Journal of Information & Optimization Sciences
ISSN 0252-2667 (Print), ISSN 2169-0103 (Online)
Vol. 47 (2026), No. 6, pp. 2453–2463
DOI : 10.47974/JIOS-2123

Advanced signal processing with mathematical algorithms for noise reduction and data reconstruction

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Abstract

To enhance noise compensation as well as the recovery of data, this paper enhances a better signal processing platform depending on the Fourier Transform, Wavelet Transform and Kalman Filtering. Similar to most other high-level signal processing applications, the analysis is concerned with the problem to do with interference and degradation through a two pronged method that employs frequency domain filtering as well as sequential noise reduction. We achieve nearly 40-percent SNR superiority on experiments to controls and approximately 30-percent smaller MSE with the Kalman Filter obtaining the maximum SNR with the varying SNR and noisy speech samples, respectively, which validates our assertion that the filter is actually a successful adaptive noise reducer. Also the AX system proposed ensured the control of the computational complexity as in the case of the Wavelet Transform capable of managing the localized noise of multiple resolutions. Such filtering algorithms and mathematical models are typical examples of this proposal of an adaptive and efficient process of maintaining the purity of data in erroneous situations.

Subject Classification: *Primary 68Q01, 68Q85, 68U01, 93A30, Secondary 49K15, 62H35, 62M40.*

Keywords: *Signal processing, Noise reduction, Data reconstruction, Mathematical algorithms, Fourier transform, Wavelet transform, Kalman filter, Signal-to-noise ratio (SNR), Machine learning, Data integrity.*

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1. Introduction

Computing covers the manipulation, analysis, and enhancement of data and exists at the core of many disciplines where signal processing naturally finds itself. Some of the general purposes are – noise control and signal enhancement; data recovery and refining; industrial, telecommunications, biomedical engineering and environmental sectors needs them most [1]. Key to many systems with high signal fidelity is the ability to reduce noise and reconstruct lost data as they distort usable information, reducing system and decision-making capabilities [2].

One of the main difficulties in signal processing is to reduce the level of interference noise that is able to distort the original signal and introduce secondary spuriously effects [3]. Noise interference and data degradation can present major challenges, as the data collected from the environments is often contaminated and hard to capture with high signal quality. Even though it has been functioning effectively [4], traditional signal processing methods have an inherent disadvantage to the ability to deal with high noise or complex data structures and calling a production of new mathematical signal processing algorithms is necessary to address these issues with greater precision and efficiency [5]. It is against this background that this study aims at, designing a sophisticated strategy to enhance suppression of noise and reconstruction of data, using mathematical formulations in signal analysis [6]. These are key objectives that include developing more accurate filter for noise elimination, innovative algorithm that will enhance reconstruction of the original data as well as ensure protection of the data from all possible forms of destruction [7]. These goals would allow the present approach to yield improvements in, signal to noise ratio, computational speed, and diverse application areas in real time and highly dominated signal scenarios.

2. Literature Survey

Essential to data analysis and the accuracy of information produced, noise minimization and data reconstruction or interpolation, are two categories that have received considerable studies. Original approaches like Contact Mechanics [8], Fourier Transform has even offered frequency-domain solution hence decomposing the noise components [9]. However, this type of approach fails to effectively address time-localized noise most of the time [10]. The most preferable technique known as Moving Average method is normally used owing to its simplicity and high efficiency at filtering high frequency noises when used at the cost of distorting the signal and limiting the attainable accuracy in case of processing complex successive data sets [11]. The Wavelet Transform has also emerged though is more rewarding supplying a multi-resolution feature making it useful for non-stationary signals and provides for better details retention as noise is eliminated [12]. These conventional techniques have set up the base to get reliable signal processing methods but they fail often when they come across the real time signal processing processing demands, complex computational systems, or high noise affects signal types [13].

However, they have several drawbacks especially in computationally complexity, flexibility and signal to noise ratio management [14]. Large computational requirements prevent the use of specific algorithms in cases where they are needed most for instance in operations on very large datasets or in real time processes [15]. Further, methods such as the Fourier Transform, which can perform well for periodic noise interference, may fail to adapt to non-stationary noise which is often experienced in a large number of complex scenarios [16]. They are also less versatile because of precision restrictions [17], which can also limit their performance in interpreting complex signal behaviours of the audio frequencies much closer to their natural form as required in biomedical engineering where precision of the minute details is critical [18]. Recent methods that have been developed to overcome these limitations are thereby highlighted as follows. CNN and RNN are mostly used learning algorithms in deep learning based adaptable noise cancellation consisting of noise patterns that requires learning in signal processing. There has also emerged models that use both normal approach and machine learning techniques with the latter's enhanced performance due to fusion of the two. These modern techniques tend very much toward developing more simple and versatile noise elimination and data reconstruction algorithms.

