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UNIVERSAL AND ADAPTIVE THRESHOLDING METHODS FOR MULTILEVEL DENOISING OF ECG SIGNALS USING ORTHOGONAL WAVELETS

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Abstract. In signal processing, discrete wavelets transform (DWT) is used to compress and denoise n-Dimensional signals. DWT can also be used to remove noises such as instrumentation noises, power line interference, noise from muscle artefacts etc., from the captured biological signals like electrocardiogram (ECG). Performing wavelet transforms on the ECG signals is like passing the signal through bandpass filters. In DWT, several wavelets have been generated for this purpose. In this work, an arrhythmic ECG signal noised with a sinewave was denoised using the orthogonal wavelets like Haar, Daubechies, Coiflets and Symlets, with adaptive and universal thresholding algorithms. The diagnostic validity of the mathematical transformation of the denoised signal is assessed computationally as well as clinically.

1. Introduction

Discrete wavelet transforms are widely used in denoising biological signals. We had previously assessed the ECG denoising capabilities of Fast Fourier Transform (FFT), and orthogonal and biorthogonal discrete wavelet transforms (DWT), where an ECG signal was mixed with a sinewave noise and attempted to denoise them using FFT and DWT [1, 2]. While denoising the signals using orthogonal and biorthogonal wavelets (sym4, coif5 and bior6.8), upon comparison of the fidelity of the denoised signals with that of the original signals and their subsequent clinical assessment by a clinician blinded to the experiments, it was observed that the clinically useful signals are not necessarily the ones the highest peak signal-to-noise ratio (PSNR). In the current work, we perform an extensive assessment of the denoising biological signals using certain orthogonal wavelets like Haar, Daubechies (db), Coiflets (coif) and Symlets (sym).

In an orthogonal wavelet, the inner product of different wavelet functions is equal to zero. i.e., in an orthogonal wavelet, the scaling function is orthogonal to wavelet function. If a wavelet is orthogonal, the wavelet transform preserves energy. There are different types of orthogonal wavelets, such as Haar, Daubechies, Coiflets and Symlets etc. The Haar is the simplest discrete wavelet which is extremely localized

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in time. They are defined by [3].
For $2^p + n \geq 1$,

$$\psi(2^p+n,t) = \begin{cases} \sqrt{2}p & \text{for } n/2^p \leq t \leq \left(n+\frac{1}{2}\right)/2^p \\ -\sqrt{2}p & \text{for } \left(n+\frac{1}{2}\right)/2^p \leq (n+1)/2^p \\ 0 & \text{otherwise} \end{cases}$$

for $p = 0, 1, 2, 3, ...,$ and $n = 0, 1, 2, 4, ..., 2^p - 1$ and $0 \leq t \leq 1$.
The Daubechies wavelets [4] are orthogonal as well as biorthogonal and characterized by maximal number of vanishing points for some given support [5]. These wavelets are not defined in terms of the resulting scaling and wavelet functions; in fact, they are not possible to be written down in a closed form. The simplest possible wavelet, Haar, is in fact the db1 wavelet.
Coiflets are a family of wavelets that are designed to have both compact support and a high number of vanishing points. The Coiflets are orthogonal, biorthogonal and near symmetric.
An orthonormal wavelet ψ with compact support is called a coiflet of order N, if the following conditions are satisfied [6].
1. $\int_{-\infty}^{\infty} x^n \psi(x)dx = 0$ for $n = 0, 1, 2, ..., N-1$.
2. $\int_{-\infty}^{\infty} x^n \phi(x)dx = \delta_n$ for $n = 0, 1, 2, ..., N-1$. where ϕ is the scaling function corresponding to ψ and δ_n is the Kronecker delta, i.e., $\delta_0 = 1$ and $\delta_n = 0$ for $n \neq 0$.
Symlets are derived from Daubechies, but have been modified to be symmetric, with good regularity and compact support. The number of vanishing moments in Symlets can be adjusted, which enhances their ability to capture detailed information about the signal or the image being analysed. A visual representation of the four wavelets is given in Figure 1.

