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A Novel Hybrid Structure of Denoising for ECG-TDM Signals using Wavelet Packet Decomposition

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Abstract: Multiplexing of signals enables the usage of same channel for multiple signals at the same time. Among multiplexing schemes, Time division multiplexing is one of the fundamental and basic multiplexing scheme. TDM was utilized in popular T1 carrier system, which transfers voice signals in a single channel. TDM divides the total time scale into serial slots, where these slots are used to carry samples of signals in a round robin manner. When the TDM signal is presented to channel, the noise in channel, effects the signal over some time, or some frequency with certain effect on amplitude. Hence, when the TDM signal is attacked by noise, few samples of few or all the base signals may be effected by noise. The solution to this problem was in many forms. But all these forms takes the TDM signal as a base or whole signal as a unit, and run the denoising schemes. But the base signals which constitutes the TDM signal may have variety of properties. These signals will be effected by noise in a different way from each other. Hence towards this end, the main objective and contribution is to perform the denoising after demultiplexing. Here, the denoising of different signals may be done with different denoising schemes or with a variety of quantity the denoising may be applied. The other aspect of this research work is to find out optimal denoising technique for base signals based on base signal properties. The denoising techniques considered are adaptive filtering techniques, wavelet based denoising and wavelet packed based denoising. ECG and Audio signals are considered as base signals in this work. Simulation results suggest that the proposed structure result in good performance.
Keywords: Adaptive filter, ECG, De-noising, Multirate filter, Wavelet packet

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I. INTRODUCTION

Multirate systems are building blocks commonly used in digital signal processing (DSP). Their function is to alter the rate of the discrete-time signals, which is achieved by adding or deleting a portion of the signal samples. Multirate systems play a central role in many areas of signal processing, such as filter bank theory and multi-resolution theory. They are essential in various standard signal processing techniques such as signal analysis, de-noising, compression and so forth. During the last decade, however, they have increasingly found applications in new and emerging areas of signal processing, as well as in several neighboring disciplines such as digital communications. Adaptive filtering techniques are used in a wide range of applications, including echo cancellation, adaptive equalization, adaptive noise cancellation, and adaptive beam-forming [1][2][3]. These applications involve processing of signals that are generated by systems whose characteristics are not known *a priori*. Under this condition, a significant improvement in performance can be achieved by using adaptive rather than fixed filters. An adaptive filter is a self-designing filter that uses a recursive algorithm. This paper presents wavelet analysis as an adaptive multirate filter. De-noising of TDM signals is considered.

As shown in the Fig. 1, an Adaptive Noise Canceller (ANC) has two inputs – primary and reference. The primary input receives a signal s from the signal source that is corrupted by the presence of noise n uncorrelated with the signal. The reference input receives a noise n_0 uncorrelated with the signal but correlated in some way with the noise n. The noise no passes through a filter to produce an output nˆ that is a close estimate of primary input noise [4][5]. This noise estimate is subtracted from the corrupted signal to produce an estimate of the signal at $\hat{s}$, the ANC system output. In noise canceling systems a practical objective is to produce a system output $\hat{s} = s + n - \hat{n}$ that is a best fit in the least squares sense to the signal s. This objective is accomplished by feeding the system output back to the adaptive filter and adjusting the filter through an LMS adaptive algorithm to minimize total system output power. In other words the system output serves as the error signal for the adaptive process [6][7]. Assume that s, n_0, n_1 and y are statistically stationary and have zero means. The signal s is uncorrelated with n_0 and n_1, and n_1 is correlated with n_0.

$$\hat{s} = s + n - \hat{n}$$

$\hat{s}^2 = s^2 + (n - \hat{n})^2 + 2s(n - \hat{n})$

Taking expectation of both sides and realizing that s is uncorrelated with n_0 and $\hat{n}$,

$E[\hat{s}^2] = E[s^2] + E[(n - \hat{n})^2] + 2E[s(n - \hat{n})]$

$= E[s^2] + E[(n - \hat{n})^2]$

The signal power $E[s^2]$ will be unaffected as the filter is adjusted to minimize $E[\hat{s}^2]$.