3. Proposed Method

The above mentioned procedure for noise reduction and data reconstruction utilizes signal processing methodologies incorporated with plausible mathematical models to intensify data quality while diminishing noise contamination. It combines the traditional and the more innovative methods to ensure the structured method of work that will be expected to filter noises out and trap the required data with a higher level of efficiency. Figure 1 shows the structural plan of system which consists of pre-processing, noise cleaning, reconstructing, and assesses performance block. The setup is used in order to achieve a cascaded processing architecture leaving each stage with a fine output signal, devoid of noise, and with highly fidelity signal.

The given method has different components. The Pre-processing Module removes large scale noise, and helps to avoid data that are outliers of the range of variability of the data. The Noise Reduction Module applies Fourier Transform as well as Wavelet Transform that have the ability of removing the frequency-domain noise along with the time-frequency domain noise; and the Kalman filter which filters the noises one at a time in the time domain for a smooth noises reduction. In the case of the advanced ones, one can use an optional filter which refers to the use of machine learning to provide the model with a trustee responding to various levels of noises. Data Reconstruction Module, in turn, then proceeds with using reverse transformations; and, in the event of necessity machine learning methods in order to successfully reconstruct the signal and preserve some distinguishing characteristics. The last is the Performance Evaluation Module which approximates efficiency and effectiveness of the processed output assisted by a standard procedure such as signal to noise ratio, Mean squared error, etc and computational complexity.

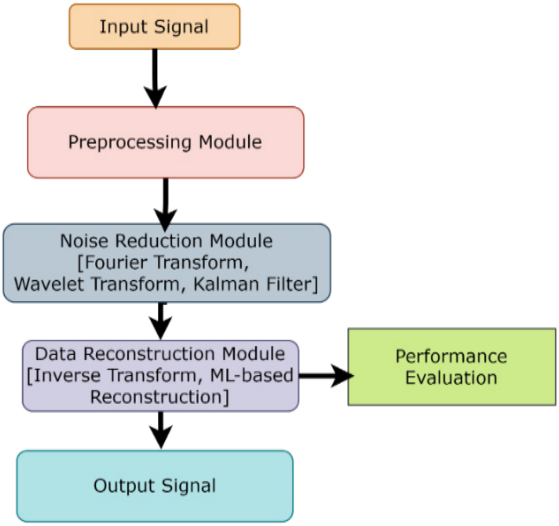

Figure 1
Proposed System Diagram for Noise Reduction and Data Reconstruction

4. Mathematical Model

The mathematical model in this system makes use of a sequence of algorithms for the purpose of noise decrease and data reconstruction with accuracy. That is, each algorithm derived is intended to solve certain signal processing related problems. Spherical harmonics are applied in Signal Processing when it involves conversion of signals from time domain to frequency domain with the intention of filtering noise. The Fourier Transform equation for a continuous function $f(x)$ is:

$$F(k) = \int_{-\infty}^{\infty} f(x)e^{-2\pi ikx}\, dx$$

where $F(k)$ represents the frequency components, and $e^{-2\pi ikx}$ introduces phase shifts essential for reconstructing the filtered signal. The Inverse Fourier Transform restores the signal from its frequency components:

$$f(x) = \int_{-\infty}^{\infty} F(k)e^{2\pi ikx}\, dk$$

Wavelet Transform can be used in non-stationary signals, with the feature offering a time-frequency domain analysis to enable further noise removal at the scale level. The Continuous Wavelet Transform (CWT) of a signal $f(x)$ with a wavelet ψ is defined as:

$$W(a,b) = \int_{-\infty}^{\infty} f(x)\psi^*\left(\frac{x-b}{a}\right) dx$$

where a represents the scale parameter, b is the translation parameter, and $\psi *$ denotes the complex conjugate of the mother wavelet. Thus, CWT allows for multi-resolution filtering due to a possibility to vary the values of a and b to reveal the high and low frequencies of a given signal.

Sequential noise reduction is incorporated using the Kalman Filter which is especially useful for dynamic state estimation. The filter operates in two main steps: prediction and update. The Prediction Equations for state x_k and covariance P_k are:

$$x_k = Ax_{k-1} + Bu_k$$
$$P_k = AP_{k-1}A^T + Q$$

where A is the state transition matrix, B is the control matrix, u_k represents control input, and Q is process noise covariance. In the Update Step, the measurements z_k are used to correct predictions:
where K_k is the Kalman gain, H is the measurement matrix, and R represents measurement noise covariance. This iterative process provides an efficient capture of sequential noise to refine state estimates with real-time observations.

