Another underwater sound that dominates the ambient noise is snapping shrimp sound. Snapping shrimp produces sound due to rapidly closure of its snapper's claw. This rapid closure produces highvelocity water jet leading to the formation of cavitation bubble which collapses rapidly causing a loud broadband snapping sound [1].

There are total around 36 species of dolphins available in the world. From which 32are marine mammals which are those that we are most aware of and 4 of them are river dolphins. The uniqueness of the dolphin is their good sonar sense. It is the only mammal which is having developed its sonar sense. They produce ultrasonic

sound up to 200khz.where as the hearing capacity of the human ear is only 18 kHz [1-3].

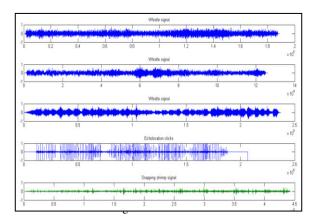
They were found in large numbers before few years but now their number has came down considerably due to various human activities like fishing, poaching, damming in Ganges and other dams sand mining and deforestation.

So there is need to understand dolphin cognition.For this the dolphin sounds affected by ambient noise are separated from mixture of other sounds.This is done by using Fast ICA.It is Independent component analysis which helps to separate mixture of unknown sources. The database of these acoustic signals in time and frequency domain is shown in fig.1.

The paper is organized as follows. Section I gives the brief introduction about bio-acoustic sound sources. Section II describes framework or algorithms that are used for separation of sources. Section III gives performance analysis of all algorithms. Andsection IV discusses results.

#### II) FRAMEWORK

The framework is divided into two parts. First is denoising and second is separation. The denoising is done by using waveletsand separation of bio-acoustic sounds is achieved by using Fast-ICA algorithm. For the processing, the database of dolphin whistles and echolocation click signals is collected from www.dosits.organd www.soundbibble.org. Signals from database consist of dolphin whistles with frequency16KHz and dolphin echolocation clicks 220KHz [4].Fig.1 shows the database of somewhistles, Echolocation clicks.



1. Wavelet Denoising



The general procedure for wavelet denoising is given in fig.2.

Ambient noise added Mixed Signal		Wavelet denoising		Denoised output Signal	Output	
Fig2. General Wavelet Denoising Procedure						

Ambient noise added signal is applied to wavelet denoising

algorithm. After that signal is denoised [5]. The steps in wavelet denoising algorithm are given in fig3.

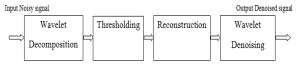


Fig3. Wavelet denoisingsteps

In that wavelet decompositionpasses signal through high pass and low pass filters and decomposes signal intohigher and lower frequency contents. Wavelet coefficients that is smaller than the thresholdvalue is removed by using thresholding.Reconstruction is used to reconstruct signal usingmodified coefficients. Finally denoising gives desired output signal [6] [7].

## 2. Independent Component Analysis

ICA is the solution for blind source separation problem. By using ICA we can separate wo mixed signals not knowing anything about source signals. The problem of extractingan audio signal from a mixture of recorded signals is often referred to as the cocktailpartyproblem [8]. Human listeners can't separate original source signals from an ensemble of signals efficiently in adverse conditions. Source separation techniques are originally developed to increase the intelligibility of each source signal [9].

Basically ICA is source separation technique and its conceptual

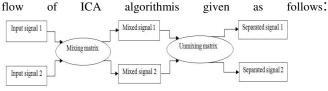


Fig.4 Conceptual flow of ICA algorithm

Consider two source signals and two observed signals for ICA estimation. Observed signals are weighted sums of the source signals emitted by two speakers. Where A ismixing matrix and W is unmixing matrix. ICA has some assumptions before signals to beseparated which are:

- 1) The independent components are assumed statistically independent.
- 2) The independent components must have non Gaussian distributions.
- 3) No. of sources equal to no. of mixtures.
- 4) For simplicity, we assume that the unknown mixing matrix A is square and invertible.

The mathematical model for ICA is given by

X = A \* S

In which X is a mixture of observed signals, A is 2x2 mixing matrix and s is source signal [10].

As measures of non-gaussianity are kurtosis and negentropy ICA is implemented using both the algorithms. The algorithm is given below

Algorithm using kurtosis

1. Center x (remove the mean from x)	2.
Whiten x (uncorrelated the components	s) 3. for
i=1 to n	W=random vector
Orthogonalize initial vector v	v in terms of the previous
components;	
Normalize w;	While (w
not converged)	
w=maximization of kurtosis of w <sup>T</sup> x	orthogonalize w in terms of
previous components; normalize w;	
end while	
W(i, :) = w;	
end for	

4. s =W \* whitenedx;

ICA estimates the linear transformation of signal that maximizes the independence of the signals. This lineartransform is referred to as the unmixingmatrix; w. since the original sources,s (t), were assumed to be independent, we know that maximizing the independence of the components of y from equation we will obtain estimates of the original sources[5-7].

