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PREDICTING THE EFFICIENCY OF DCT-BASED DENOISING OF 1-D SIGNALS CORRUPTED BY ADDITIVE WHITE GAUSSIAN NOISE

Abstract. The object of the study is the process of 1-D signal processing by means of DCT-based filter. **The subject of the study** is the method for prediction of filtering efficiency in terms of signal-to-noise ratio improvement. **The goal of the study** is to identify which parameters can be used for prediction, evaluate the potential accuracy of the predictions, and assess whether the proposed approach is sufficiently generalizable. **Methods used:** numerical simulation, verification for a set of test 1-D signals of different origins. **Results obtained:** (1) accurate prediction is feasible, with a high level of accuracy achieved; (2) prediction accuracy depends on an input parameter that can be computed relatively easily; and (3) the proposed approach is sufficiently general to be applicable to both speech and medical signals affected by additive white Gaussian noise. **Conclusions:** (1) If the input SNR is below 30 dB, DCT-based filtering with appropriately chosen parameters can enhance it; (2) the extent of this improvement varies significantly but is predictable; and (3) this predictability enables informed decisions about whether filtering is beneficial and how to optimally configure its parameters.

Keywords: DCT-based filtering; denoising efficiency prediction; 1-D signals of different origins.

Introduction

Numerous information systems are designed to record and process one-dimensional (1-D) signals to measure their parameters or extract meaningful data. Notable examples include speech processing [1], medical diagnostics [2], control systems [3] and others. In most practical cases, the recorded signals are imperfect—noise or other factors degrade quality of signals to varying degrees [4–6]. In some cases, the noise is negligible – it is not visually apparent in signal/noise mixture and its negative impact on parameter estimation or information extraction is minimal and acceptable [7–9]. However, in many practical situations, the influence of noise is significant, requiring the use of signal denoising [10, 11] or enhancements to parameter estimation methods [12].

A wide range of denoising techniques – including filtering and smoothing methods – have been developed to date [13, 14]. These methods span various categories, such as non-adaptive and adaptive linear filters [15], non-adaptive and adaptive nonlinear filters [16], and orthogonal transform based techniques utilizing, e.g., wavelets [17] and discrete cosine transform (DCT) [18]. Additionally, neural network-based methods trained for specific noise patterns have also been employed [19]. Among these, DCT-based techniques have demonstrated high effectiveness in suppressing Gaussian [20] and mixed [21] noise. As with other filtering methods, the performance of DCT-based denoising techniques depends on multiple factors [21, 22], including:

1) signal complexity, which is difficult to characterize quantitatively and generally refers to spectral content, the presence of abrupt changes, etc.

2) noise intensity often expressed in terms of input signal-to-noise ratio (SNR);

3) filter parameter settings, such as block size, threshold type, and the proportionality factor between noise standard deviation (assumed to be known a priori or accurately estimated [23, 24]) and the threshold value, etc.

Studies presented in [21, 22] demonstrate that 1) filtering may be ineffective or even unnecessary when the input SNR is sufficiently high or signal is highly complex resulting in low filtering efficiency; and 2) when the noise is additive white and Gaussian (AWGN), the filtering efficiency can be predicted in advance, provided that specific offline analyses are performed. If this prediction is both accurate and computationally efficient, it enables informed decisions about whether filtering should be applied. In cases where it is deemed unnecessary, skipping the filtering step can save both processing time and computational resources.

The study presented in [22] was conducted on a limited set of test 1-D signals and validated using a single medical signal - an electrocardiogram (ECG). Other types of 1-D signals, particularly audio signals, were not considered. Additionally, the input parameter used for prediction in [22] was selected empirically, leaving it unclear whether alternative parameters could yield more accurate prediction.

Th**e focus of this study** is the application of DCT-based filtering to 1-D signals of various origins, with particular emphasis on speech and medical signals. Our **core hypothesis** is that a single, simple, and easily calculatable parameter can enable fast and accurate prediction of SNR improvement for signals corrupted by AWGN with a known variance.

The goal of this paper is twofold:

1) to analyze parameters that can be used as inputs for predicting filtering efficiency, compare their performance, and provide practical recommendations for their use;

2) to demonstrate that the proposed prediction approach is general - i.e. accurate and applicable to various types of 1D signals, including speech and

medical (e.g., electrocardiographic). Additionally, the study aims to identify the range of input SNRs for which filtering is typically beneficial.