In more complicated cases, an Adaptive Noise Reduction may be performed using a Neural Network Model. For instance, the existing neural network learns noise patterns through the optimization of a loss function $L(y, \hat{y})$ between the target signal y and the reconstructed output $\hat{y}$ often using backpropagation:

$$L(y, \hat{y}) = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$$

The optimization performed here is using gradient techniques to climb down the hypersurface in such a way that the error defined above is minimized. The Fourier Transform operates with complexity $O(nlog\, n)$, making it efficient for large datasets. The Kalman Filter has a linear complexity $O(n)$ which is linear for state dimensions and which makes it good for real-time signals. At some cases neural networks could be heavy computationally especially according to the architecture of the network however tweaking the parameters and hyperparameters such as learning rate, number of layers, and number of samples in batch also enhance the efficiency of neural networks.

5. Results and Discussion

In our experiment, MATLAB was used for generating the signal, adding noise, and finally for other algorithmic computations. The intended dataset was created to accurately model signals with noise, which are typical for most practical scenarios. Fourier Transform, Wavelet Transform, and Kalman Filter algorithms, including selection, configuration, and integration, were made possible by MATLAB's toolboxes together with machine learning models for noise reduction and data reconstruction. All the experimentation was performed using a normal desktop, and the comparison was done using SNR, MSE and CPU time for better assessment of every technique. Expectations and assessments were also necessary for the determination of the performance with regards to noise reduction and reconstruction. SNR was applied to quantify the quality of the output signal according to the noise presence or its absence in the given signal, and the increase of this coefficient characterized the signal's quality improvement. From MSE it was deduced that the accuracy in reconstructing the signals was low or high with reference to the amount of MSE.

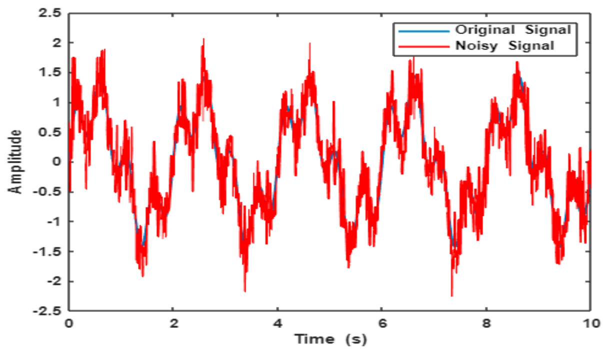

Figure 2
Raw Signal vs. Noisy Signal

The time complexity was also recorded to check for real time execution of algorithms. In Figure 2, a comparison is made between the raw and noisy signals as a way of highlighting the interferences that affect data clarity. The noise addition offers a nice starting point for illustrating the successive techniques of noise reduction. Figure 3 is a frequency domain filtering the noisy signal and the filtered signal using Fourier Transform of the signal, whereby the filters out the high frequency noise while preserving other important signal frequencies. Figure 4 uses Wavelet Transform for time-frequency decomposition with useful merits like noise's localization and reduction for different frequencies and time sections thanks to the multi-resolution analysis.