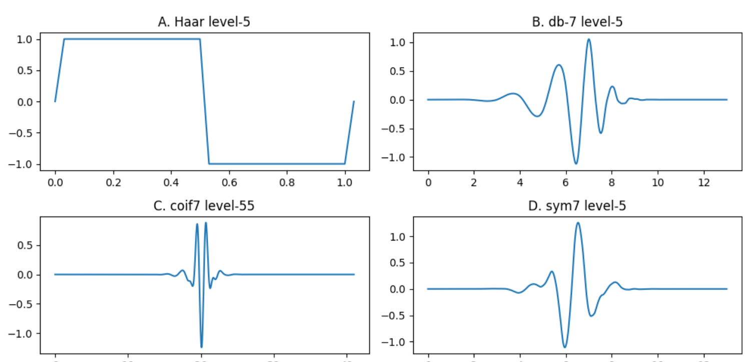

FIGURE 1. Visualization of the wavelet functions of the orthogonal wavelets. A- Haar (or db1) wavelet, at level 5; B, C, D- Daubechies, Coiflet and Symlet respectively, each with 7 vanishing moments, at level 5.

For discrete transformation using wavelets, several wavelet coefficient thresholding approaches are used. In this research work, we have performed wavelet transform analysis of a noised ECG signal using the VisuShrink a single and "universal threshold" applied to all detail coefficients of the wavelets, and the BayesShrink, which is an adaptive thresholding method that computes discrete thresholds for each wavelet sub-band.
The VisuShrink technique consists of applying the soft thresholding operator using a universal thresholding proposed by Donoho [7] and this threshold is given by the equation

$$T_{visu} = \sigma_n \sqrt{2} logL$$

where σ_n^2 is the noise variance of Adaptive White Gaussian Noise (AWGN) and 'L' represents the total number of samples in the 1-D signal. This method gives a highly smoothed reconstruction of a noisy signal, but compromises on many of the important features of the signal, since the threshold tends to be high for large values of 'L' which may eliminate the signal coefficient along with noise.
The adaptive thresholding method, BayesShrink, has been discussed by Chang et al. [8] where the threshold is derived using the Bayesian method. BayesShrink method is sub band-dependent which means that the thresholding is done at each sub band in the wavelet decomposition. In this method, it is assumed that the wavelet coefficients are in the generalized Gaussian distribution, and the appropriate threshold formula can be obtained based on Bayesian estimation criteria, which is expressed as

$$\sigma_B = \frac{\lambda_{noise}^2}{\lambda_{signal}} = \frac{\lambda_{noise}^2}{\sqrt{max(\lambda_G^2 - \lambda_{noise}^2, 0)}}$$

where $\lambda_G^2 = \frac{1}{P_S} \sum_{x,y=1}^{P_S} V_{xy}^2$ and P_S is the number of wavelet coefficients V_{xy} on the sub band under consideration [9].

$$\lambda_{noise} = \frac{median(|V_{xy}|)}{0.6745}, V_{xy} \in \text{subband } HH$$

where V_{xy} is HH wavelet coefficients which forms the finest decomposition levels.
In this paper, we have performed a detailed evaluation of the DWT-based denoising of a noised ECG signal to evaluate the validity and clinical usefulness of orthogonal wavelets like Haar, Daubechies (db), Coiflets (coif) and Symlets (sym), with adaptive and universal thresholding algorithms.

