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Haar Wavelet Method to Spectral Analysis Continuous Wavelet Transform 1D Using Whistle Sound to Position of Dolphins (Tursiops aduncus)

Lubis MZ*, Pujiyati S, Hestirianoto T and Wulandari PD

[1]Department of Marine Science and Technology, Bogor Agricultural University Jln. Agatis, Indonesia

Abstract

In wavelet method have a wavelet transform is a signal processing technique was developed as a method to obtain simultaneous, have high resolution frequency and time. Mother wavelet have one method with namely haar wavelet, haar wavelet had become an effective tool for solving many problems arising in many branches of sciences. Haar wavelet functions have been used since year at 1910. It was introduced by the Hungarian mathematician Alfred Haar. This article discuss about signal processing with haar wavelet (continuous wavelet transform) using whistle sound and position of dolphins. Results of modulus of Ca, b Coefficients-Coloration init mode + scale, demonstrating the maximum yield that is in the frequency of 4.1 kHz-5.9 kHz with the brightest colors, and need for the process of de-noising 1D to a level that is more, such as level 10. In this article indicates a change in position dolphins to signal that it generates, and proved this by using the haar wavelet analysis on a dependent threshold level. haar wavelet analysis on a dependent threshold level. Retained energy is 65, 87%-zeros 87, 01% in original and compressed signal with haar wavelet using dolphins whistle sound, Equations or methods used in this article is very effective to remove noise from whistle sound of dolphins.

Introduction

Wavelet transform (WT) is a signal processing technique was developed as a method to obtain simultaneous, have high resolution frequency and time, Wavelet Transform (WT) too for image processing and compressing from the Fourier transform (FT) and has been widely used to signal processing application [1]. The WT presents an improvement over the STFT and possesses multidimensional characters and are able to adjust their scale to the nature of a signal features [2]. Singularities and irregular structures in signal waveform often carry important information from an informatics-theoretic point of view. Wavelet Transform (WT) is Analyzes provides a kind of mathematical functions in zoom out or zoom in, on those interesting structures of sound and image [3]. Wavelets can be are able to capture deterministic features and orthonormal. Therefore, WT can decompose a signal into translation parameters and localized contributions labeled by so-called dilation. These parameters represent the information of different frequency component contained in the analyzed signals [4]. Wavelet transform or wavelet analysis is a recently developed mathematical tool for many problems. One of the popular families of wavelet is Haar wavelets. Haar wavelet function in fact the Daubechies wavelet of order 1. Due to its simplicity, the Haar wavelet had become an effective tool for solving many problems arising in many branches of sciences. Haar wavelet functions have been used since year at 1910. It was introduced by the Hungarian mathematician Alfred Haar [5].

A short introduction to the continuous wavelet transform (CWT) is presented next. For more details on this subject, interested in these topics, readers can consult in Lange et al. [6] or other texts. In order to build a robust pattern matching method, we also applied the CWT in MS peak detection. In contrast to the algorithm proposed by Mallat [7] we directly apply the CWT over the raw spectrum and utilize the information over the 1D CWT coefficients matrixes, which provide additional information on how the CWT coefficients change over scales.

Dolphins family in mammals have good hearing of sensitivity. It is caused by a network system senses of hearing has been well. Dolphins can be hearing of click sounds with frequencies range 1-150 kHz [8,9]. Previous research by looking at a whistle sound vocalizations of dolphins and a clicking sound is [10-12]. Vocalizations research about *stidulatory* ever done with object *Guppy* fish in [13-16]. In this article discuss about haar wavelet method to spectral analysis continuous wavelet transform 1D using whistle sound and position dolphins (*Tursiops aduncus)*, dolphins measured in captive of safari park, Cisarua, Indonesia. Data analysis in this research with MATLAB R2011a software with haar wavelet method in signal processing using MATLAB R2011.

Wavelet Method

In mathematically, the process of Fourier analysis is represented by the *Fourier transform*:

$$F(\omega) = \int_{-\infty}^{\infty} f(t) e^{-j\omega t} dt \qquad (1)$$

Which is the sum over all time of the signal f(t) multiplied by a complex exponential. (Recall that a complex exponential can be broken down into real and imaginary sinusoidal components.).

The results of the transform are the Fourier coefficients F(ω̇), which when multiplied by a sinusoid of frequency yield the constituent sinusoidal components of the original signal. Graphically, the process of Fourier transform can be seen in Figure 1.