General signal/noise model and basic principles of DCT-based filtering

Assume that signal contaminated by noise can be expressed as

$$S_n(i) = S(i) + n(i),\ i = 1, ..., I, \quad (1)$$

where $\{S(i),\ i = 1,...,I\}$ is a noise-free signal, i is the sample index, I is the total number of registered samples, $\{n(i),\ i = 1, ..., I\}$ is zero mean additive white Gaussian noise with variance σ^2.

Unlike many wavelet-based filters, DCT-based denoising is performed on fixed size blocks. To ensure efficient computation, the block size is typically chosen as a power of two – commonly 16, 32, 64 or 128, which allows the use of fast DCT algorithms. For each l-th block, the following three steps are performed:

1) direct DCT is applied, producing N DCT coefficients $\{D_l(k),\ k = 1, ..., N\}$, where N denotes the block size;

2) thresholding is then performed resulting in a set of modified coefficients $\{D_{l\ thr}(k),\ k = 1, ..., N\}$ where many $D_{l\ thr}(k)$ values have reduced magnitudes compared to the original $D_l(k)$ (the details of thresholding will be explained below);

3) an inverse DCT is applied to the thresholded coefficients $\{D_{l\ thr}(k),\ k = 1, ..., N\}$ producing N denoised signal values $S_{f\,l}(m = l, \ldots, l + N–1)$ for a given l-th block. It is important to note that, unlike sliding-window filtering, this approach yields denoised values for all samples within each block.

The fundamental idea behind DCT-based denoising is that DCT coefficients with relatively large absolute values are likely to represent meaningful signal components, while those with small amplitudes are typically associated with noise. Therefore, during the thresholding stage, it is desirable to reduce or to eliminate the small magnitude DCT coefficients. Various thresholding techniques exist to achieve this. In the following, we focus on two methods known as hard thresholding, which is defined as

$$D_{l\,thr}(k) = \begin{cases} D_l(k), & if\ |D_l(k)| > T, \\ 0, & if\ |D_l(k)| \le T, \end{cases} k = 2, \ldots N, \quad (2)$$

and on combined thresholding defined as

$$D_{thr}(k) = \begin{cases} D_l(k), & if\ |D_l(k)| > T, \\ D_l{}^3(k)/T^2, & if\ |D_l(k)| \le T, \end{cases} k = 2, \ldots N, \quad (3)$$

where, in both (2) and (3), T denotes the threshold parameter, which is typically set proportional to the noise standard deviation σ, such as T = βσ. The optimal (or recommended) value of β depends on thresholding method, the characteristics of signal and noise, and the chosen optimality criterion. As a guideline, β is commonly set to approximately 2.6 for hard thresholding (as in equation (2)), and around 4.5 for the combined thresholding approach.

Typically, the signal length I is much greater than the block size N, and there are various ways to position the blocks along the signal. In this study, we consider the case of full overlapping, where the l-th block starts at the l-th sample and covers the range $\{S(m),\ m=l,...,l+N–1\}$. This results in $I–N+1$ possible block positions. For any sample index i within the range $N–1 \le i \le I–N$, there are N filtered values of $S_{f\,l}$ corresponding to overlapping blocks with $l = i–N+1, \ldots,$ i. These multiple estimates can be combined in various ways to obtain the final denoised value, with simple averaging being the most straightforward approach. DCT-based filtering with full block overlapping generally provides more efficient noise suppression compared to partial overlapping, albeit at the cost of increased computational load. However, DCT-based methods remain computationally efficient in practice. Another advantage is that this filtering scheme introduces a fixed delay of N samples relative to the incoming data, which is acceptable in many applications. It should also be noted that noise suppression is typically less effective near the edges of the signal, compared to the central portion.

Noise removal efficiency also depends on the block size N. To illustrate this dependence, as well as the impact of thresholding type and the parameter β, Fig. 1 shows the behavior of the SNR improvement metric, defined as

$$ISNR = 10log_{10}(\sigma^2/\text{MSE}) = SNR_{\text{out}} - SNR_{\text{inp}}\ ,$$

where MSE is the mean square error at the filter output, SNR_{out} and SNR_{inp} are output and input SNRs, respectively. The results presented in Fig. 1 were obtained using the speech file F1, which contains English language Harvard phrases [25].