2. Methods

An ECG signal from the Massachusetts Institute of Technology and Boston's Beth Israel Hospital (MIT-BIH) Arrhythmia Database [10] available on the PhysioNet [11] was used for the study. The database contains two-channel ambulatory recordings of ECG (30 Hz sampling rate) of subjects. From the database, the raw signal from the record number 100 was selected for this study, and the signal from the modified limb II (MLII) was used for denoising and clinical interpretations.
All the analyses were performed using Python language (3.12 stable release), on a locally installed Jupyter Notebook (version 7.0.6) platform. The Python library

Waveform Database Software Package (WFDB version 4.1.0) [12], was used to access the record- 100 from MIT-BIH database. The Python libraries used for processing the ECG signals and their visualization include- NumPy (v.1.26.3, for numerical computing) [13], matplotlib (v.3.8.4, for visualization), SciPy (v.1.13.1, for scientific computing) and its subpackages -io, wavfile and stats [14], Librosa (v. 0.10.2.post1, for processing of audio files) [15], os, pandas (v.2.2.2, for data analysis) [16] and scikit-image [v. 0.23.2, for image and signal processing] [17]. The orthogonal wavelet based denoising of signals were performed using skimage.restoration module which is an edge-preserving, denoising filter that can be applied to 1-D signals as well. We performed multilevel decomposition of the noised ECG signal using Haar (1-wavelet up to 15-levels), Daubechies (1-38 wavelets each up to 15 levels), Coiflets (1-17 wavelets each up to 15 levels) and Symlets (2-20 wavelets each up to 15 levels). All the decompositions were performed using both the universal (VisuShrink) and the adaptive (BayesShrink) thresholding algorithms for denoising the signals.
The processing of ECG signal and its denoising using orthogonal wavelets was performed in the following manner.

2.1. Adding 40 Hz noise to the ECG signal-. The ECG signal (record 100, with 65000 data points and sampling rate of 360/s) obtained from the MIT-BIH arrhythmia database was an already preprocessed and clean signal. Therefore, to add noise to the signal, a sinewave of 40 Hz was added to the signal to obtain the noised ECG signal. Figure 2 Shows the clean and noised signals.

2.2. Multilevel 1-D discrete wavelet transforms of the noised signal. The denoise_wavelet() function of skimage.restoration module was used for multilevel decomposition of the noised ECG signal. The denoise function takes parameters such as the wavelet, wavelet level, thresholding method, noise standard deviation etc. The noised signal was denoised using the adaptive thresholding method-BayesShrink applied to all the wavelets, up to 15 levels. Similarly, the universal thresholding (VisuShrink) based denoising was performed using all the wavelets and the levels.

2.3. Assessment of the fidelity of denoised ECG signals with the original ECG signal and their clinical evaluation. The peak signal to noise ratio (PSNR) between the original ECG (clean signal) and the denoised signal of each wavelet at each level was calculated using the peak_signal_noise_ratio() function of the skimage.metrics module. The fidelity of the denoised signal with the highest PSNR value was then evaluated by a cardiologist. The signals were visually evaluated and compared with the original ECG to check similarities between the wave components (P-, Q-, R-, S- and T-subwaves), their characteristics, precision etc. The denoised signal with the highest resemblance to the original ECG signal was identified by the observer. To avoid any bias, the evaluating clinician was blinded to the noising and denoising processes.