*Corresponding author: Lubis MZ, Department of Marine Science and Technology, Bogor Agricultural University Jln. Agatis, Kampus IPB, Dramaga Bogor, 16680 Indonesia, Tel: +622518622642; E-mail: lubiszainuddin@gmail.com
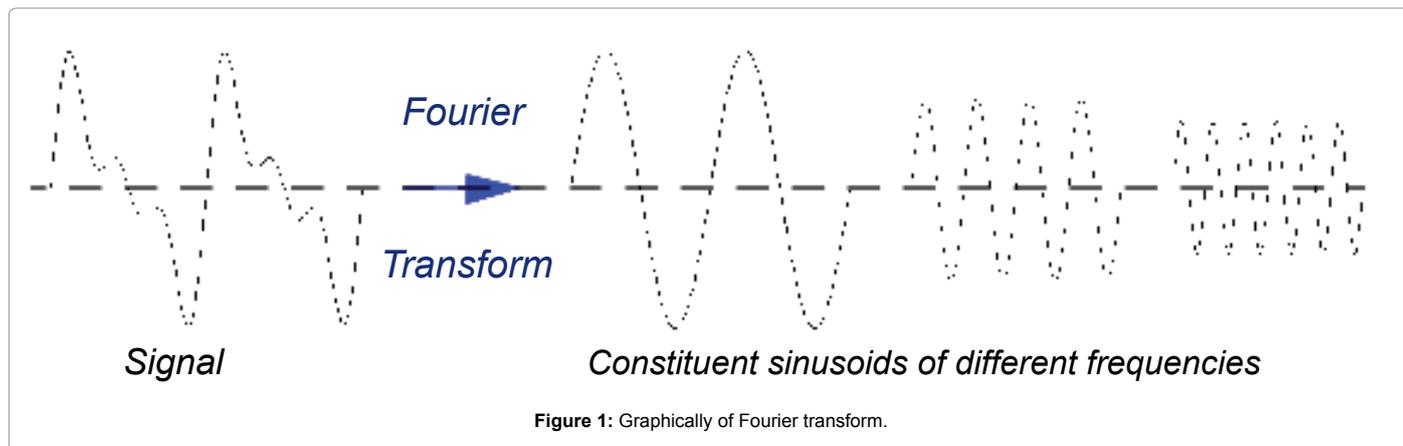
Figure 1: Graphically of Fourier transform.

Similarly, the Continuous Wavelet Transform (CWT) is defined as the sum over all time of the signal multiplied by scaled, shifted versions of the wavelet function ψ:

$$C\left(scale, position\right) = \int_{-\infty}^{\infty} f\left(t\right)\psi\left(scale, position, t\right) dt \qquad (2)$$

The results of the Continuous Wavelet Transform (CWT) are many wavelet coefficients C, which are a function of scale and position. Multiplying each coefficient by the appropriately scaled and shifted wavelet yields the constituent wavelets of the original signal. Graphically, the process of Continuous Wavelet Transform (CWT) can be seen in Figure 2.

Notation

Considers n locations in chromosome at which the relative copy number is measured by the log2-ratios of fluorescence intensities between in tumor and reference samples. A log2-ratio of 0 for a location means no aberration is observed at this locus whereas a positive in negative value indicates a possible gain in loss at the locus. Denote by $Y(Xi)$ observed copy of number make changes at the i-th genomic location Xi for $i = 1, . . . , n$. In the additive measurement error model is postulated for relating the true latent signal $f(Xi)$ and the observed copy number change $Y(Xi)$. This method model can be expressed as:

$$Y\left(Xi\right) = f\left(Xi\right) + \in i, \qquad (3)$$

where function of {∈i, $i = 1, . . . , n$ } are identically distributed and independent $N(0, \sigma 2)$ and σ is standard deviation (SD). In what follows, we will describe the wavelet analysis and various thresholding methods for denoising the data.

Wavelet Analysis

Wavelets method is provide a popular tool for the nonparametric of regression analysis and for this a variant of wavelet families are used, the choice being dependent on the particular of application. Modified of Simplest wavelet family method is generated by the Haar function is [17] (Figures 3a and 3b).