$\min E[\hat{s}^2] = E[s^2] + \min E[(n - \hat{n})^2]$

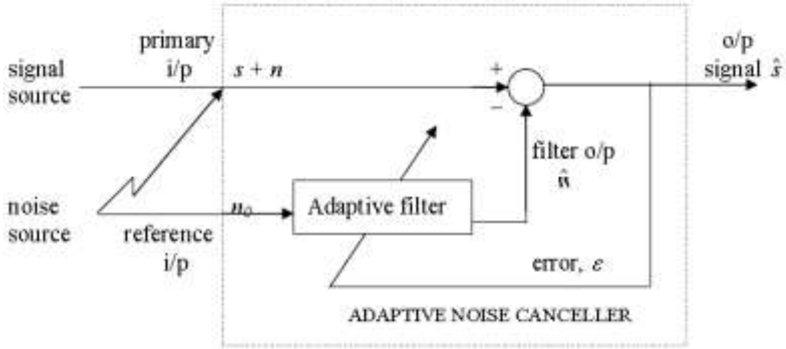

Fig. 1 Adaptive Noise Canceller

Thus, when the filter is adjusted to minimize the output noise power $E[\hat{s}^2]$, the output noise power $E[(n - \hat{n})^2]$ is also minimized. Since the signal in the output remains constant, therefore minimizing the total output power maximizes the output signal-to noise ratio. Since $(\hat{s} - s) = (n - \hat{n})$. This is equivalent to causing the output $\hat{s}$ to be a best least squares estimate of the signal s. The rest of the paper is organized as follows. In the section II, a review of traditional adaptive filters is given. In section III, wavelet and wavelet packet decomposition and reconstruction processes along with new wavelet packets are presented. In section IV, the simulation results including the ANC performance of traditional adaptive filters, wavelets, existing wavelet packets and new wavelet packets are discussed. The section V concludes the paper.

II. TRADITIONAL ADAPTIVE FILTERS

Least mean squares (LMS) algorithms are a class of adaptive filter used to mimic a desired filter by finding the filter coefficients that relate to producing the least mean squares of the error signal (difference between the desired and the actual signal). It is a stochastic gradient descent method in that the filter is only adapted based on the error at the current time. It was invented in 1960 by Stanford University professor Bernard Widrow and his first Ph.D. student, Ted Hoff [4]. The Fig. 2 shows the LMS adaptive filtering.

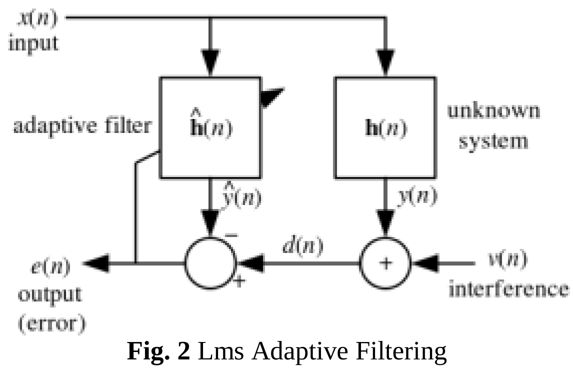

Fig. 2 Lms Adaptive Filtering

The realization of the causal Wiener filter looks a lot like the solution to the least squares estimate, except in the signal processing domain. The least squares solution, for input matrix X and output vector Y is $\hat{\beta} = (X^T X)^{-1} X^T y$. The FIR Wiener filter is related to the least mean squares filter, but minimizing its error criterion does not rely on cross-correlations or auto-correlations. Its solution converges to the Wiener filter solution. Most linear adaptive filtering problems can be formulated using the block diagram above. That is, an unknown system h(n) is to be identified and the adaptive filter attempts to adapt the filter $\hat{h}(n)$ to make it as close as possible to h(n), while using only observable signals x(n), d(n) and e(n); but y(n), v(n) and h(n) are not directly observable. Its solution is closely related to the Wiener filter. The basic idea behind LMS filter is to approach the optimum filter weights ($R^{-1}P$) by updating the filter weights in a manner to converge to the optimum filter weight. The algorithm starts by assuming a small weights (zero in most cases), and at each step, by finding the gradient of the mean square error, the weights are updated. That is, if the MSE-gradient is positive, it implies, the error would keep increasing positively, if the same weight is used for further iterations, which means we need to reduce the weights. In the same way, if the gradient is negative, we need to increase the weights. So, the basic weight update equation is $W_{n+1} = W_n - \mu\Delta\varepsilon[n]$, where ε represents the mean-square error. The negative sign indicates that, we need to change the weights in a direction opposite to that of the gradient slope. The mean-square error, as a function of filter weights is a quadratic function which means it has only one extreme that minimizes the mean-square error, which is the optimal weight. The LMS thus, approaches towards these optimal weights by ascending/descending down the mean-square-error versus filter weight curve [5][6][7]. The LMS algorithm for p^{th} order algorithm can be summarized as

Parameters: p is the filter order,

μ is the step size

Initialization: $\hat{h}(0) = 0$

Computation: For n = 0, 1, 2,….