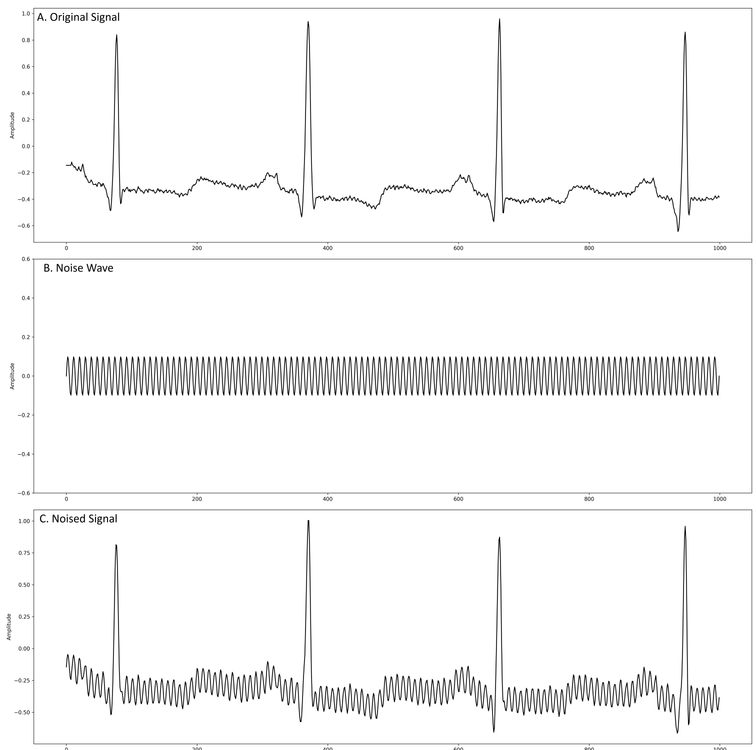

Figure 2. (A) Original signal (ECG signal from record no. 100) accessed from MIT-BIH arrhythmia Database. (Sampling rate: 360/s, first 1000 data points); (B) sinewave of 40 Hz (noise, sampling rate: 360/s, sampling points: 1000); (C) Noised signal (sampling points: 1000).

3. Results

The raw ECG (record No 100) signal obtained from the MIT-BIH arrhythmia database is shown in Figure 2A. In the signal, the wave components (P, Q, R, S, T) and the pathological characteristics of arrhythmia can be observed. Then, a 40 Hz sinewave noise was added to the ECG signal to create the noised signal, which was then denoised using DWT (Haar, db, coif and sym) using universal and adaptive thresholding algorithms.

3.1. Multilevel denoising using the adaptive thresholding method. Multilevel denoising of the noised signal was performed using BayesShrink algorithm using the wavelets- Haar, db (1-38), Coif (1-17) and Sym (2-20), each up to 15 levels, employing denoise_wavelet() function. During denoising, the boundary effects become predominant while nearing level 15. Therefore, denoising beyond level 15 was not attempted. Table 1 shows the obtained PSNR values of denoised signals when compared to the original signal. Only the data of the 10 wavelets from each

family, up to 7 levels are shown in the table due to space constraints.
While denoising with each wavelet, the signal with the highest PSNR was obtained within 10 levels of denoising using BayesShrink. However, in most cases, the denoised signals with the highest PSNR values were found to be not suitable for diagnostic purposes since the denoising process causes changes in the wave component characteristics. Figure 2 shows representative denoised signals, with the highest PSNR value from each wavelet, and their distortions in wave components when compared to the original ECG signal. Also, subjecting to discrete wavelet transformation introduced distortions in certain components of the ECG. For e.g., in all the denoised signals, artifacts were observed at the end of QRS complex.

Wavelet	Level 1	Level 2	Level 3	Level 4	Level 5	Level 6	Level 7
Haar	35.472	34.712	36.452*	36.177	36.023	35.932	35.859
db2	35.691	35.559	37.195	37.3*	37.051	37.163	36.999
db3	35.578*	32.257	29.862	30.679	30.788	30.49	30.877
db4	35.51	33.228	40.192	40.284*	40.047	39.858	39.817
db5	35.483	36.429	41.068*	40.385	39.542	38.923	38.845
db6	35.372	34.878	39.487*	38.29	36.952	36.707	36.847
db7	35.253	33.213	41.067*	39.899	39.735	39.389	39.196
db8	35.265	36.189	40.827*	39.541	39.24	38.48	38.577
db9	35.392	34.859	40.382*	38.54	37.811	36.465	36.603
db10	35.501	32.791	39.299*	38.328	37.282	37.558	37.369
Coif1	34.627*	27.781	30.53	30.803	31.586	31.404	31.358
Coif2	35.304	30.633	38.73	39.418*	39.137	38.985	38.887
Coif3	35.388	32.253	35.74	37.233*	36.785	36.956	36.851
Coif4	35.397	32.901	41.026*	40.592	40.316	40.103	40.032
Coif5	35.392	33.196	39.028	39.852	40.035*	40.005	39.95
Coif6	35.385	33.346	41.126*	40.424	39.942	39.601	39.47
Coif7	35.379	33.431	40.358	40.541*	40.251	40.001	39.901
Coif8	35.375	33.485	41.041*	40.482	39.957	39.535	39.363
Coif9	35.371	33.522	40.571*	40.567	40.19	39.948	39.829
Coif10	35.369	33.552	40.941*	40.202	39.698	39.526	39.446
Sym2	35.691	35.559	37.19	37.3*	37.051	37.163	36.999
Sym3	35.578*	32.257	29.86	30.679	30.788	30.49	30.877
Sym4	35.205*	29.768	31.243	30.636	31.246	31.158	31.134
Sym5	35.174	33.264	39.578	40.089*	39.893	39.816	39.741
Sym6	35.342	34.991	37.54	39.344	39.45*	39.005	39.078
Sym7	35.473	34.381	40.554*	40.364	40.184	39.992	39.901
Sym8	35.371	31.998	40.65*	40.572	40.241	39.99	39.915
Sym9	35.297	33.705	39.359*	38.783	39.095	39.11	39.284
Sym10	35.376	35.293	41.08*	40.553	40.191	39.978	39.799
Sym11	35.491	34.896	40.373	40.406*	40.223	40.106	40.031