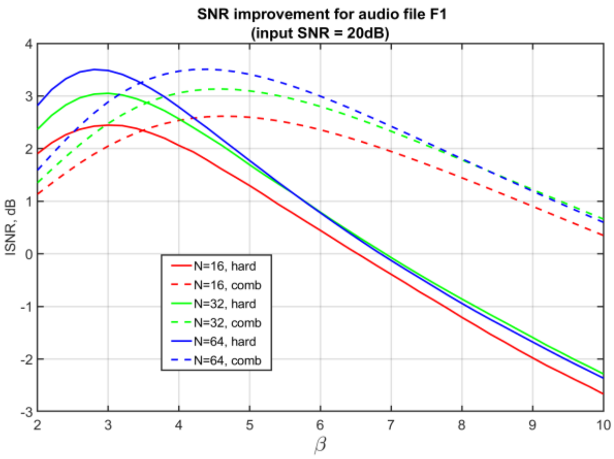


Fig. 1. Dependences of ISNR on β for audio file F1 denoising by the DCT-based filters with types of thresholds for three values of N (16, 32, and 64)

As shown in the results, ISNR reaches approximately 2.5 dB for $N = 16$, about 3 dB for $N = 32$, and around 3.5 dB for $N = 64$. This indicates that using $N = 64$ is a reasonable choice. The optimal results for both types of thresholds are nearly identical for the same block size, with the optimal β values aligning closely with those recommended earlier. A noisy speech signal with the input SNR of 10 dB is presented in Fig. 2, a. The corresponding residual noise after filtering – defined as $\{n_{res}(i) = S_f(i) – S(i),\ i = 1, ..., I\}$ is shown in Fig. 2, b, where different colors represent the two thresholding methods. The *MSE* for hard thresholding is 0.0000163, while for the combined thresholding – 0.0000155, indicating the minimal difference. Given that the noise variance is 0.0000620.0000620.000062, the resulting ISNR is approximately 6 dB for both methods.

An interesting observation from the comparison of Figs. 2, a and 2, b is that residual noise tends to be more pronounced in segments where the original signal has higher intensity. This can be explained, at least, for hard thresholding, by the fact that noise suppression is reduced when a larger number of DCT coefficients retain relatively high absolute values after thresholding. The combined thresholding behaves similarly, though in a smoother manner. Therefore, for more complex signals - characterized by a higher proportion of large-amplitude DCT coefficients - the expected ISNR tends to be lower. This observation forms the basis for the proposed ISNR prediction approach.