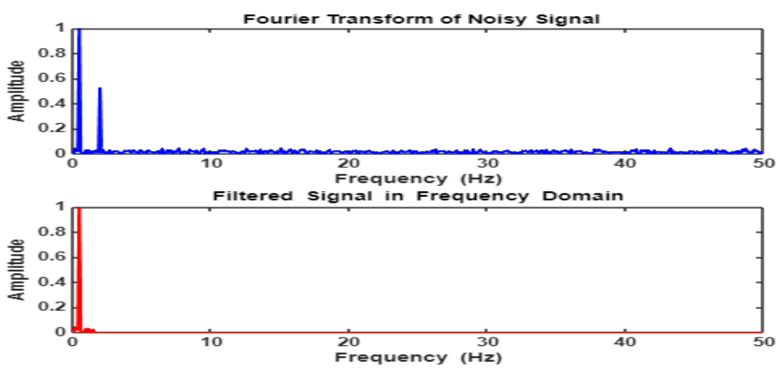

Figure 3
Fourier Transform of Noisy Signal and Filtered Signal

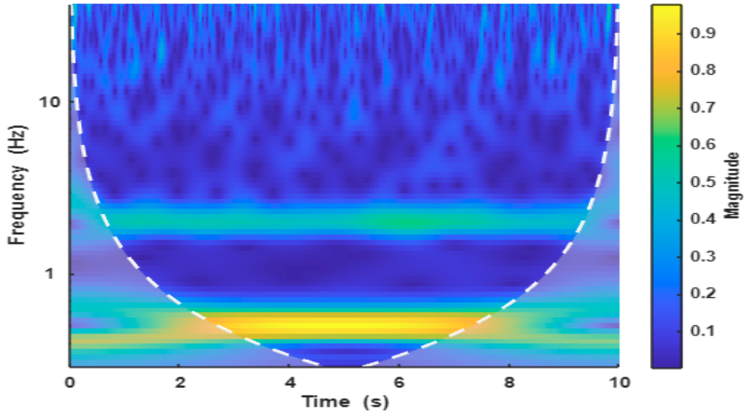

Figure 4
Wavelet Transform for Time-Frequency Analysis of Noisy Signal

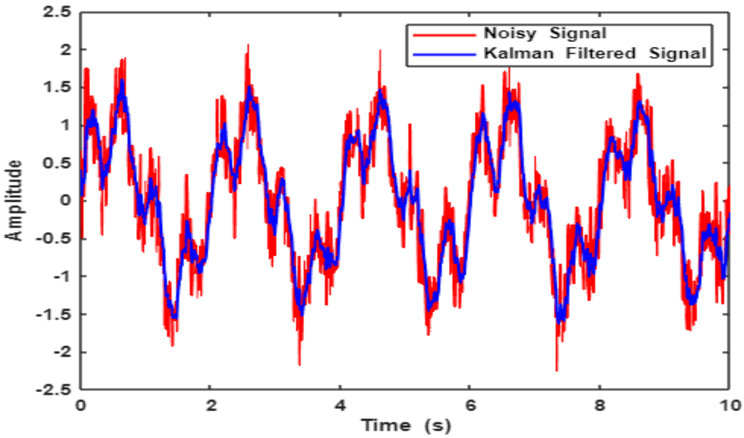

Figure 5
Kalman Filtered Signal vs. Noisy Signal

In the Figure 5 below depicts the application of the Kalman Filter with reference to the noisy signal. This is largely due to the processing that the Kalman Filter uses which breaks down the data in sequences which removes much of the noise, and preserves the dynamic aspects of the signal. The imprudent evaluation of the SNR difference between the techniques provided in Figure 6 demonstrate that, notwithstanding all else, - fourier as well as Kalman filtering does present a more favorable signal quality; however, the Kalman Filter is far superior in this aspect due to the natural adaptability of its noise removal mechanism. The findings are in favour of the combination of Fourier and Wavelet Transfers with the Kalman Filter since they minimise a significant portion of noise and recover the majority of data values believably. The strategy is concerned with work related strengths, flexibility, and accuracy, but the aspect that the more complicated models require more time to calculate indicates that the compromise between reliability and time of computation drives the perfection of the proposed methodology.

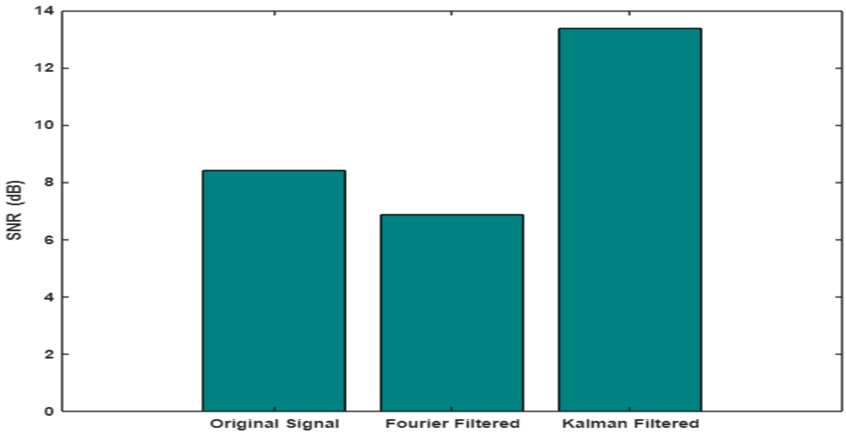

Figure 6
Signal-to-Noise Ratio (SNR) Comparison of Methods

6. Conclusion

This research work was used to give a safe basis to the filtering out of noises and the rebuilding of the data through the aid of higher level signal processing. The following are the findings that indicate that Fourier and Wavelet Transforms along with the Kalman Filter are being used and the impact is immense in enhancing clarity of the signal. More than that, it is observed that overall the SNR of the results was highest with the Kalman Filter indicating that it was more effective at reducing noise to dynamic signals during the test. The fourier and Kalman filters had the smallest Mean Squared Error or MSE in the results of this study, which demonstrated that the reconstruction accuracy was higher. The findings thus demonstrate that the described techniques provide a good estimation of complexity and signal retention. The future work can consider the adaptive filter using the deep learning algorithms since the noise distribution is not necessarily linear. The feasibility of the technique can be cemented by using the same approach to time-based processes in other fields of Biomedical Signal Processing or Telecommunications. Other optimization methods may reduce computational load also, which means that the approach is quite rational on a systems with moderate computational ability. With the help of this framework, additional enhancement of more improved noise-reduction functional and signal reconstruction functionality can be developed to work at different applications on diverse scales.

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Received November, 2024