TABLE 1. PSNR values of the denoised signal with respect to the original ECG signal. ∗Indicates the denoising level at which the highest PSNR value is obtained. # indicates that the corresponding denoised signal is not clinically acceptable for diagnostic or prognostic purposes when examined by the clinician.

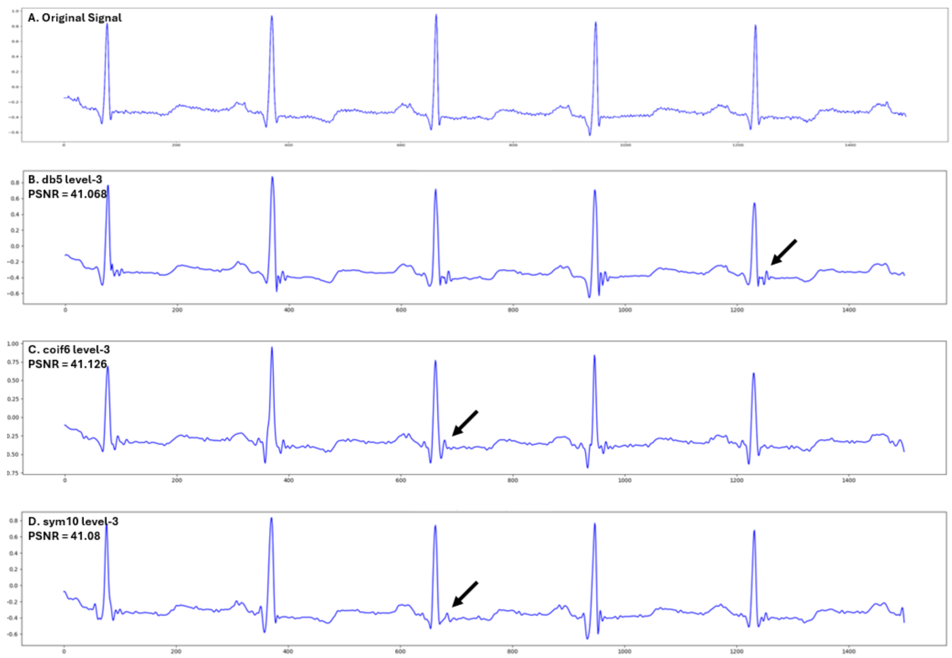

FIGURE 3. Orthogonal wavelet based denoised signals using adaptive thresholding method. Representative samples from each orthogonal wavelet family with the highest PSNR are shown. The initial 1500 samples of the signals (sampling rate 360/s) are plotted against amplitude. A) The original signal from record 100 of MIT-BIH arrhythmia database; B,C,D - denoised signal using db5, coif6 and sym10 respectively (each one at level-3). Arrow indicates the resulting artefacts.