## III) PERFORMANCE ANALYSIS OF ALGORITHMS

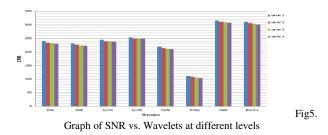
The performance analysis of above mentioned algorithms is done on the basis of parameters like Mean square error and Signal to noise ratio which are explained as below [8-10]:

## A. Performance analysis of Wavelet denoising

Performance of wavelet denoising is measured using following parameters [11-14]:

1) Signal to Noise Ratio

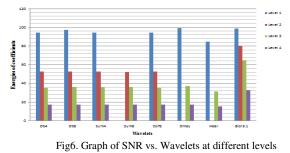
Fig.5 is the graph of SNR vs. wavelets. Wavelet decomposition is done at differentlevels and SNR is measured at each level. SNR is found to be higher at level 1 forhaarwavelet. So, by using haar wavelet for decomposition maximum SNR can obtained.



2) Energies of Wavelet Coefficients



Fig.6 is the graph of Energies if wavelet coefficients vs wavelets. Wavelet decompositionis done at different levels and energies is measured at each decompositionlevel 1. Energies are found to be higher at level



3) Correlations between Original Signal and Denoised

Signal Correlation is also an important parameter while denoising. The different wavelets are used for denoising. After denoising, correlations between original and denoised signals are measured. Fig 31 is graph of Correlations vs. wavelets. Graph shows maximum values for dmey wavelet.

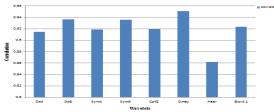


Fig7. Graph of SNR vs. Wavelets at different levels

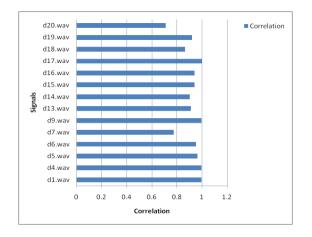


Fig8. Graph of signals vs correlations using dmey wavelet

B) Performance analysis of Fast-ICA

The performance analysis of ICA algorithms is done using 3 parameters:

Signal to Noise Ratio

It is the signal to noise ratio of original signal andestimated component before and after separation [15-20].

> MSE b.

a.

Error between original source signal and Independent component.

estimated

Kurtosis c.

It is the measure of non-gaussianity. Its non-zero value shows that signals are separated.

Parameter	Values				
	Before sep	paration	After separation		
	Source 1 w.r.to. mixture	Source 2 w.r.to. mixture	IC1 w.r.to. mixture	IC2 w.r.to. mixture	
1) SNR	-2.3925	-9.6487	1.5064	1.5463	
2) MSE	1.0000	1.0000	0.0392	0.0170	

IC1	IC2
3.4491	5.0078

Table 1. Performance analysis of ICA algorithm

## IV) RESULTS AND DISCUSSIONS

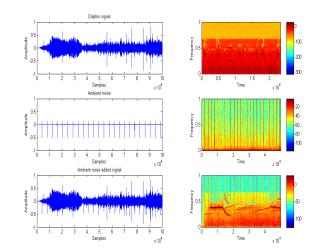


Fig.9Ambient noise added signal



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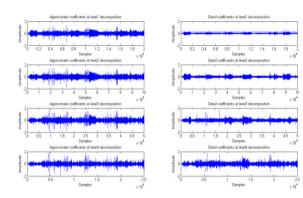


Fig10. Wavelet decomposition upto 4 levels

Levels	Correlation between approximate coefficients and noise	Correlation between detail coefficients and original signal
Level 1	-0.0067	4.8077e-004
Level 2	0.0035	-0.0010
Level 3	0.0011	4.8077e-004
Level 4	0.0019	-0.0080

 Table 2. Selection of level for reconstruction

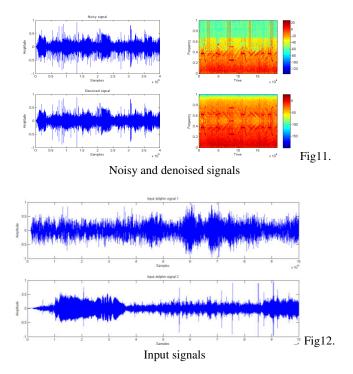
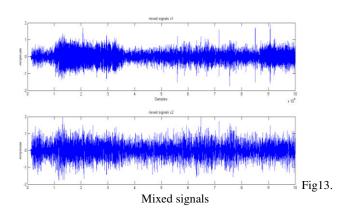


Fig.12shows the two source signals dolphin signal 1, and dolphin signal 2 given asinput to ICA.



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Fig.13 is the signals that are mixed by mixing matrix of 2x2. For the sources to bemixed the number of sources equal to number of mixtures.

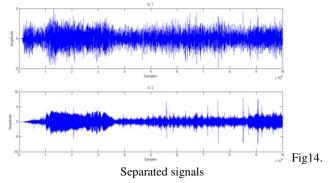


Fig 14 is the separated signals using ICA algorithm by kurtsis maximization. Afterseparation kurtosis of each ic is checked and depending on that performance of algorithm isanalysed.