$$ø\left(u\right) = \begin{cases} -\dfrac{1}{\sqrt{2}} & -1, u \le 0, \\ \dfrac{1}{\sqrt{2}} & 0 < u \le 0, \\ 0 & otherwise \end{cases}$$
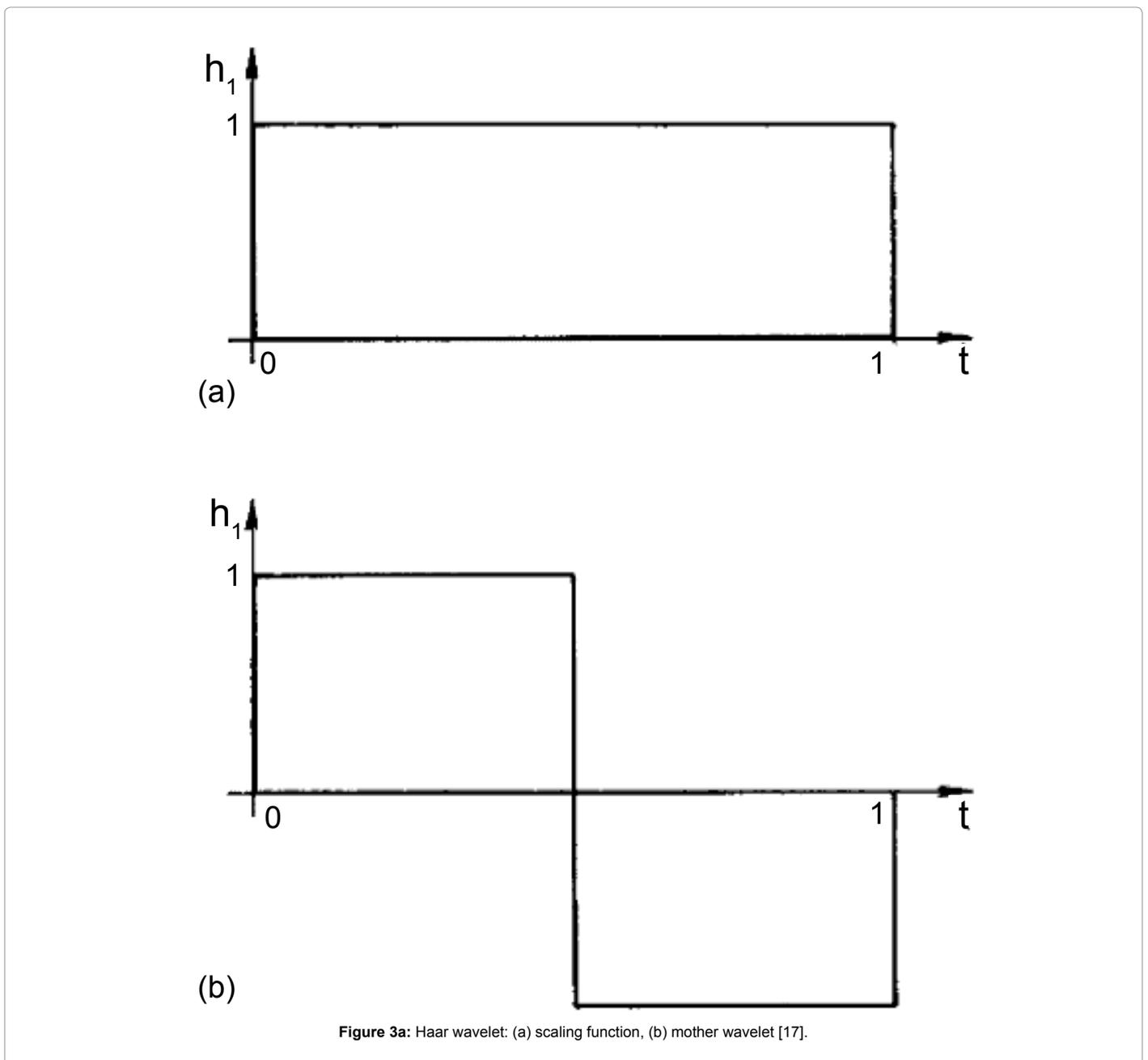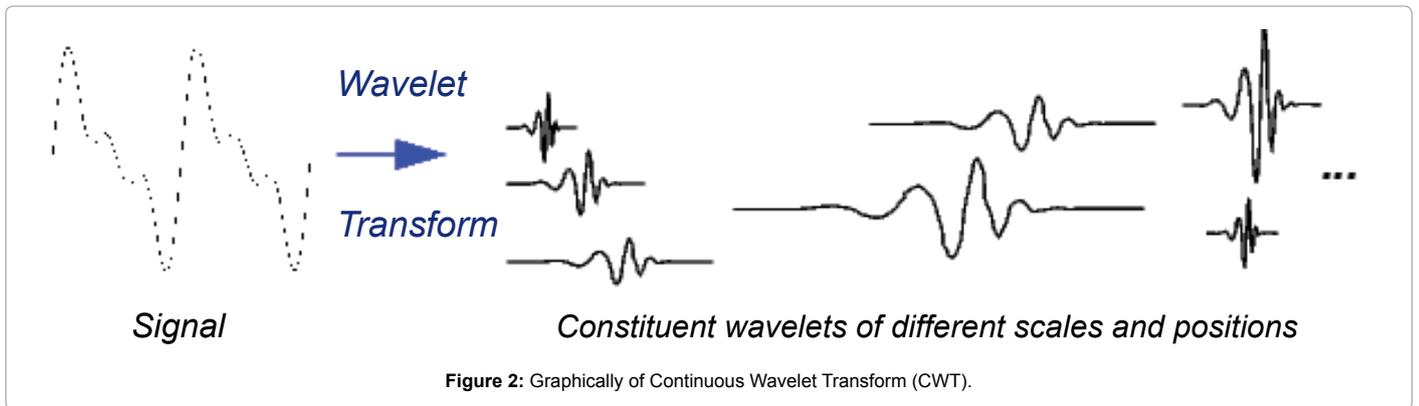
Haar wavelet family for $t \in [0, 1]$ is defined:

$$h_i\left(t\right) = \begin{cases} 1 \quad for & t \in \left[\dfrac{k}{m}, \dfrac{k+0.5}{m}\right) \\ 1 \quad for & t \in \left[\dfrac{k}{m}, \dfrac{k+0.5}{m}\right), \dfrac{k+1}{m} \\ 0 elsewhere \end{cases} \qquad (4)$$
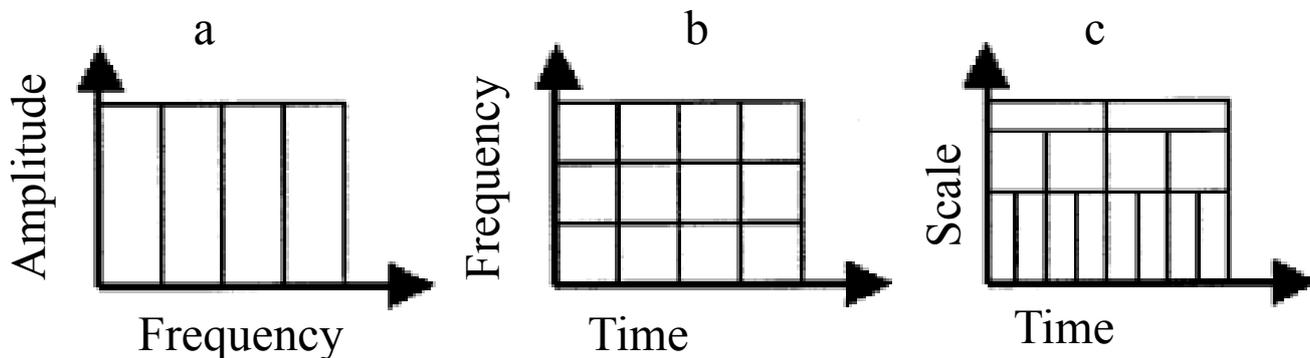
Result and Discussion