$$x(n) = [x(n), x(n-1), ..., x(n-p+1)]^T$$

$$e(n) = d(n) - \hat{h}^H(n)x(n)$$

$$\hat{h}(n+1) = \hat{h}(n) + \mu e^*(n)x(n)$$

Normalized Least Mean Squares Filter (NLMS)

The main drawback of the "pure" LMS algorithm is that it is sensitive to the scaling of its input $x(n)$. This makes it very hard (if not impossible) to choose a learning rate μ that guarantees stability of the algorithm. The *Normalized least mean squares filter* (NLMS) is a variant of the LMS algorithm that solves this problem by normalizing with the power of the input [8][9]. The NLMS algorithm can be summarized as:

Parameters: p - filter order

μ - step size

Initialization: $\hat{h}(0) = 0$

Computation: For n = 0, 1, 2, …

$$x(n) = [x(n), x(n-1), ..., x(n-$$

$$e(n) = d(n) - \hat{h}^H(n)x(n)$$

$$\hat{h}(n+1) = \hat{h}(n) + \frac{\mu e^*(n)x(n)}{x^H(n)x(n)}$$

III. WAVELET AS A MULTIRATE ADAPTIVE FILTER

For almost all signals, the low-frequency component is the most important part. It is what gives the signal its significance and identity. The high-frequency content, on the other hand, adds flavor. Consider an audio signal. If the high frequency components are removed, the audio sounds different, but one can still tell what's being said in the audio [10]. However, if enough of the low-frequency components are removed, one hears gibberish.

Wavelet analysis often speaks about approximations and details. The approximations are the low-frequency, high-scale components of the signal. The details are the high-frequency, low-scale components [11]. The filtering process in wavelet analysis, at its basic level, looks like this.

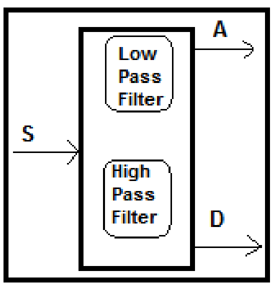

Fig. 3 Filtering Process in Wavelet Analysis

The original sequence, S, applied to two complementary filters and emerges as two signals as shown in Fig. 3. If a digital sequence of say 512 samples is applied to the filter bank consisting of one low and one high pass filter as mentioned above, the length of A will be 512 and that of D will also be 512. Hence the data to handle was doubled. But note that in A as well as in D only 256 samples are irredundant. To remove the redundant samples, the downsamplers are employed as shown in Fig. 4. The outputs are denoted by cA and cD [12][13].

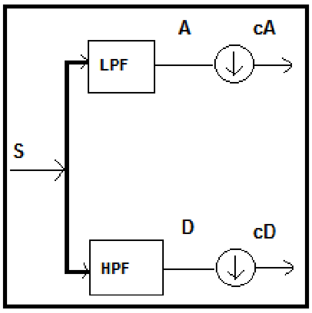

Fig. 4 Wavelet processing with downsamplers

This process, i.e., the conversion of S into cA and cD is called decomposition; the filters at this stage are referred as decomposition low pass and decomposition high pass filters. These filters have direct relation to the basis function used in a specific wavelet. The vectors cA and cD constitutes the DWT coefficients. The decomposition process can be repeated means iterated, with successive approximations being decomposed in turn, so that one signal is broken down into many lower resolution components. This is called the wavelet decomposition tree shown in Fig. 5.

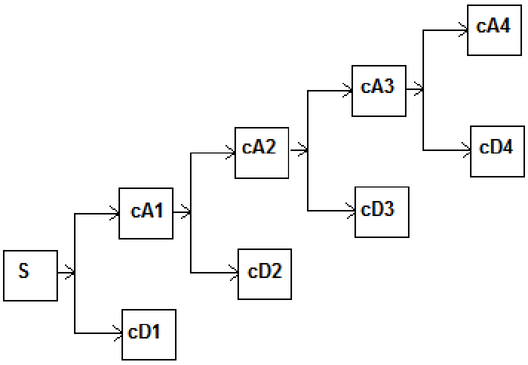

Fig. 5 Multistage Decomposition

The maximum number of decomposition stages should be taken so that the length of the sequence in the last stage is not less than 1. From the wavelet coefficients the original signal need to be recovered. The process of obtaining the original signal by using the wavelet coefficients is called reconstruction or synthesis shown in Fig. 6.