## V) CONCLUCION

Wavelet denoising method improves the SNR of signal. Performance of wavelet denoisingusing Signal to Noise ratio, Energies of coefficients, Correlations between originaland denoised signal is observed good. Performance analysis on the basis of SNR haveshown that haarwavelet is suitable at decomposition level 1 for all signals. Performanceanalysis on the basis of Energies of coefficients have shown that energies of coefficientshave high value at decomposition level 1. Performance analysis on the basis of correlationsbetween original and denoised signal have shown that correlations are higher using dmey wavelets. Performance analysis using standard deviation has given haar wavelet suitable for denoising. Performance analysis usingSNR shows that SNR is improved using both the algorithms. Performance analysis usingMSE shows that error between original and separated signal is minimized. Performanceanalysis using Kurtosis shows that kurtosis is non-negative means signals got are separated.

## REFERENCES

 SankarSeramani, Taylor, P. J. Seekings, "Wavelet denoising with independent component analysis for the segmentation of dolphin whistles in anoisy underwater environment", IEEE Journal 2006.



ISSN: 2582-3930

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- [2] G.LathaS.Ramji, "Identification and Analysis of Dolphin Signatures from Ocean Ambient Noise Measurements, IEEE journal of oceanic engineering, vol. 31, no. 2, april 2006.
- [3] AsithaMallawaarachchi "Spectrogram denoising for the automated extraction of dolphin whistle contours", M.S. thesis, National University of singapore, September 2007.
- [4] Discovery of the Sound in the Sea website. [Online]. Available:http://www.dosits.org.
- [5] Ramesh D, Ranjani G, "Wavelet based denoising technique for underwater signal affected by wind driven ambient noise", IJECET ,Volume 5, Issue 4, April(2014), pp.57-64.
- [6] Slavy G. Mihov, Ratcho M. Ivanov, Angel N. Popov "Denoising Speech Signals by Wavelet Transform", Annual journal of electronics, 2009, ISSN 1313-1842
- [7] B. C. B Naik, B. Anuradha, "Speech signal denoising using different wavelet techniques", Journal of International academic research for multidisciplinary, ISSN: 2320-5083, Volume 2, Issue 2, March 2014.
- [8] N.Tripathi, Dr. A Kumar Sharma, "Efficient algorithm based on blind source separation Independent component analysis using MATLAB", IJECET, Volume 4, Issue 6, November-December, 2013, pp. 14-20.
- [9] James P. Leblanc Phillip L. De Leion, "Speech separation by kurtosis maximization", Acoustics, Speech and Signal Processing, 1998, Volume 6, May 12-15, 1998.
- [10] L. Hongyan, R. "Blind separation of noisy mixed speech signals based Independent Component Analysis", First International Conference on Pervasive Computing, Signal Processing and Applications, 2010.
- [11] R. J. E. Merry, "Wavelet Theory and Applications- A literature study", by Eindhoven University of Technology, Department of Mechanical Engineering Control Systems Technology Group, Eindhoven, June 7, 2005.
- [12] Abdul J. Jerri, Introduction to Wavelets, A Handbook
- [13] A. K. Verma, N. Verma "A Comparative Performance Analysis of Wavelets in Denoising of Speech Signals", National Conference on Advancement of Technologies Information Systems Computer Networks (ISCON 2012)J. Acoust. Soc. Am. vol. 34, no. 12, pp. 1936-1956, 1962.
- [14] R. Kumar, P. Patel, "Signal Denoising with Interval Dependent Thresholding Using DWT and SWT" International Journal of Innovative Technology and Exploring Engineering (IJITEE) ISSN: 2278-3075, Volume-I, Issue-6, November 2012.
- [15] K. Mohanaprasad, P. Arulmozhivarman "Comparison of Fast ICA and Gradient Algorithms of Independent Component Analysis for Separation of Speech Signals", International Journal of Engineering and Technology (IJET), ISSN: 0975-4024 Vol 5 No 4 Aug-Sep 2013.
- [16] AapoHyvarinen, JuhaKarhunen, and ErkkiOja, Independent Component Analysis, Handbook 3rd Edition.
- [17] E. Bingham, AapoHyvarinen, "A fast fixed-point algorithm for Independent Component Analysis of complex valued signals", International Journal of Neural Systems, Vol. 10, No. 1 (February, 2000).
- [18] Hyvarinen, E. Oja, "Independent component analysis: algorithms and applications, Neural Networks 13 (2000) 411430.
- [19] Jutten and J. Herault, "Independent component analysis versus principal components analysis" Signal Processing IV, Theories and Applications (EUSIPCO88), pp.643,646 Grenoble, France, Sept. 1988
- [20] Grellier and P. Comon, "Performance of discrete source separation, EUSIPCO96, pp.20612064, Rhodes, Greece, Sept. 1998.