In signal processing, haar wavelets are used for instance for edges detection, watermarking, texture detection, compression, denoising, and coding of interesting features for subsequent classification [18,19]. Signal denoising by thresholding of the Continuous wavelet transform (CWT) coefficients is discussed in the following subsections. Decomposition in continuous wavelet transform with the basic functions of compact support roughly matched to neural scale transients, the temporal contiguity in the wavelet domain is inherently preserved. The scale contiguity follows from a broad frequency whistle sound spread of a time-limited signal of whistle sound, namely if a scale is thought of as an approximation of the frequency, a time-limited transient will be spread across many scales.
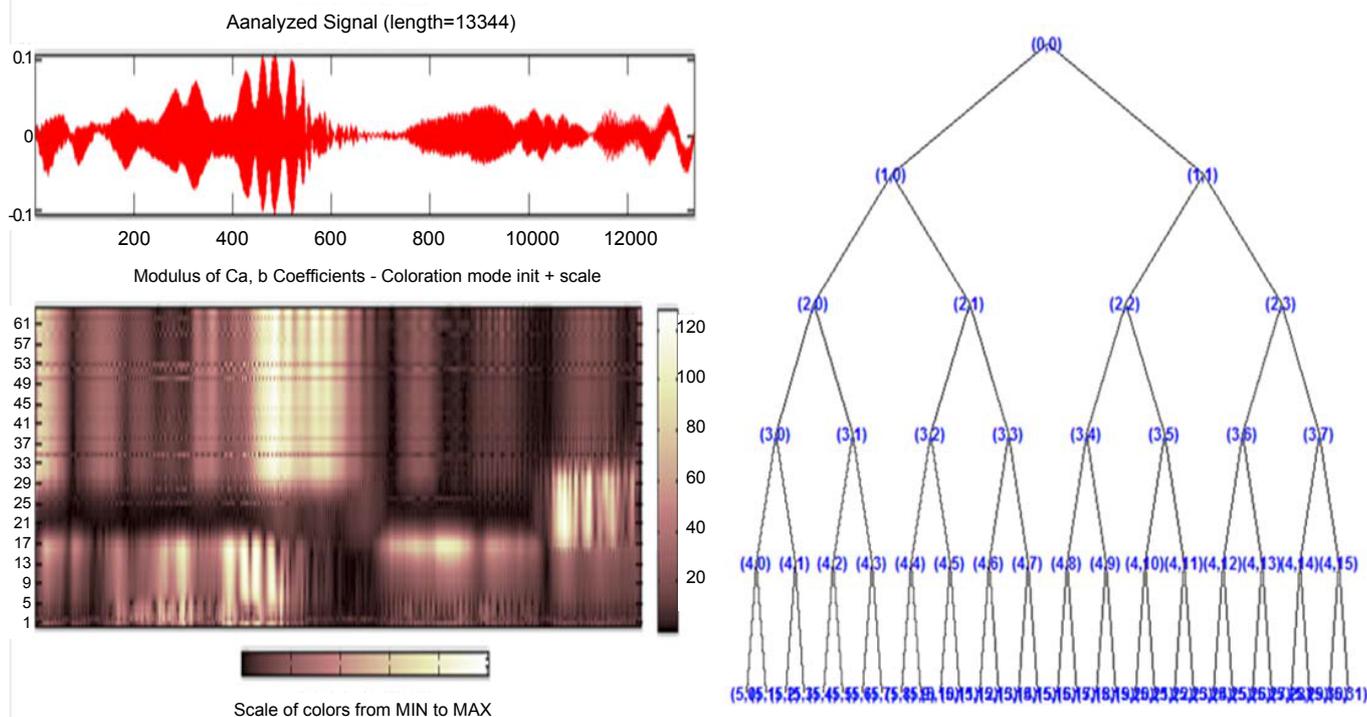
Analyze signal and decomposition Tree of whistle sound in level 5 using whistle sound can be seen in Figure 4 with spectral color is red. There are the results of modulus of Ca, b Coefficients-Coloration in it mode + scale, demonstrating the maximum yield that is in the frequency of 4.1 kHz-5.9 kHz with the brightest colors are shown in Figure 4, while the decomposition Tree of whistle sound in level 1-5 exposed in Figure 4, and Continuous wavelet transform De-Noising 1D level 5 with haar wavelet of whistle sound in Figure 5. Figure 5 shows a peak identification process using whistle sound. In order to provide a better visual image, we performed the CWT at 32 scale levels (from 1 to 50 at an interval of 2) directly over in raw MS spectrum. A segment of the computed 1D CWT coefficients are shown in Figure 5.

On the results of Continuous wavelet transform denoising 1D level 5 (Figure 5) with Haar wavelet of whistle sound is seen that there is no difference and magnitude pattern noise spectrum whistle performed up to level 4 using the Haar wavelet, but at level 5 results shown distant and very different with the result 1-4 level, de-noised signal (D5) (Figure 5) showed in spectral color is green, produces the largest signal that is worth 0.02 kU at a frequency of 12.5 kHz, and a frequency range of very little noise is at 3 kHz 9 kHz. This show is still need for the process of de-noising 1D to a level that is

Figure 2: Graphically of Continuous Wavelet Transform (CWT).