Multilevel denoising using the universal thresholding method. In this process, the VisuShrink universal thresholding algorithm was applied in the denoise_wavelet() function to denoise the signals at each level of the orthogonal wavelets. Since boundary effects become predominant approaching level 15, the denoising was restricted at level 15. Table 2 shows the PSNR values of denoised signals when compared to the original signal. Similar to BayesShrink, the highest PSNR value for each level was obtained within the first 10 levels with VisuShrink. Compared to the original ECG wave, considerable distortions still existed in the denoised signal, as seen in Figure 4. The signals corresponding to the highest PSNR values had high levels of noise and were not of diagnostic quality. On the other hand, certain signals with lower PSNR values showed more similarity with the original signal when assessed visually as indicated in Table 2.

Wavelet	Level 1	Level 2	Level 3	Level 4	Level 5	Level 6	Level 7
Haar	35.472*#	34.712	30.908	28.012	25.596	23.864	26.322
db2	35.691*#	35.559	34.17	30.44	30.833	27.378	27.557
db3	35.578*#	32.257	31.723	31.9	30.327	26.676	29.065
db4	35.51*#	33.228	35.127	24.675	26.152	25.84	25.086
db5	35.483	36.429*#	33.248	27.54	23.295	24.23	21.982
db6	35.372*#	34.878	34.659	29.748	26.065	28.927	28.678
db7	35.253*#	33.213	34.353	24.852	28.26	27.588	28.897
db8	35.265	36.189*#	34.489	27.883	26.523	25.084	26.074
db9	35.392*#	34.859	34.051	25.05	26.717	26.961	26.05
db10	35.501*#	32.791	32.658	26.333	28.779	25.406	27.985
Coif1	34.627*#	27.781	32.069	30.219	30.57	28.806	29.417
Coif2	35.304*#	30.633	33.707	24.738	26.86	27.676	25.015
Coif3	35.388*#	32.253	35.191	25.97	27.4	27.355	25.098
Coif4	35.397*#	32.901	35.15	29.586	26.932	26.392	24.644
Coif5	35.392*#	33.196	33.69$	26.201	24.229	24.231	22.721
Coif6	35.385*#	33.346	34.128	24.355	22.464	21.003	20.278
Coif7	35.379*#	33.431	32.716	26.192	23.778	21.896	21.091
Coif8	35.375*#	33.485	33.505$	28.501	27.569	24.203	23.589
Coif9	35.371*#	33.522	32.102	26.319	27.971	25.903	25.231
Coif10	35.369*#	33.552	33.15	24.484	28.595	27.022	26.41
Sym2	35.691*#	35.559	34.17$	30.44	30.833	27.378	27.557
Sym3	35.578*#	32.257	31.723$	31.9	30.327	26.676	29.065
Sym4	35.205*#	29.768	34.464$	31.897	30.576	29.948	27.77
Sym5	35.174*#	33.264	34.677$	26.652	26.44	27.282	25.875
Sym6	35.342*#	34.991	35.219$	25.658	29.255	28.902	26.845
Sym7	35.473*#	34.381	34.727$	26.421	25.095	23.07	22.289
Sym8	35.371*#	31.998	35.187$	24.796	27.891	27.49	25.674
Sym9	35.297*#	33.705	33.384$	27.19	26.305	27.291	25.717
Sym10	35.376*#	35.293	32.968$	26.047	29.124	28.623	27.147
Sym11	35.491*#	34.896	33.867$	27.369	24.548	25.013	24.104

TABLE 2. PSNR values of the denoised ECG signal with respect to the original ECG signal. ∗Indicates the denoising level at which the highest PSNR value is obtained. # indicates that the corresponding denoised signal is not clinically acceptable for diagnostic or prognostic purposes when examined by the clinician. $ indicates signal with more resemblance to the original signal than that with the highest PSNR.