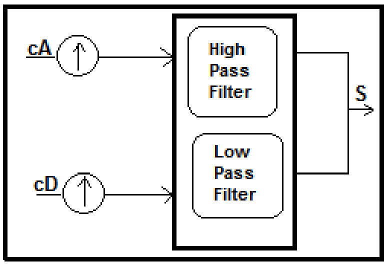

Fig. 6 Reconstruction Stage

The downsampling performed at decomposition stage introduces an aliasing effect. The reconstruction filters need to be selected so that the aliasing effect introduced at the decomposition stage should be cancelled. The overall process of wavelet is depicted in the Fig. 7.

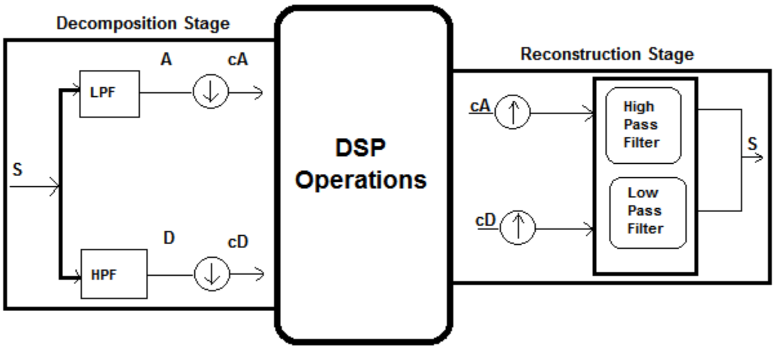

Fig. 7 Wavelet as a Multirate Adaptive Filter

The wavelet packet analysis is an extension of wavelet analysis with an inclusion of analysis of both approximation (cA) and detail (cD) components. The wavelet packet analysis looks like a complete tree structure. The multistage wavelet packet analysis looks like as shown in Fig. 8.

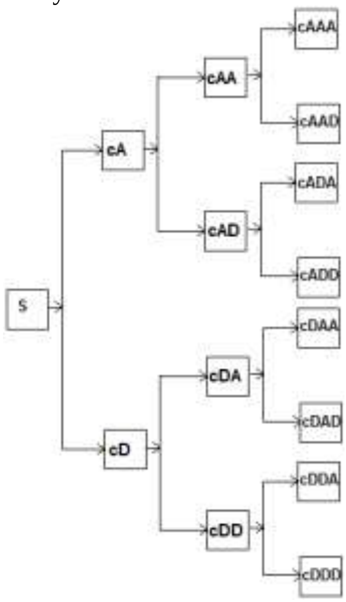

Fig. 8 Wavelet Packet Analysis

The wavelet packets use the wavelet filters to decompose and reconstruct the signals. The wavelet filters corresponds to the perfect reconstruction condition as well as to represent the data to suite different applications [14][15].

IV. PROPOSED SCHEME

The general structure of TDM signal is shown in Fig 9.

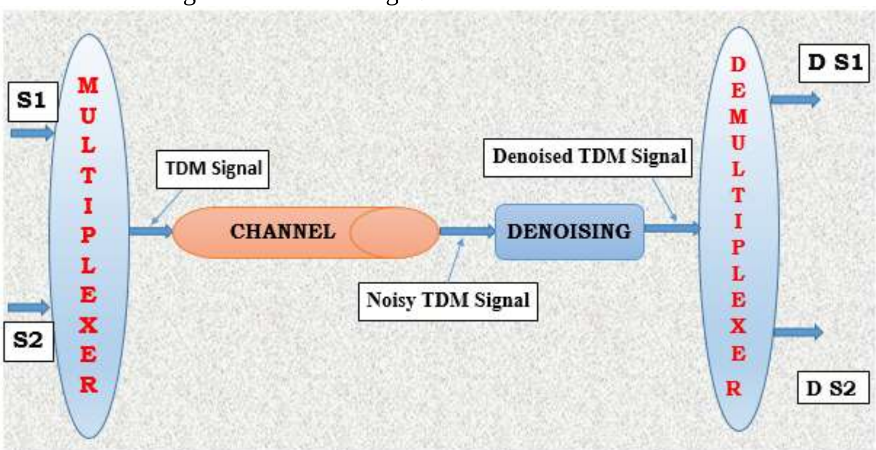

Figure 9. General structure of TDM Denoising

Here the base signals which constitutes the TDM signal may have variety of properties. These signals will be effected by noise in a different way from each other. Hence there is no choice to use different denoising scheme for individual signals. The usage of different denoising scheme will results optimum results. It is because the signal characteristics decides how a base signal is affected by noise. Also, the charactersitics of base signals decides how the denoising scheme results in denoising. Witht the existing structure there is no chance to use specialized or customized deoising scheme on individual signal. Hence a new structure is proposed where the denoising takes place after denoising at the receiver end. This enables the application of customized denoising schemes to individual signals. The proposed TDM denosing scheme is shown in Fig. 10.