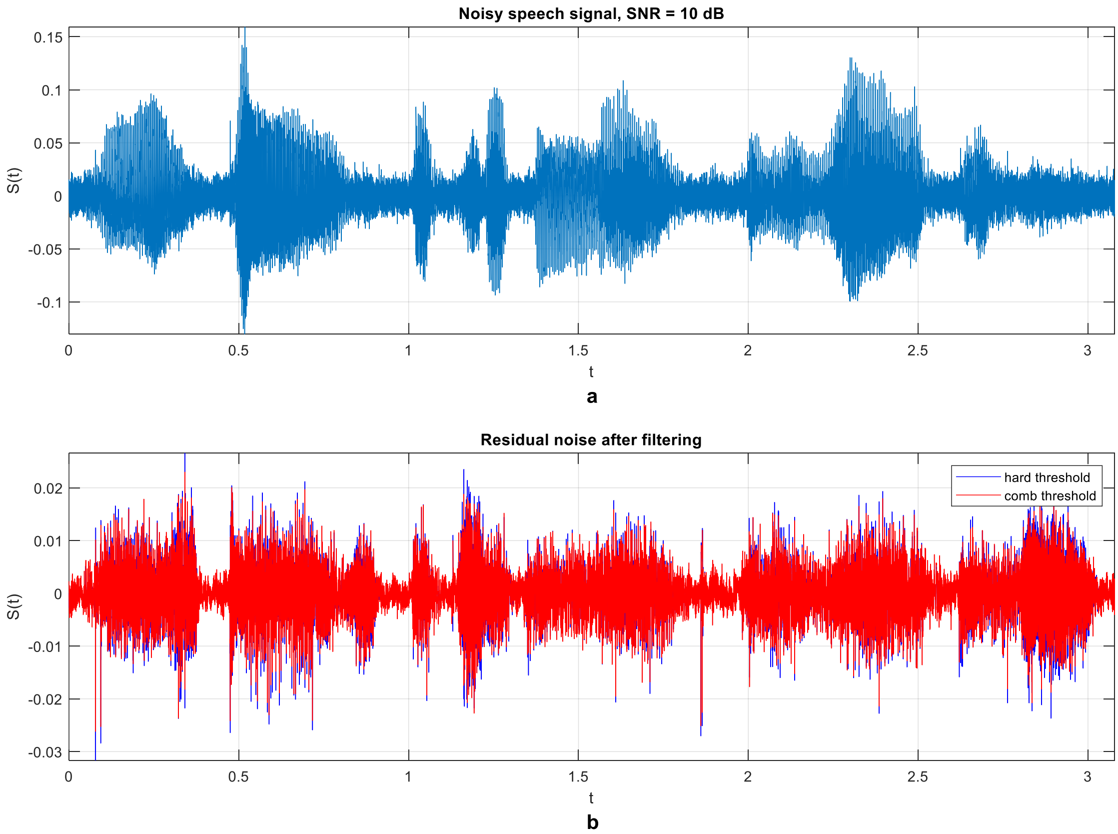


Fig. 2. Noisy speech signal with input SNR equal to 10 dB (a)
and residual noise after denoising by two versions of the DCT-based filters (b)

Efficiency prediction method and its performance analysis

Before proposing a method for predicting filtering efficiency, it is important to define the requirements such a method should meet. To be practically useful, the prediction method should satisfy the following criteria:

1) It must be faster than the filtering process itself, keeping in mind that DCT-based denoising is already a relatively fast technique.

2) It should be sufficiently accurate, providing ISNR predictions with an error margin small enough to support reliable decisions—such as whether filtering is worthwhile or which filter parameters to choose.

3) It should be simple and lightweight, ideally implementable using the same computational framework as the filtering algorithm itself.

Fortunately, prior work has provided us experience in developing methods for predicting filtering efficiency for both 1-D signals [22] and images [26]. In both cases, the core assumption is that there exists a well-defined relationship between a parameter representing denoising efficiency and an input parameter that jointly reflects signal/image complexity and noise intensity. This relationship is established offline—that is, it is derived in advance and made available by the time a noisy signal or image needs to be processed. Ones the input parameter is computed for the current data, it is used as the argument in the pre-established relationship to obtain the predicted filtering efficiency.

Following this general overview, we now provide some specific details. Suppose that the improvement in SNR (or in peak signal-to-noise ratio (PSNR) in the case of image processing) can be used as an representative parameter for characterizing denoising efficiency. As demonstrated in [22] and [26], it is possible to predict not only *SNR* or PSNR improvements, but also other output metrics related to denoising performance.

In both studies, the parameters denoted as $P_{2\sigma}$ and $P_{0.5\sigma}$ – defined as the probabilities that absolute values of DCT coefficients within blocks do not exceed 2σ and 0.5σ, respectively – are proposed as input features for prediction. The use of $P_{2\sigma}$ is motivated by the assumption of normality in the distribution of AC DCT-coefficients for constant level signals or images, where $P_{2\sigma}$ approaches 0.95. In contrast, the use of $P_{0.5\sigma}$ is more empirical choice, based on observed predictive performance rather than theoretical justification.

As demonstrated in [22] and [26] the parameter $P_{2\sigma}$ typically ranges from approximately 0.2 (for highly complex signals with low noise levels) to about 0.9 (for structurally simple signals under high noise conditions). Similarly, $P_{0.5\sigma}$ ranges from around 0.07 to 0.35. These observations were derived using six standard test images (Blocks, Bumps, Doppler, etc.). For each test signal and each input SNR level considered, both input and output parameters were collected. Scatter-plots of ISNR vs $P_{2\sigma}$ and ISNR vs $P_{0.5\sigma}$ were generated, and simple monotonously increasing curves were fitted to the data. The quality of these fits, measured by the coefficient of determination R^2, was approximately 0.92 for both polynomial and exponential models, with a root mean square error (RMSE) of about 0.7.

One might reasonably question whether the prediction models derived from these test signals – none of which are related to speech – are applicable to speech denoising tasks. To investigate this, we analyzed five speech signals from [25] covering a broad range of input SNR values. Scatter plots for both hard and combined thresholding approaches were created, as shown in Fig. 3.

In both cases, second-order polynomial models were used, yielding an R^2 of approximately 0.988 and of RMSE of about 0.23, indicating a very strong predictive capability.

