Denoising Poultry Bird Sound Using Daubiche And Symlet Wavelet

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Abstract- *This paper is DWPT based adaptive block algorithm with modified threshold for denoising the sounds of poultry birds is proposed. Wavelets have been widely applied in signal processing, sampling, coding and communications, filter bank theory, system modelling etc. The discrete wavelet packet transform provides more coefficients than the conventional discrete wavelet transform (DWT), representing additional subtle detail of the signal but decision of optimal decomposition level is very important. As the four domestic female chickens were determined from 2 Hz to 9 kHz using the method of conditioned suppression/avoidance. At a level of 60 dB sound pressure level (re 20 μN/m(2)), their hearing range extends from 9.1 Hz to 7.2 kHz, with a best sensitivity of 2.6 dB at 2 kHz. Chickens have better sensitivity than humans for frequencies below 64 Hz .When the sound signal corrupted with additive white Gaussian noise is passed through this algorithm, the obtained peak signal to noise ratio (PSNR) depends upon the level of decomposition along with shape of the wavelet. Hence, the optimal wavelet and level of decomposition may be different for each signal. The obtained denoised signal with this algorithm is close to the original signal.*

Keywords- Audio denoising, block thresholding, DWPT, MSE ,PSNR, , thresholding.

I. INTRODUCTION

In the area of speech processing there are a lot of techniques that manipulate the signal in order to enhance the quality of the signal, to identify patterns, to classify sounds, to compress the signal or to change the some features of the voice. Pre-processing of the speech signal is vitally important for recognition. In order to compare the recognition performance with and without duration modelling, one needs a baseline recogniser. It is important then that the pre-processing part of the baseline recogniser is optimised. Audio signals are often disturbed by background noise and buzzing or humming noise from manmade equipments. Audio denoising aims at removal of the noise while restoring the underlying signals. such as music and speech denoising applications are numerous. Diagonal time-frequency audio denoising algorithms attenuate the noise by processing each window Fourier or wavelet coefficient independently, with empirical Wiener [2], power subtraction [3], [4], [5], or thresholding operators [6]. These algorithms create isolated time-frequency structures that are perceived as a “musical noise” [7], [8]. Ephraim and Malah [9], [10] showed that this musical noise is strongly attenuated with nondiagonal time-frequency estimators that regularize the estimation by recursively aggregating time-frequency coefficients. However, these parameters should be adjusted to the nature of the audio signal, which often varies and is unknown. The main step in the adaptation process is the relocation of the wavelet coefficients of the Poultry Birds signals so that they resemble the behaviour of the wavelet coefficients of the target Poultry Birds signal. It is feasible because the distribution of the wavelet coefficients of the Poultry Birds can be similar to the distribution of the wavelet coefficients of the Types of Poultry Birds signal even if the signals have different behaviour. To obtain an adapted-speech signal similar to the target speech signal (the purpose of the adaptation process) it is necessary to satisfy the requirements of adaptation. According to the previous study, it was found that the adaptation is feasible if and only if both signals have the same sampling frequency, time-scale and similar size of the non-silent time (or in other words, similar size of the non-zero wavelet coefficients). The two important types of thresholding, hard and soft have been used to denoise the signal. In hard thresholding the wavelet coefficients below the given threshold are set to zero but in soft thresholding the wavelet coefficients are reduced by a quantity equal to the threshold value The extension of discrete wavelet transform is discrete wavelet packet transform in which we split both low pass and high pass filters at all scales in filter bank implementation to obtain flexible and detail analysis transform for denoising the sound signals [11]. In [12], wavelet packet approach which deals with heterogeneous noise for pre-processing of mass spectrometry data is discussed which incorporate a variance change point detection method in thresholding. Wavelet packet method has been used to reduce the Additive White Gaussian Noise from the speech signal which shows significant SNR improvement [13]. The pure-tone thresholds of four domestic female chickens were determined from 2 Hz to 9 kHz using the method of conditioned suppression/avoidance. At a level of 60 dB sound pressure level (re 20 μN/m(2)), their hearing range extends from 9.1 Hz to 7.2 kHz, with a best sensitivity of 2.6 dB at 2 kHz. Chickens have better sensitivity than humans for frequencies below 64 Hz[27].The rest of the article is organized as follows: In Section II, brief theory of discrete wavelet packet transform (DWPT) is given. Wavelet packet adaptive block denoising scheme is discussed in Section III, which is preceded by block denoising algorithm based on DWPT in Section IV. The various experimental results are discussed in Section V. Section VI gives the concluding remarks based on the experimental results. This paper introduces a new audio denoising algorithm through time frequency block thresholding to the types of Poultry Birds sound.