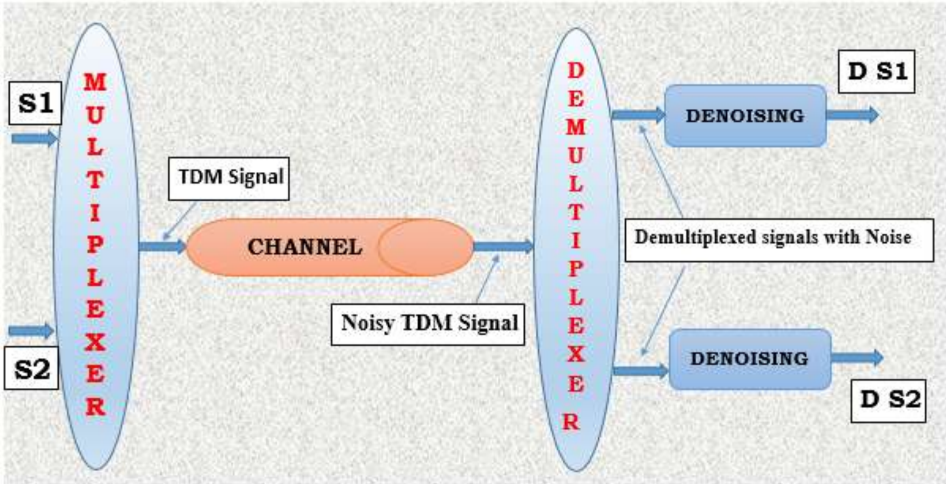

Figure 10. Proposed structure of TDM Denoising

V. SIMULATION RESULTS

In this section the simulation results of Traditional adaptive filters, Wavelets, Wavelets Packets using existing structure and proposed structure are presented. Two cases of inputs are considered. One case considers two ECG signals as base signals. The second case considers one ECG and one audio signal as base signals. A sample MATLAB output is shown in Fig. 11 which depicts the application of existing structure of TDM denoising on two ECG signal case. Table 1 and 2 presents the performance of adaptive filters using existing TDM desnoising structure in two cases of input. Table 3 and 4 presents the performance of wavelet based thresholding denoising scheme using existing TDM desnoising structure in two cases of input.

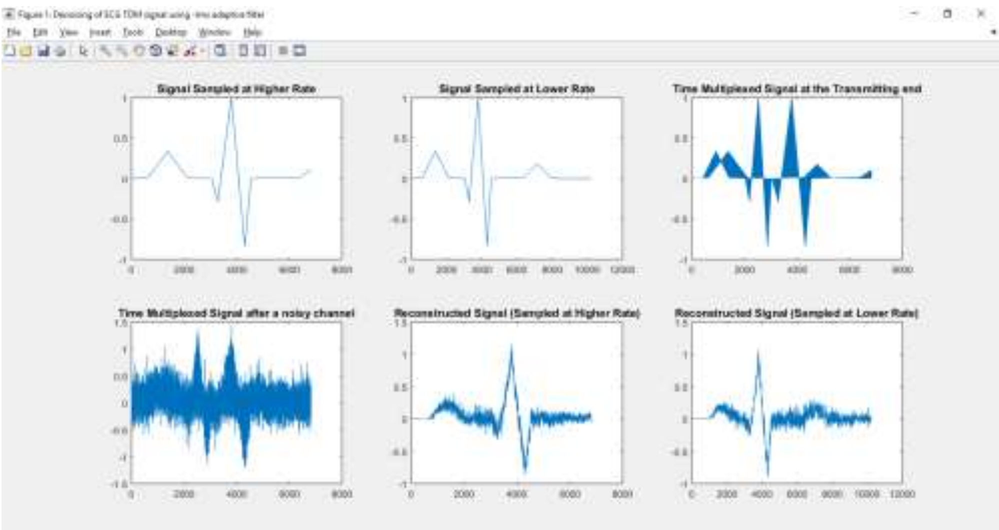

Figure 11. Sample Output Screen Of TDM Denoising In MATLAB

Table 1. Performance Of Adaptive Filters With Existing Denoising Structure In Case – I Of Inputs