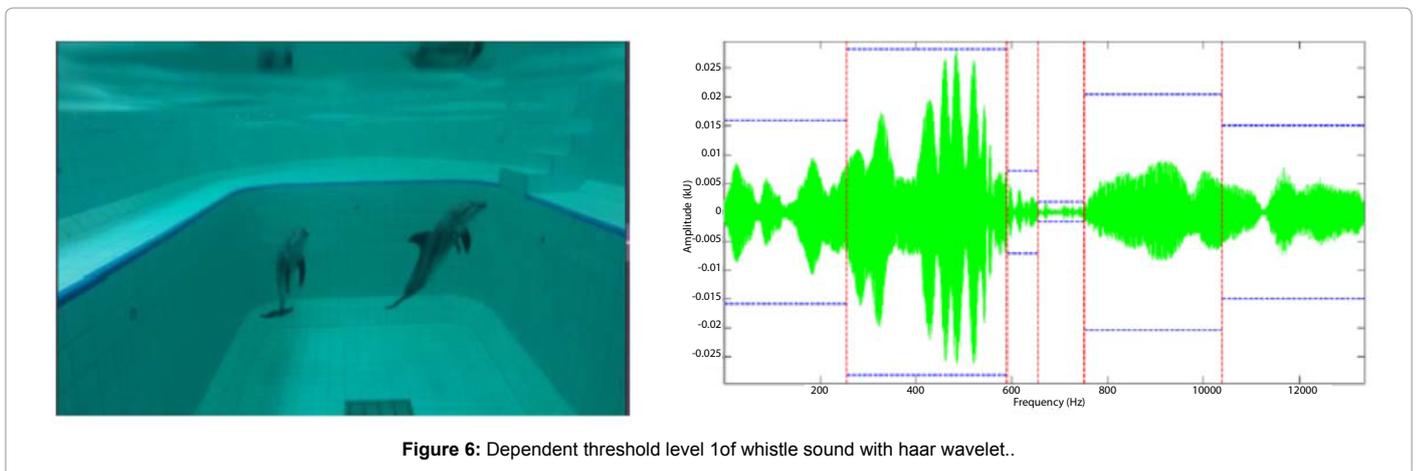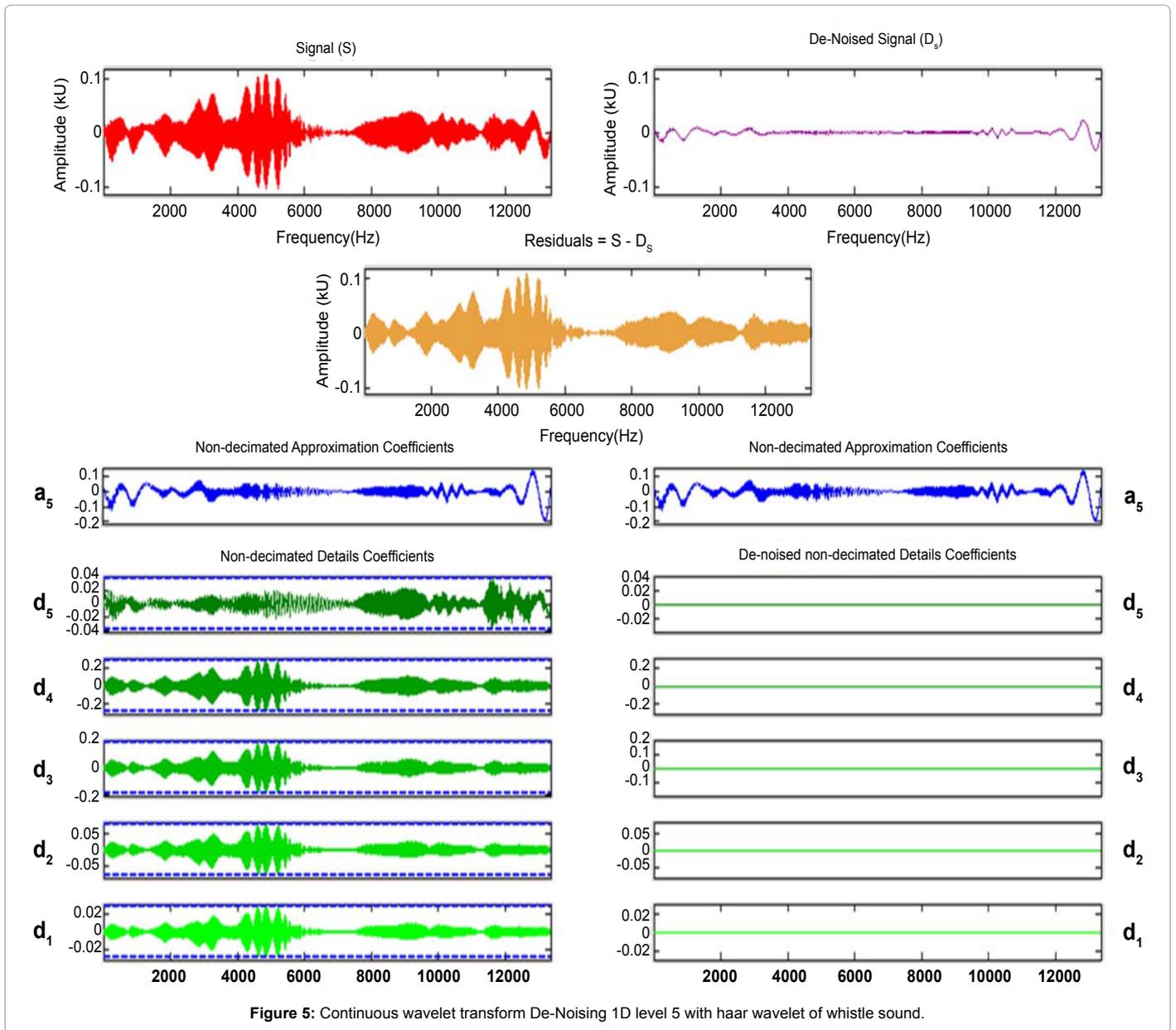Figure 3a: Haar wavelet: (a) scaling function, (b) mother wavelet [17].

Figure 3b: Signal comparison represented in different domains with (a) Corresponding to the Fourier transform representation, (b) representing the short of Fourier transform, and (c) result of wavelet transform.