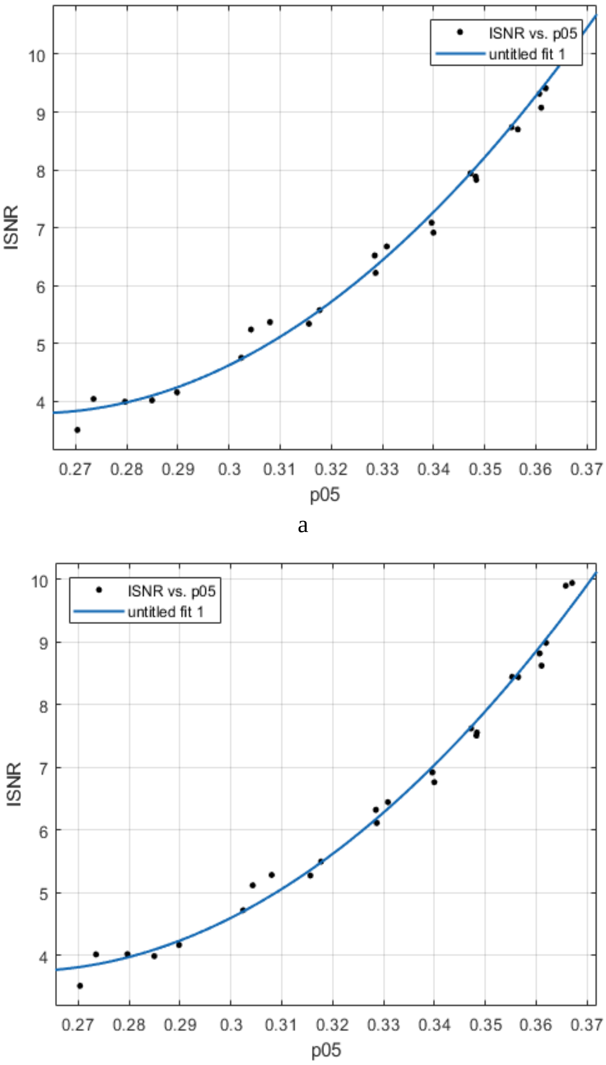
In other words, the fitting results in our study are significantly better than those reported in [22]. However, an important question remains: how similar are the fitted curves themselves? To assess this, we compare the predicted ISNR values for $P_{0.5\sigma}$ = 0.28, 0.32, and 0.36. According to [22], the corresponding ISNR predictions are approximately 5.2, 6.0, and 8.7, respectively. In our case, the predicted ISNRs are about 4.0, 5,6, and 8.8, respectively indicating good agreement between the two models.

As noted earlier, both input parameters, $P_{0.5\sigma}$ and $P_{2\sigma}$, are somewhat empirical choices. To further explore this, we evaluated additional cases of $P_{\varepsilon\sigma}$ where ε was set to 0.25, 0.75, 1.0, and 1.5. Overall, the prediction quality remained high across all values of ε, with R^2 exceeding 0.98 and RMSE not exceeding 0.305. Formally, the best performance was achieved using $P_{0.25\sigma}$, with R^2=0.988, RMSE=0.244 - the results nearly identical to those obtained with $P_{0.5\sigma}$.

Therefore, for practical purposes, values of ε in the range $0.25 \le \varepsilon \le 0.5$ are recommended.

It is important to recall that ISNR prediction -, i.e. the calculation of $P_{\varepsilon\sigma}$, - should be performed quickly. If $P_{\varepsilon\sigma}$ is calculated using all possible block positions (as in full-overlap filtering), the computation time is approximately half that of the full denoising process, since filtering involves two DCT operations per block.

However, further acceleration of prediction may be necessary in practice. One efficient approach is to compute the input parameter using partially overlapping or non-overlapping blocks.



a

b

Fig. 3. Scatter-plots of ISNR vs $P_{0.5\sigma}$
for hard (a) and combined (b) thresholding

For example, in the case of speech signals sampled at 16 kHz with a duration of about 2 s, using half-overlapping blocks yields a prediction RMSE of approximately 0.27 dB, while using non-overlapping blocks results in an RMSE of about 0.3 dB. These results suggest that both configurations are acceptable for practical use, offering prediction speeds one to two orders of magnitude faster than full denoising.

It should also be noted that the prediction accuracy data discussed above for speech signals were obtained using the same signals that were used to generate the scatter plots during the "training" phase. A natural question arises: how well does the prediction generalize to new, unseen signals? To investigate this, we applied the fitted prediction curves from Fig. 3 to estimate ISNR ($ISNR_{pred}$) for five speech signals (F5-F9 from the dataset [25]) that were not used in constructing the scatter-plots. The predicted ISNR values were then compared with the true calculated ISNR values ($ISNR_{calc}$), as presented in Tables 1 and 2 for hard and combined thresholding, respectively. It should be noted that the test here that signals vary in power, and the AWGN standard deviation σ was adjusted accordingly to achieve the desired input SNR.