II. .DISCRETE WAVELET PACKET TRANSFORM (DWPT)

Discrete wavelet packet transforms are used to get the advantage of better frequency resolution representation. When the wavelet transform is generalized to wavelet packet transform, not only the low pass filter output is decomposed through further filtering, but the high pass filter output decomposed as well. The ability to decom-pose the high pass filter outputs means that the wavelet packet allows for more than one basis function at a given scale, versus the wavelet transform which has one basis function at each scale other than the deepest level, where it has two.

The set of wavelet packets collectively make up the complete family of possible basis, and many potential basis can be constructed from them. If only the low pass filter is decomposed, the result is wavelet basis. If all low pass and high pass filters are decomposed, the complete tree basis results. This basis has the time frequency partitioning like STFT. Between these two extremes lie a large number of possible basis and their associated sub trees. Nodes can be merged or split based on the requirement of application. In all cases, the leaves of each connected sub tree of the complete wavelet packet tree from the basis of initial space; they span the space in linearly independent fashion. The tree diagram of a depth-3 complete tree basis is shown in the Figure 1.

As with the wavelet transform tree diagram in [14], denotes the depth within the transform and k the position of each node (j,k) but now the position index conveys more information, specifically which wavelet packet it corresponds to a given scale. It is supposed to refer to the associate wavelet packet as Wj,k,p analogus to Wk,p..The tree diagram does not convey time domain information, so the index p is not used in node naming. Hence in wavelet packet, if all the packets are at the same scale, we may simply refer to them as as shown in the Figure 1.

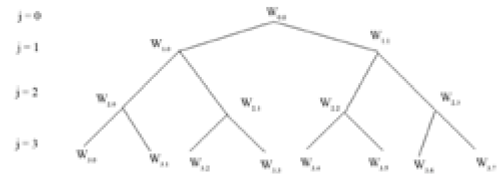

Figure1 Depth-3 discrete wavelet packet transform tree

Furthermore, wj,k is either the scaling function, or derived from the scaling function. DWPT does not re-quire the explicit definition of wavelet, only filter definitions are enough. To see the wavelet packet at given level of decomposition, we can do a recursion of them at each node moving down the tree, to get the wavelet at next level. Specifically, if we split a wavelet packet node at level j and position k into two nodes at level j+1 and 2k & 2k+1 locations and , we get the following two packets

$$w_{j+1,2k}(n) = \sum_{m=0}^{M-1} h_0[m] w_{j,k}(2n - m) \quad (1)$$

$$w_{j+1,2k}(n) = \sum_{m=0}^{M-1} h_1[m] w_{j,k}(2n - m) \quad (2)$$

Then the wavelet packet transform coefficients Cj, k, p are given by:

$$C_{j,k,p} = \sum_{m=0}^{M-1} s[m] w_{j,k,p}(m) \quad (3)$$

And the original signal can be expressed in terms of these coefficients and the corresponding wavelet packets as:

$$s[m] = \sum_{j,k,p}^{m} C_{j,k,p} w_{j,k,p}[m] \quad (4)$$

j,k,p ϵ all leaf nodes of basis Where p ranges over all time offsets at scale j for which signal s is defined

III. WAVELET PACKET ADAPTIVE BLOCK DENOISING

The wavelet packet based denoising technique employs the decomposition concept in adaptive base of wavelets. This technique is efficient in denoising the musical sound signal corrupted with additive white Gaussian noise (AWGN), which is evenly distributed over the entire signal, and removal of AWGN from noisy signal is difficult task. Donoho and Johnstone pioneered the work of filtering the additive white Gaussian noise using wavelet thresholding [15].

The block denoising is explained in the following sub sections:

1) Thresholding Based Denoising
   A noise reduction technique developed by donoho, uses the wavelet coefficients contraction and its principle consists of three steps;
   a)Apply discrete wavelet transform to noisy signal:

$$W.y=W.s + W.z \qquad (5)$$

   Where y, s, z and W are the noisy bird sound, original clean sound signal, noise signal and the matrix associated to the discrete wavelet trans- form respectively.
   b) Threshold the obtained wavelet coefficients.
   c) Reconstruct the desired signal by applying the inverse wavelet transform to the threshold wavelet coefficients.