Figure 4: Signal processing with haar wavelet in (a) Analyse signal and (b) decomposition Tree of whistle sound in level 5.

more, such as level 10 or by improving the quality of wavelets to 3D as it had done [20]. Residuals S-Ds Results showed very different results with the original signal, it is similar to the results of non-decimated coefficients details vary much with the results of De-noised-decimated details coefficients. De-noised results-decimated details coefficients will eliminate noise contained in level 1-5 (Figure 5). Equations or methods used in this article is very effective to remove noise from sound like the previous studies in Messer et al., Yunhui and Tang et al. [21-23], but the method in this article not same. CWT 1D in (Figure 5) had a very different outcome by the method of discrete wavelet transform (DWT 1D) in Coombes et al. [24], it is proved that any differences in the method will produce a different picture though both using Haar wavelet. Dependent threshold level can be seen in Figures 6-10.

Modifying the equation , object analysis and the wavelet method will inevitably result in continuous wavelet denoising and different, it is unclear if the results of this study compared with previous studies in Du et al., Dubnov et al., Babaei and Nenadic [25-28]. Position dolphins have a difference to the threshold level Dependent with Haar wavelet. At level 1 and 4 dolphins are more likely to be at the bottom of the pool shown in Figures 6 and 9, while the level of 2, 3, 5 dolphins are more likely to be on the surface of pool (7, 8, 10), and it indicates a change in position dolphins to signal that it generates, and proved this by using the haar wavelet analysis on a dependent threshold level. Retained energy is 65.87%-zeros 87.01% in original and compressed signal with haar wavelet using dolphins whistle sound, the method haar wavelet noise successfully lost and this can be seen in (Figure 11).
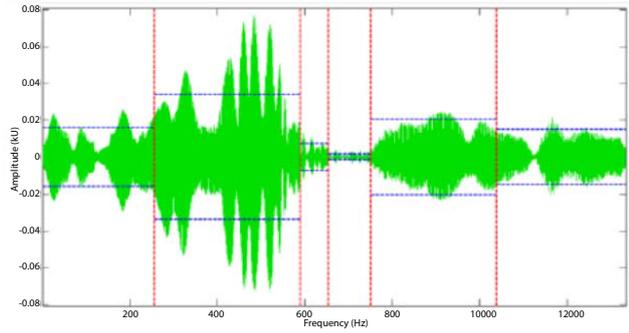
Figure 5: Continuous wavelet transform De-Noising 1D level 5 with haar wavelet of whistle sound.

Figure 6: Dependent threshold level 1of whistle sound with haar wavelet..

Figure 7: Dependent threshold level 2 of whistle sound with haar wavelet.
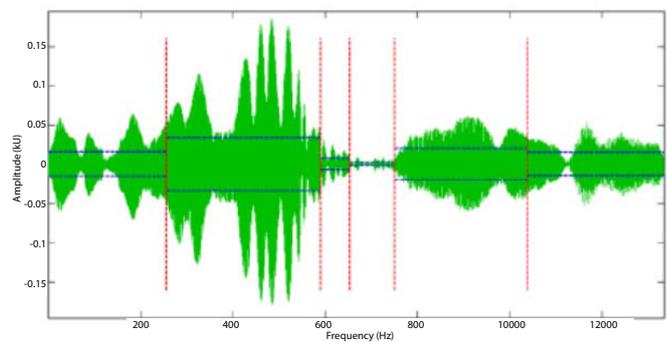

Figure 8: Dependent threshold level 3 of whistle sound with haar wavelet.
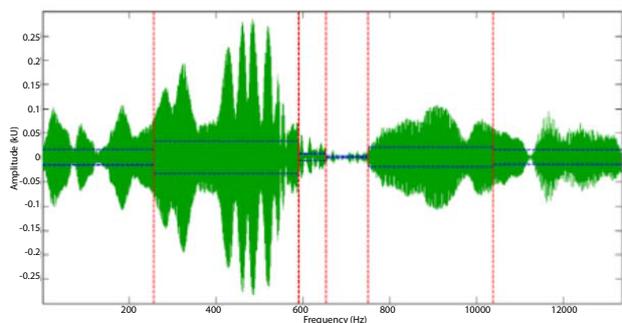

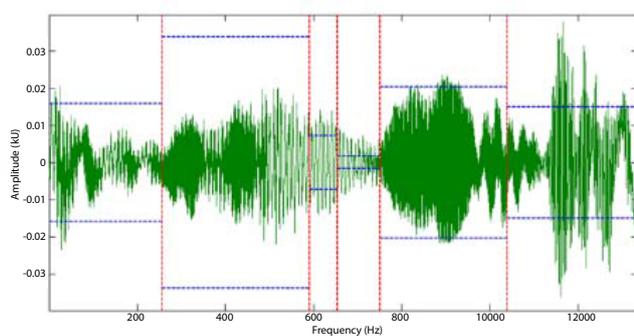**Figure 9:** Dependent threshold level 4 of whistle sound with haar wavelet.