	ECG – 1				ECG – 2			
	PSNR	MSE	MAX ERR	L2RAT	PSNR	MSE	MAX ERR	L2RAT
Lms	71.1479	0.005	0.2698	0.8849	69.9318	0.0066	0.2595	0.8583
Nlms	76.6507	0.0014	0.1652	0.9754	75.045	0.002	0.1523	0.9579
Rls	74.8156	0.0021	0.2049	1.0361	73.6319	0.0028	0.2346	1.0346
Dft	74.6653	0.0022	0.2024	1.0269	74.4878	0.0023	0.1941	1.0559
Dct	75.0906	0.002	0.1889	1.0071	74.5877	0.0023	0.1659	1.0055
Lsl	74.9682	0.0021	0.171	1.0186	74.0235	0.0026	0.2344	1.0505

Table 2. Performance Of Adaptive Filters With Existing Denoising Structure In Case – II Of Inputs

	ECG				Audio			
	PSNR	MSE	MAX ERR	L2RAT	PSNR	MSE	MAX ERR	L2RAT
lms	67.4405	0.011723	0.43271	0.85787	63.9394	0.02625	0.66104	0.32064
nlms	70.2938	0.006077	0.32304	1.0215	65.353	0.018958	0.66305	0.47756
Rls	69.3986	0.007468	0.36256	1.1073	65.5325	0.01819	0.59324	0.56218
Dft	69.7881	0.006828	0.42941	1.0983	65.5424	0.018149	0.51375	0.60964
Dct	69.6029	0.007125	0.41589	1.0877	65.4979	0.018335	0.57639	0.60006
Lsl	69.7207	0.006934	0.41976	1.0772	65.4369	0.018595	0.61023	0.51005

Table 3. Performance Of Wavelet Based Scheme With Existing Denoising Structure In Case – I Of Inputs

	ECG – 1				ECG – 2			
	PSNR	MSE	MAX ERR	L2RAT	PSNR	MSE	MAX ERR	L2RAT
Haar	61.6775	0.0442	0.802	0.7795	61.8524	0.0424	0.9391	1.1262
Db10	61.3701	0.0474	0.7789	0.8797	61.9389	0.0416	0.8225	1.0865
Db45	61.7597	0.0434	0.7351	0.7536	61.8288	0.0427	0.7645	1.155
Sym6	62.2917	0.0384	0.7803	0.7076	61.3264	0.0479	0.8078	1.2606
Coif4	62.4603	0.0369	0.7551	0.7032	61.1901	0.0494	0.8909	1.2592
bior2.4	62.6396	0.0354	0.7938	0.6445	60.9527	0.0522	0.9742	1.3122
Dmey	61.8533	0.0424	0.7389	0.7036	61.692	0.044	0.7975	1.1328
rbio1.3	61.6148	0.0448	0.7381	0.7915	61.7644	0.0433	0.7894	1.1435

Table 4. Performance Of Wavelet Based Scheme With Existing Denoising Structure In Case – II Of Inputs

	ECG				Audio			
	PSNR	MSE	MAX ERR	L2RAT	PSNR	MSE	MAX ERR	L2RAT
Haar	61.3344	0.047823	0.97719	0.80216	61.314	0.048048	0.87929	0.95372
db10	61.1298	0.05013	0.91588	0.78172	61.1184	0.050262	0.87855	0.72356
db45	61.382	0.047302	0.8373	0.78162	61.2853	0.048367	0.94247	0.98151
sym6	62.3472	0.037875	0.86574	0.65364	61.4091	0.047008	1.0054	1.2353
coif4	62.236	0.038858	0.81524	0.67397	61.4204	0.046886	0.96533	1.2581
bior2.4	62.7175	0.03478	0.78932	0.54356	61.562	0.045381	0.97887	1.4131
dmey	61.6966	0.043997	0.90541	0.74007	61.2989	0.048215	0.88991	1.0364
rbio1.3	61.3386	0.047777	0.94733	0.80462	61.2172	0.049131	0.9735	0.95628

Table 5 and 6 presents the performance of wavelet packet based thresholding technique using existing TDM desnoising structure in two cases of input.

Table 5. Performance Of Wavelet Packet Based Scheme With Existing Denoising Structure In Case – I Of Inputs

	ECG – 1				ECG - 2			
	PSNR	MSE	MAX ERR	L2RAT	PSNR	MSE	MAX ERR	L2RAT
Haar	62.0427	0.0406	0.8221	1.716	62.3138	0.0382	0.8312	1.9521
db10	61.5315	0.0457	0.924	0.8405	62.1974	0.0392	0.7756	1.0392
db45	61.7722	0.0432	0.7732	0.7373	61.8549	0.0424	0.8245	1.1242
sym6	62.3339	0.038	0.7212	0.6903	61.2024	0.0493	0.8833	1.2558
coif4	62.1523	0.0396	0.7986	0.7185	61.2493	0.0488	0.7849	1.2766
bior2.4	61.864	0.0423	0.7921	0.783	61.473	0.0463	0.8536	1.2536
dmey	61.9565	0.0414	0.8021	0.7569	61.4964	0.0461	0.7803	1.2026
rbio1.3	62.3539	0.0378	0.8181	1.5839	62.262	0.0386	0.7161	1.9139