The thresholding function which is also known as wavelet shrinkage function is categorized as hard thresholding and soft thresholding function. The hard thresholding function retains the wavelet coefficients which are greater than the threshold λ and sets all other to zero. The hard thresholding is defined as:

$$f_h(x) = \begin{cases} x, & if\ |x| \geq \lambda \\ 0, & otherwise \end{cases} \qquad (6)$$

The threshold □ is chosen according to the signal energy and the standard deviation □ of the noise. If the wavelet coefficient is greater than □ , then it is assumed that it is significant and contributes to the original signal. Otherwise it is due to the noise and discarded. The soft thresholding function shrinks the wavelet coefficients by □ towards zero. Hence this function is also called as shrinkage function. The soft thresholding function is defined as

$$f_s(x) = \begin{cases} x - \lambda, & if\ |x| \geq \lambda \\ 0, & if\ |x| < \lambda \\ x + \lambda, & if\ |x| \leq \lambda \end{cases} \qquad (7)$$

In [15], we see that the soft thresholding gives lesser mean square error. Due to this reason soft thresholding is preferred over hard thresholding.

IV. DENOISING ALGORITHM

The proposed wavelet packet based block denoising algorithm for reduction of white Gaussian noise is ex-plained in the following steps:

1) Take a bird sound signal of suitable length.
2) Add White Gaussian Noise to the original signal de-pending upon the standard deviation .
3) Divide the noisy signal into blocks of different length depending upon the length of the signal in time do-main, and the number of samples should be to a power of two.
4) Determine the optimal block size based on minimum mean square error criteria.
5) Compute the discrete wavelet packet transform (DWPT) of one block of the noisy signal at level 1.
6) Estimate the standard deviation of the noise using Equation (8) and determine the threshold value using Equation (9), then apply the different thresholding techniques for time and level dependent wavelet coefficients using Equations (6) and (7).
7) Take inverse discrete wavelet packet transform (IDWPT) of the coefficients obtained through step 6, which has reduced noise.
8) Calculate mean square error (MSE), peak signal to noise ratio (PSNR) for denoised signal.
9) Repeat steps 4 to step 7 for other level of decomposition 2 - 5.
10) Concatenate all the blocks of the denoised signals obtained through step 8 and do averaging operation for MSE and PSNR of the musical instrument sound signal.

The complete DWPT based denoising algorithm is shown graphically in Figure 2..

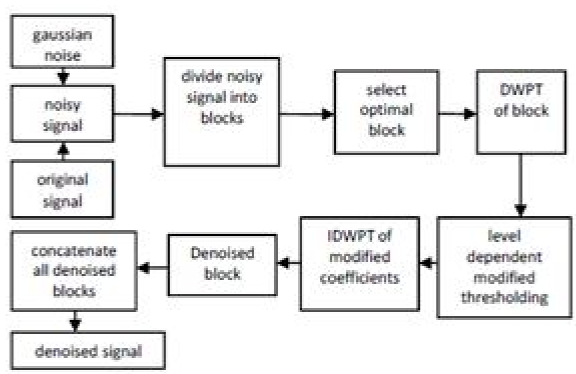

Figure2 DWPT based block denoising algorithm with modified threshold.

V. EXPERIMENTS AND RESULTS

The experiments presented below have been performed on 3 types of Poultry Birds sound signals(Kalinga brown, Japanese quail, Guinea fowl). Matlab7 is used in simulation for denoising. They were corrupted by Gaussian white noise of different amplitude over almost all the original noise. For comparing the performance of the various wavelets for poultry bird sound signals, four wavelets db4, db10, sym 3 & sym 8 are taken. Besides observing the performance of the wavelets, the effect of decomposition is also discussed. For comparing the performance and measurement of quality of denoising, the peak signal to noise ratio (PSNR) is determined between the original signal Si and the signal denoised Sd by our algorithm.

$$PSNR = 10 log_{10}\left(\frac{S_{max}^2}{MSE}\right) \qquad (3)$$

Where Smax is the maximum value of the signal and is given by,

$$S_{max} = max\ (max\ (s_i),\ max\ (s_d)) \qquad (4)$$

And MSE is mean square error, given by:

$$MSE = \frac{1}{N}\sum_{i=1}^{N}[S_d\,(I) - S_i(I)]^2 \qquad (5)$$

where N is the length of the signal. The PSNR values obtained for different wavelets applied on poultry bird signals at different level of decomposition are shown in Tables 1

The additive white Gaussian noise is taken which is approximately 50% of the signal value. It is observed from Tables 1 that the PSNR values are dependent upon the shape of the wavelet, type of thresholding and the level of decomposition. Sometimes Hard thresholds are better than soft thresholds for denoising the bird sound signals. The selection of level of decomposition plays a significant role, and should be optimal for best denoising results. Hence, the kalinga brown sound will give best results when denoised with db10 wavelet at level 5, Japanese Quail sound with sym3 at level 5 and Guinea Fowl sound with db10 at level5, respectively. The different signals denoised with optimal wavelet and level of decomposition are shown in the figure 3,4,5.