Table 1 – **Predicted and calculated ISNRs for five signals processed with hard thresholding, $SNR_{inp} \approx 10$**

File name	Input SNR	σ	$P_{0.5\sigma}$	$ISNR_{calc}$	$ISNR_{pred}$
F5.wav	9.98	0.0079	0.328	6.16	6.25
F6.wav	9.97	0.0021	0.335	6.43	6.80
F7.wav	9.97	0.0147	0.333	6.51	6,69
F8.wav	9.98	0.0119	0.332	6.98	6.61
F9.wav	9.97	0.0088	0.330	6.48	6.42

Table 2 – **Predicted and calculated ISNRs for five signals processed with combined thresholding, $SNR_{inp} \approx 10$**

File name	Input SNR	σ	$P_{0.5\sigma}$	$ISNR_{calc}$	$ISNR_{pred}$
F5.wav	9.98	0.0079	0.328	6.03	6.10
F6.wav	9.97	0.0021	0.335	6.33	6.61
F7.wav	9.97	0.0147	0.333	6.31	6.51
F8.wav	9.98	0.0119	0.332	6.79	6.44
F9.wav	9.97	0.0088	0.330	6.26	6.26

Analysis of the data in Tables 1 and 2 shows that the predicted $ISNR_{pred}$ and calculated $ISNR_{calc}$ differ by no more than 0.37 dB, indicating a high level of prediction accuracy. It is also noteworthy that $ISNR_{calc}$ values for all five considered speech signals are very similar at the same input SNR, suggesting consistent denoising performance across different signals.

Applicability of prediction method to ECG signals

Now, a question arises whether ISNR can also be accurately predicted for ECG signals. To explore this, we selected several clean ECG signals from CEBSDB database [28–30], added AWGN of varying intensities to simulate different input SNRs, applied DCT-based denoising, and measured the resulting true ISNR. In parallel, we predicted ISNR using the fitted curves previously obtained for speech signals. Selected results are presented below.

Fig. 4, a shows an example of a clean ECG signal and Fig. 4, b displays the same signal corrupted with AWGN at an input SNR of 15 dB. The noise is clearly visible and its suppression is necessary. Fig. 4, c illustrates the output of the DCT-based filter with hard thresholding and an optimal value of β. As seen, the noise is significantly reduced, while the essential structure of the ECG signal is preserved well.

Fig. 5 presents the ISNR as a function of β for both thresholding types, based on the signal shown in Fig. 4. As observed, the maximum ISNR values are nearly identical for hard and combined thresholds. The optimal values of β are slightly larger than those recommended earlier, which can be attributed to the relatively high noise level in this example. The achieved ISNR (approximately 6 dB) is greater than that shown in Fig. 1, which is explained by two factors: the lower input SNR and a simpler (smoother) structure of the ECG signal compared to speech.