Figure 10: Dependent threshold level 5 of whistle sound with haar wavelet.
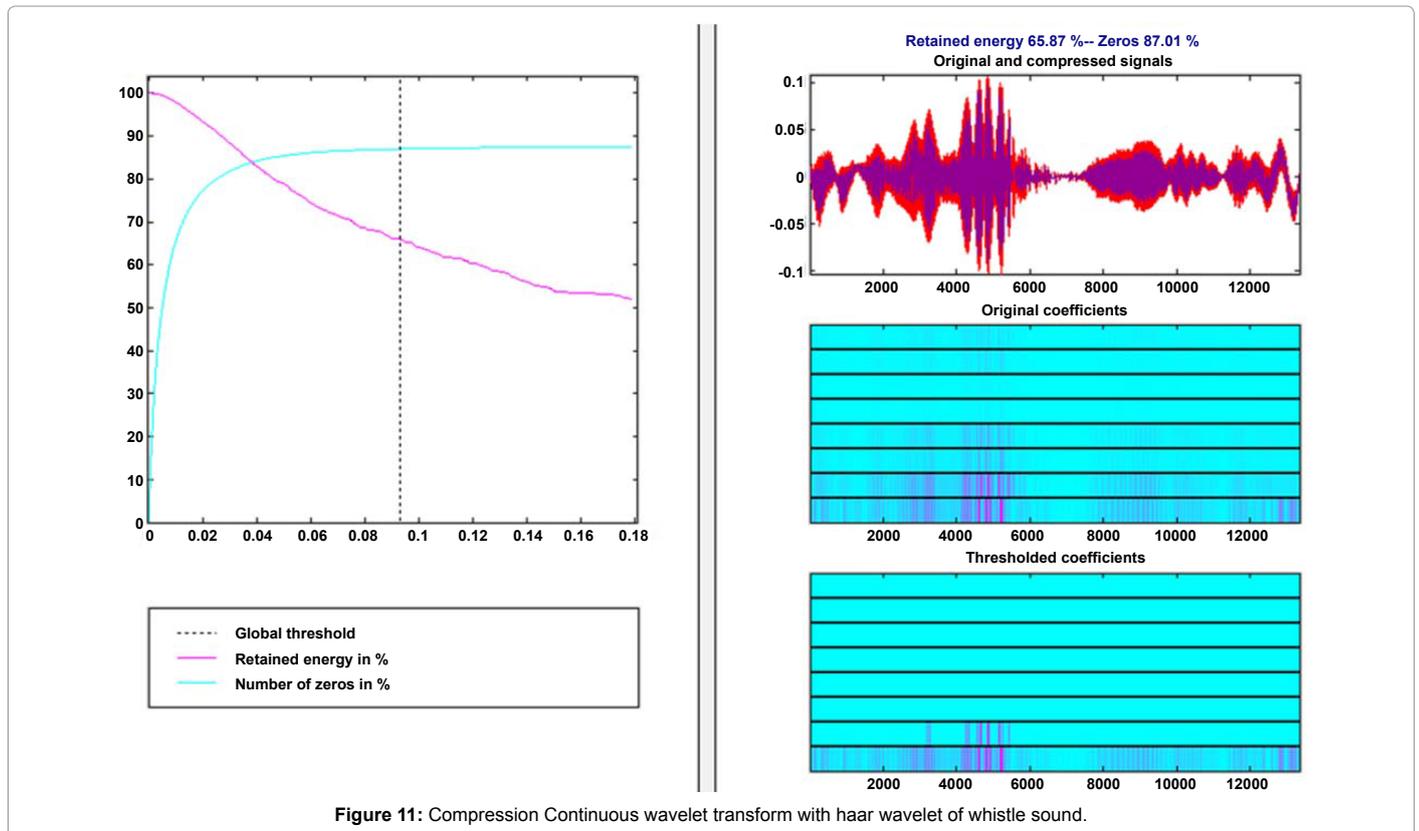
Figure 11: Compression Continuous wavelet transform with haar wavelet of whistle sound.

Conclusion

We have demonstrated in wavelet denoising techniques and removing noise from whistle sound of dolphins. Using haar wavelet method can be produce wavelet denoising in continuous Wavelet Transform (CWT), Analyze signal, decomposition Tree of whistle sound in level 5, and influence the position of the dependent threshold, but this result need for the process of de-noising 1D to a level that is more.

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