Table 6. Performance Of Wavelet Packet Based Scheme With Existing Denoising Structure In Case – II Of Inputs

	ECG				Audio			
	PSNR	MSE	MAX ERR	L2RAT	PSNR	MSE	MAX ERR	L2RAT
Haar	61.9606	0.041402	0.8434	1.7214	62.0216	0.040825	0.69001	1.8493
db10	61.2538	0.048719	1.0218	0.84411	60.9011	0.052841	1.0196	0.80964

db45	61.4621	0.046438	0.79184	0.74507	61.3805	0.047318	1.0713	0.9388
sym6	62.0986	0.040107	0.94148	0.6777	61.3838	0.047282	1.0174	1.308
coif4	62.0062	0.040969	0.91609	0.66529	61.4514	0.046552	0.92223	1.2394
bior2.4	62.0294	0.040751	0.71833	1.6573	62.2452	0.038776	0.72331	1.7862
Dmey	61.6728	0.044238	0.91198	0.71727	61.4169	0.046924	0.86963	1.0148
rbio1.3	62.0031	0.040998	0.77763	1.6847	62.0973	0.040119	0.82023	1.7903

Table 7 and 8 presents the performance of adaptive filters using proposed TDM desnoising structure in two cases of input.

Table 7. Performance Of Adaptive Filters With Proposed Denoising Structure In Case – I Of Inputs

	ECG – 1				ECG – 2			
	PSNR	MSE	MAX ERR	L2RAT	PSNR	MSE	MAX ERR	L2RAT
Lms	72.5369	0.003626	0.18928	0.91656	72.5294	0.003632	0.2039	0.89324
Nlms	77.1644	0.001249	0.1267	0.98001	75.5608	0.001807	0.19645	0.95868
Rls	75.9522	0.001651	0.21142	1.0355	75.129	0.001996	0.22431	1.067
Dft	75.9105	0.001667	0.20092	1.0435	76.3026	0.001523	0.19407	1.048
Dct	75.3714	0.001888	0.18569	1.0852	74.5125	0.002301	0.26324	1.043
Lsl	75.1114	0.002004	0.18701	1.0631	75.1275	0.001997	0.2001	1.0448

Table 8. Performance Of Adaptive Filters With Proposed Denoising Structure In Case – II Of Inputs

	ECG				Audio			
	PSNR	MSE	MAX ERR	L2RAT	PSNR	MSE	MAX ERR	L2RAT
Lms	74.7988	0.002154	0.17124	0.92744	66.46	0.014692	0.69136	0.4842
Nlms	79.1613	0.000789	0.14247	0.98362	68.0482	0.010192	0.61721	0.69021
Rls	80.716	0.000551	0.11709	1.0229	69.9537	0.006572	0.30298	0.91
Dft	80.9593	0.000521	0.11691	1.0173	69.7915	0.006822	0.3302	0.92167
Dct	79.7776	0.000684	0.11159	1.025	69.5399	0.007229	0.36763	0.89543
Lsl	80.0573	0.000642	0.10086	1.015	70.0688	0.0064	0.32396	0.88573

Table 9 and 10 presents the performance of wavelet based thresholding denoising scheme using proposed TDM desnoising structure in two cases of input.

Table 9. Performance Of Wavelet Based Scheme With Proposed Denoising Structure In Case – I Of Inputs

	ECG – 1				ECG – 2			
	PSNR	MSE	MAX ERR	L2RAT	PSNR	MSE	MAX ERR	L2RAT
Haar	74.2244	0.002458	0.16163	1.0331	74.4073	0.002357	0.14979	1.0633
Db10	74.3383	0.002395	0.18172	1.0596	74.5304	0.002291	0.16214	1.0618
Db45	74.3763	0.002374	0.15644	1.0537	74.1202	0.002518	0.23188	1.0483
Sym6	74.1768	0.002485	0.18387	1.0441	74.1447	0.002504	0.18023	1.0712
Coif4	73.8546	0.002677	0.17066	1.0573	74.1805	0.002483	0.16587	1.0304
bior2.4	73.9389	0.002625	0.23476	1.0156	74.2227	0.002459	0.19799	1.0527
Dmey	74.1462	0.002503	0.1928	1.0444	73.9439	0.002622	0.17886	1.0689
rbio1.3	73.7431	0.002747	0.21595	1.0625	74.4199	0.00235	0.16162	1.069