The best result is found in Kalinga brown poultry bird is db10 using thresholding selection rule Minimaxi with soft thresholding having PSNR 5.0074 and MSE 2.74. The best result is found in Japanese quail poultry bird is sym3 using thresholding selection rule Minimaxi with soft thresholding having PSNR 4.9963 and MSE 4.4356 in Japanese quail poultry bird. . The best result is found in Guinea fowl db10 using thresholding selection rule Sqtwolog with hard thresholding having PSNR 5.0072 and MSE 1.4690

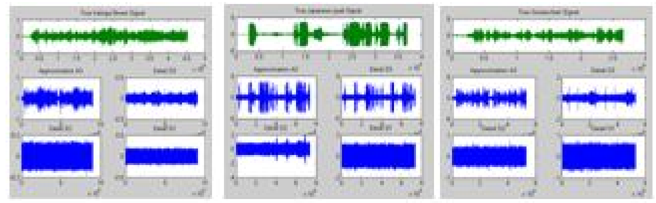

Figure 3 represents bird Kalinga brown, Japanese quail, Guinea fowl sound.

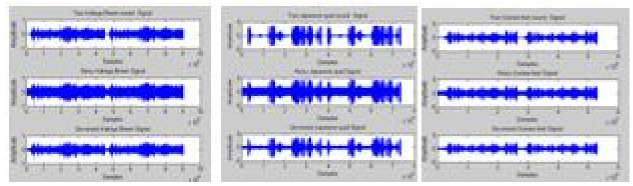

Figure 4 represents true bird sound, noisy bird sound & denoised bird sound

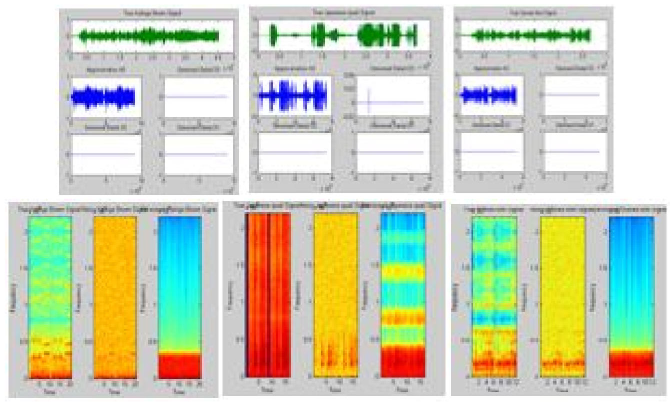

Figure 5 Denoised Bird Sound Approximation and Spectrogram Representation of Kalinga brown, Japanese quail, Guinea fowl

Table 1 for Denoising of Kalinga Brown ,Japanese Quail , Guinea Fowl bird sound using Daubechies and symmlet wavelet