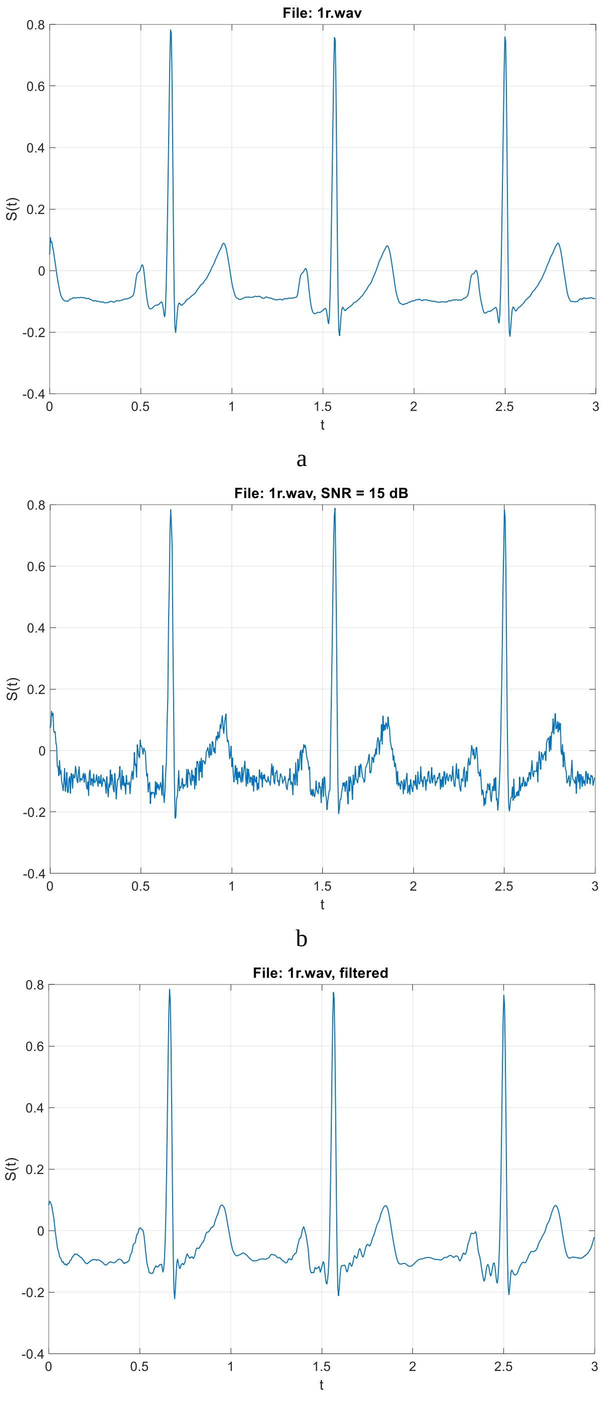


Fig. 4. Noise-free ECG signal (a), its noisy version for SNR_{inp}=15 dB (b), and filtered version (c)

Preliminary analysis of the data obtained for ECG signals reveals the following observations:

1) At an SNR_{inp} of 30 dB, filtering is generally unnecessity for two reasons. First, noise is visually negligible (Fig. 6). Second, the ISNR achieved is only about 1 dB, which is relatively small. Moreover, if the noise variance is known or can be reliably estimated, the SNR_{inp} can also be estimated, allowing the filtering step to be skipped entirely.

2) When SNR_{inp} is lower, filtering becomes more beneficial. For example, at SNR_{inp}=25 dB, the ISNR is approximately 2.5 dB; if SNR_{inp}=20 dB, ISNR increases

to about 4.3 dB. This trend is consistent with the behavior observed in speech signals—ISNR increases as the input SNR decreases;

3) The optimal values of β remain nearly the same across both types of thresholding. Specifically, they are slightly above 3 for hard thresholding, and 5 for combined thresholding;

4) For a given signal, noise realization, and input SNR, the output SNR values resulting from the two thresholding methods differs very little - typically by less than 0.2 dB, as shown in Fig. 5). Therefore, in practice, either thresholding method can be used with comparable results.

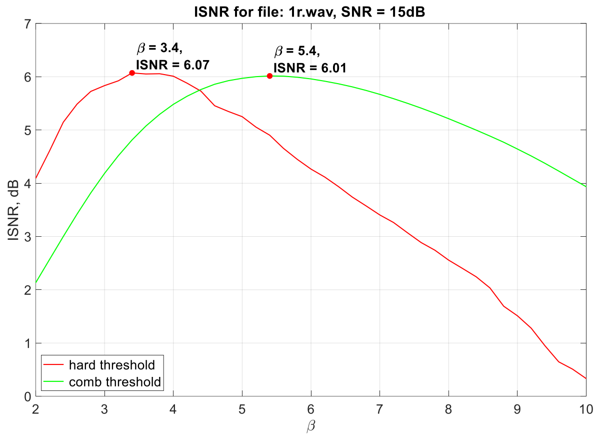


Fig. 5. Dependences of ISNR on β for two types of thresholds for DCT-based denoising of the signal in Fig. 4, b

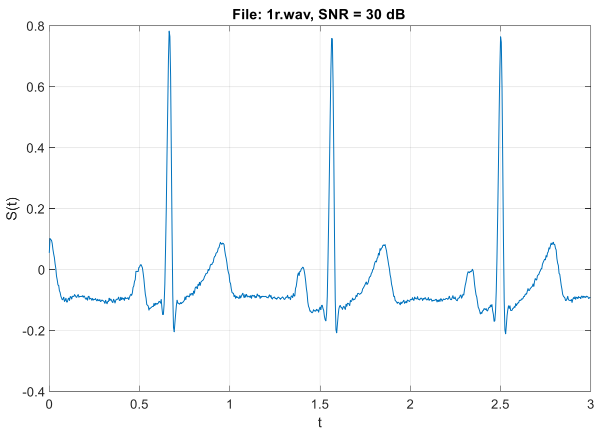


Fig. 6. Example of noisy signal for input SNR equal to 30 dB

Let us now assess whether ISNR can be predicted with sufficient accuracy. Table 3 presents representative results, structured similarly to those shown in Tables 1 and 2.