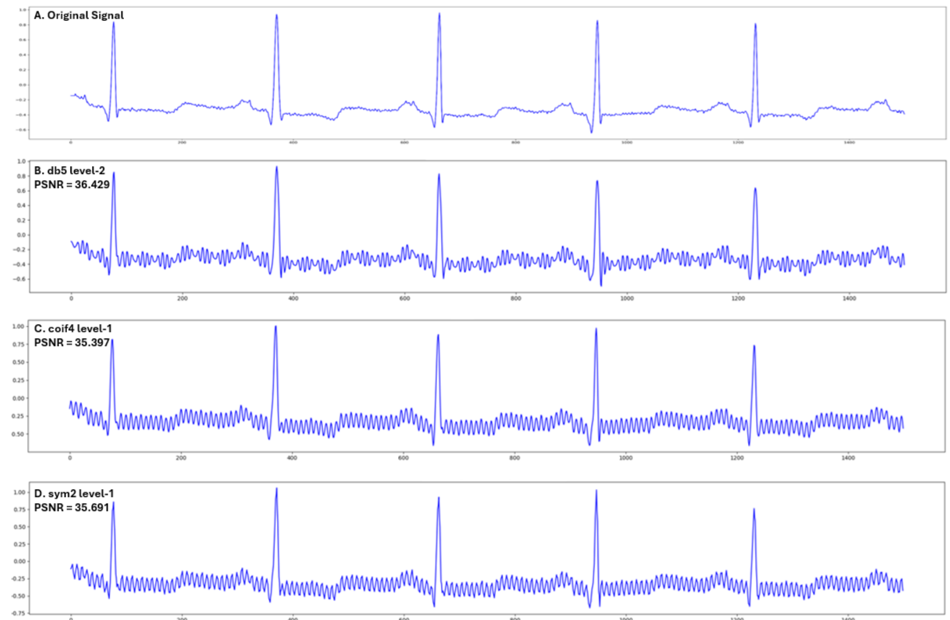

FIGURE 4. Orthogonal wavelet based denoised signals using the universal thresholding method (VisuShrink). Representative samples from each orthogonal wavelet family with the highest PSNR are shown. The initial 1500 samples of the signals (sampling rate 360/s) are plotted against amplitude. A) The original signal from record 100 of MIT-BIH arrhythmia database; B,C,D - denoised signal using db5 at level-2, coif4 at level-1 and sym2 at level-1 respectively.

4. Discussion and conclusion

There are several mathematical functions to compress and denoise signals. Among these, the Discrete Wavelet Transforms can be used to efficiently denoise N-dimensional signals. In this work, we performed denoising of an ECG signal (from record No. 100) from the MIT-BIH arrhythmia database that was noised using 40 Hz sinewave. All the orthogonal wavelets supported by the PyWavelet library for Python such as Haar, db, coif and sym were used to denoise the signal. Transformations of up to 15 levels were performed for each wavelet and the denoised signals were compared with the original signal (record 100) computationally by calculating peak signal to noise ratio (PSNR), and evaluated visually by a cardiologist to determine the fidelity, precision and diagnostic value of the denoised signal.

General observations include decrease in PSNR values of the denoised signals with increasing levels of transformations. Overall, with BayesShrink method, the most common level at which highest PSNR values were obtained was the level-3, whereas

with VisuShrink, the maximum number of highest PSNRs were observed at level-1. Computationally denoising with adaptive thresholding algorithm yielded higher PSNRs than the universal thresholding method. Additionally, in universal thresholding method, with symlet transformation certain denoised signals with lower PSNRs showed better similarity with the original signal than their higher PSNR counterparts.
None of the signals corresponding to the highest PSNR values were suitable for diagnostic purposes. The main reasons for this include- presence of excessive noise that prevented identification of the characteristic features of cardiac rhythm, alternations in the wave components of the denoised signals, wave distortions, presence of artefacts in the signals etc., that interfered with diagnostic values of these signals. In conclusion, the signals denoised using adaptive as well as universal threshold methods in the orthogonal wavelets db, coif, and sym were found to be not helpful for noised ECG signals. Biorthogonal wavelets may be more appropriate for the noised biological signals to provide better precision and fidelity.

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