	THRESHOLD	THRESHOLD SELECTION RULE	WAVELET	PSNR	MSE
Kalinga brown	Soft	Heursure	Db4	5.0028	4
			Db10	5.0028	3.2
			Sym3	4.995	4.11
			Sym8	5.0045	3.13
		Rigrsure	Db4	3.9989	4.99
			Db10	5.0060	2.9
			Sym3	4.9967	4.08
			Sym8	4.9959	4.9959
		Minimaxi	Db4	5.0070	4.04
			Db10	5.0074	2.74
			Sym3	5.0004	3.81
			Sym8	5.0025	3.7833
		Sqtwolog	Db4	4.9967	3.8134
			Db10	5.0024	2.89
			Sym3	5.0039	4.1684
			Sym8	4.9981	3.320
	Hard	Heursure	Db4	4.9985	4.0694
			Db10	5.0100	2.9768
			Sym3	5.0072	3.9530
			Sym8	4.9976	3.0708
		Rigrsure	Db4	5.0033	4.1348
			Db10	5.0034	3.0926
			Sym3	4.9910	3.8962
			Sym8	5.0010	3.3309
		Minimaxi	Db4	4.9971	4.0975
			Db10	5.005	2.9366
			Sym3	4.9954	3.9739
			Sym8	4.9967	3.1415
		Sqtwolog	Db4	4.9908	4.7650
			Db10	4.9916	3.0171
			Sym3	4.9997	3.8408
			Sym8	5.0027	3.6239
Japanese quail	Soft	Heursure	Db4	5.0048	4.8718
			Db10	4.9908	4.9405
			Sym3	4.9989	4.7702
			Sym8	5.0078	4.9989
		Rigrsure	Db4	5.0006	4.5689
			Db10	5.0108	4.9113
			Sym3	4.9970	4.6047
			Sym8	4.9914	4.6818
		Minimaxi	Db4	5.0018	4.6061
			Db10	5.0129	4.6378
			Sym3	4.9963	4.4356
			Sym8	5.0116	4.5334
		Sqtwolog	Db4	5.0021	4.7320
			Db10	5.0036	4.5735
			Sym3	4.9971	4.4970
			Sym8	4.9944	4.6718
	Hard	Heursure	Db4	5.0097	4.7826
			Db10	4.9972	4.7427
			Sym3	5.0013	4.5927
			Sym8	4.9988	4.9488
		Rigrsure	Db4	4.9983	4.7757
			Db10	5.0069	4.9671
			Sym3	5.0100	4.5175
			Sym8	5.0010	5.3752
		Minimaxi	Db4	4.9986	4.6658
			Db10	4.9932	4.6331
			Sym3	5.0111	4.7418
			Sym8	5.0039	4.7359
		Sqtwolog	Db4	4.9947	4.9758
			Db10	4.9970	5.0195
			Sym3	4.9957	4.8265
			Sym8	4.9934	4.5855
		Heursure	Db4	5.0075	1.7809

Guinea Fowl	**Soft**		Db10	4.9974	1.67
			sym3	4.9886	2.0229
			Sym8	5.0050	1.5964
		Rigrsure	Db4	5.0048	1.4971
			Db10	4.9916	1.7951
			sym3	5.0031	1.8724
			Sym8	5.0078	1.7640
		Minimaxi	Db4	5.0032	1.5432
			Db10	4.9919	1.505
			sym3	4.9999	1.7850
			Sym8	4.9958	1.7813
		Sqtwolog	Db4	5.0086	2.2006
			Db10	5.0043	1.6521
			sym3	4.9973	2.0454
			Sym8	5.0034	1.9467
	Hard	**Heursure**	Db4	5.0136	1.7903
			Db10	5.005	1.7015
			sym3	4.9938	1.7051
			Sym8	5.0147	1.7759
		Rigrsure	Db4	4.9954	1.7211
			Db10	5.0009	1.4729
			sym3	4.9929	1.8260
			Sym8	5.00112	2.2795
		Minimaxi	Db4	4.9954	1.7937
			Db10	5.0004	1.6042
			sym3	5.0017	1.8535
			Sym8	4.9945	1.8694
		Sqtwolog	Db4	5.0021	2.0037
			Db10	5.0072	1.4690
			sym3	5.0032	1.7387
			Sym8	5.0073	2.0298

VI. CONCLUSION

Adaptive wavelet packet transform has been widely used in denoising the sounds of Poultry and Providing better performance in terms of PSNR values than the other denoising techniques. In this paper, discrete wavelet packet transform is used for denoising Kalinga brown, Japanese quail & Guinea fowl Poultry Bird sound signal corrupted with additive white Gaussian noise, 50% of the signal strength. First, sound signal is divided into multiple blocks de-pending upon the optimal block size for each signal. De-noising of signal is performed with these optimal block sizes in wavelet packet domain by thresholding the wavelet coefficients at different level of decomposition. It is observed that hard thresholding gives better PSNR than soft thresholding at all the decomposition levels. The choice of the optimal level of decomposition is important, and different for each sound signal. If the level of decomposition is not optimal then the PSNR value will not be maximum, hence denoising will not be the best. Maximum PSNR value for Kalinga Brown bird sound is at level 5 with db40 wavelet, Japanese quail at level 5 with dmey and Guinea fowl at level 4 with db10 respectively. When each block is denoised, all the blocks are concatenated to form the final denoised signal. It is also observed that when modified threshold with is used, the PSNR values are in-creased. Higher thresholds remove the noise well but some parts of the original signal are also removed because it is not possible to remove the noise without affecting the original signal.

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