As observed, the prediction accuracy for ECG signals is lower than for speech signals (refer to Tables 1 and 2), with discrepancies reaching up to 2.8 dB. We attribute this to two main factors.

First, the prediction curves used for ECG signals were originally derived from speech signal data. Similar cross-domain discrepancies have been reported for test signals of different nature in [22]. Second, for the same value of $P_{0.5\sigma}$, the RMSE of ISNR is higher for ECG signals than for speech signals.

Table 3 – **Predicted and calculated ISNRs for five signals processed with hard thresholding**

File name	Input SNR	σ	$P_{0.5\sigma}$	$ISNR_{calc}$	$ISNR_{pred}$
1r.wav	15.66	0.028	0.334	5.96	6.74
2r.wav	15.12	0.028	0.325	6.75	6.09
3r.wav	15.00	0.028	0.324	8.14	5.99
4r.wav	15.33	0.031	0.332	7.74	6.62
5r.wav	16.84	0.030	0.343	4.87	7.60
1r.wav	20.59	0.0161	0.328	4.18	6.30
2r.wav	19.99	0.157	0.307	6.16	4.96
3r.wav	19.97	0.159	0.299	6.46	4.57
4r.wav	20.23	0.178	0.310	7.00	5.11
5r.wav	21.75	0.168	0.321	3.58	5.80

Therefore, it can be concluded that while the previously derived prediction curves (i.e. the ISNR vs. $P_{0.5\sigma}$) are applicable to DCT-based denoising of ECG signals, the prediction accuracy is notably lower. The underlying causes of this reduced accuracy warrant further investigation.

Conclusions

This study investigates the use of DCT-based filters with two types of thresholding—hard and combined—for denoising two types of one-dimensional (1-D) signals: speech and ECG, across a wide range of input SNR values.

The results show that denoising is generally beneficial when the input SNR is below 30 dB for both threshold types, which yield comparable performance when optimal or recommended values of β are used. Furthermore, it is demonstrated that ISNR can be effectively predicted using a simple statistical parameter computed over a set of blocks, which may be either non-overlapping or half-overlapping This prediction method is significantly faster that filtering itself and achieves high accuracy for speech signals, with acceptable accuracy for ECG signals. Among the tested input parameters, $P_{0.5\sigma}$ is the recommended due to its strong predictive performance; however, other parameters such as $P_{0.25\sigma}$ or $P_{0.75\sigma}$ can also be used provided that corresponding prediction curves are established in advance.

Future work will focus on a more detailed investigation of prediction methods for ECG denoising efficiency.

Conflicts of interest

The authors declare that they have no conflicts of interest in relation to the current study, including financial, personal, authorship, or any other, that could affect the study, as well as the results reported in this paper.

Use of artificial intelligence

The authors confirm that they did not use artificial intelligence technologies when creating the current work.

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Прогнозування ефективності DCT-методів приглушення шуму в одновимірних сигналах, спотворених адитивним білим гаусівським шумом

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Анотація. Об'єктом дослідження є процес обробки одновимірних сигналів за допомогою фільтра на основі ДКП. **Предметом дослідження** є метод прогнозування ефективності фільтрації з точки зору покращення співвідношення сигнал/шум. **Метою дослідження** є визначення параметрів, які можна використовувати для прогнозування, оцінка потенційної точності прогнозів та оцінка того, чи є запропонований підхід достатньо узагальнюваним. **Використані методи**: числове моделювання, верифікація для набору тестових одновимірних сигналів різного походження. **Отримані результати**: (1) точне прогнозування можливе, з високим рівнем досягнутої точності; (2) точність прогнозування залежить від вхідного параметра, який можна відносно легко обчислити; та (3) запропонований підхід є достатньо загальним, щоб бути застосовним як до мовних, так і до медичних сигналів, на які впливає адитивний білий гауссовий шум. **Висновки:** (1) Якщо вхідне співвідношення сигнал/шум нижче 30 дБ, фільтрація на основі DCT з відповідно вибраними параметрами може його покращити; (2) ступінь цього покращення значно варіюється, але є передбачуваною; та (3) ця передбачуваність дозволяє приймати обґрунтовані рішення щодо того, чи є фільтрація корисною та як оптимально налаштувати її параметри.

Ключові слова: фільтрація на основі DCT; прогнозування ефективності шумозаглушення; одновимірні сигнали різного походження.