Table 10. Performance Of Wavelet Based Scheme With Proposed Denoising Structure In Case – II Of Inputs

	ECG				Audio			
	PSNR	MSE	MAX ERR	L2RAT	PSNR	MSE	MAX ERR	L2RAT
Haar	77.116	0.001263	0.1258	1.0247	61.1731	0.049633	0.86453	0.054853
db10	77.4952	0.001158	0.11485	0.9909	61.1024	0.050447	0.83107	0.03746
db45	77.8391	0.00107	0.10381	1.0157	61.1026	0.050445	0.87981	0.041583
sym6	76.6917	0.001393	0.12046	1.0239	61.1036	0.050434	0.83457	0.041741
coif4	76.5337	0.001445	0.13794	1.0364	61.103	0.050441	0.82447	0.04175
bior2.4	76.7211	0.001384	0.14742	1.0292	61.1067	0.050398	0.86535	0.040639
dmey	77.5016	0.001156	0.1067	0.99332	61.1069	0.050395	0.83183	0.043193
rbio1.3	76.5944	0.001424	0.15179	1.0343	61.029	0.051308	0.88936	0.064241

Table 11 and 12 presents the performance of wavelet packet based thresholding technique using proposed TDM desnoising structure in two cases of input.

Table 11. Performance Of Wavelet Packet Based Scheme With Proposed Denoising Structure In Case – I Of Inputs

	ECG – 1				ECG – 2			
	PSNR	MSE	MAX ERR	L2RAT	PSNR	MSE	MAX ERR	L2RAT
Haar	77.1111	0.001265	0.12466	0.99977	77.0328	0.001288	0.11168	1.037
db10	77.2816	0.001216	0.13171	1.0176	77.8696	0.001062	0.1283	1.0274
db45	77.3125	0.001207	0.14558	1.0226	77.1226	0.001261	0.11689	1.0581

sym6	76.8887	0.001331	0.17204	1.0198	77.591	0.001132	0.15171	0.99122
coif4	77.4226	0.001177	0.15342	1.0328	77.2826	0.001216	0.11939	1.0129
bior2.4	77.0963	0.001269	0.15099	1.0333	76.6641	0.001402	0.1468	0.99143
dmey	77.1887	0.001242	0.12873	1.0036	76.5195	0.001449	0.15325	1.051
rbio1.3	76.7639	0.00137	0.12211	1.0294	76.6162	0.001417	0.11751	1.0435

Table 12. Performance Of Wavelet Packet Based Scheme With Proposed Denoising Structure In Case – II Of Inputs

	ECG				Audio			
	PSNR	MSE	MAX ERR	L2RAT	PSNR	MSE	MAX ERR	L2RAT
Haar	76.9006	0.001327	0.12252	1.0185	61.1879	0.049465	0.83803	0.048999
db10	77.2847	0.001215	0.13146	1.0234	61.0982	0.050496	0.8769	0.040875
db45	76.9484	0.001313	0.16597	1.0189	61.1155	0.050296	0.8628	0.038224
sym6	77.4308	0.001175	0.13017	1.0327	61.1038	0.050431	0.84827	0.038682
coif4	76.5847	0.001428	0.14355	1.0426	61.0983	0.050495	0.8717	0.041197
bior2.4	77.0963	0.001269	0.15099	1.0333	61.0893	0.0506	0.83541	0.044395
Dmey	77.1887	0.001242	0.12873	1.0036	61.0893	0.050599	0.79144	0.043795
rbio1.3	76.7639	0.00137	0.12211	1.0294	61.0469	0.051097	0.87136	0.05896

VI. CONCLUSION

Wavelets, with its powerful strength of adaptive nature, are applicable to many applications where adaptive filters are in use. In this paper the de-noising of TDM signal is considered. Two cases of input signals are considered. One with two ECG signals, another with one ECG and one audio signal. The resulting TDM signal has undergone a noisy channel. The channel is assumed to have uniform noise. In the existing structure of TDM denoising, the signal at the output of the channel is given as input to the de-noising unit. The signal from the de-noising unit is given to the de-multiplexing section of TDM; two signals are separated and compared with the original input signals. This structure does not support individual denoising on signals. Hence In this work, a new structure of TDM signal denoising is proposed, where the denoising is done on demultiplexed signals separately. This makes the possibility of applying a more suitable technique of denoising to respective signals. The simulation results prove that the usage of different schemes on different signals gives the optimum performance.

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