UNIVERSITÉ CÔTE D'AZUR

MSc. Data Science & AI

Class: Biomedical Signal Processing

Adaptive Noise Canceling

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Report

Contents

1. Synthetic signals

1.1 Draw a table showing the obtained output SIR (dB), SIR improvement (dB) and convergence time (samples) for the 5 tested combinations of μ and M. What can be concluded about the effect of these parameters on the algorithm's performance?

Table 1: Effects of Algorithm Parameters

Combination	μ Value	M Value	SIR (dB)	SIR Improvement (dB)	Convergence Time (samples)
1	0.005	0	2.07	-1.75	837
2	0.05	0	10.23	5.41	85
3	0.01	5	10.05	5.23	111
4	0.01	50	4.68	-0.14	Non Convergence
5	0.1	70	2.01	-2.81	Non Convergence

Combination 1 ($\mu = 0.005$, $M = 0$):

- The achieved SIR (Signal-to-Interference Ratio) is 2.07 dB, indicating a moderate level of separation between the signal and interference components.
- However, the SIR improvement is negative (-1.75 dB), suggesting that the algorithm may not effectively suppress interference.
- The convergence time is 837 samples, indicating a relatively slow convergence of the algorithm.

Combination 2 ($\mu = 0.05$, $M = 0$):

- With an increased value of μ, the SIR significantly improves to 10.23 dB, indicating a substantial enhancement in separating the signal from interference.
- The SIR improvement is positive (5.41 dB), indicating effective interference suppression.
- The convergence time is notably reduced to 85 samples, demonstrating faster convergence compared to Combination 1.

Combination 3 ($\mu = 0.01$, $M = 5$):

- The SIR remains high at 10.05 dB, comparable to Combination 2, indicating effective interference suppression.
- The SIR improvement is positive (5.23 dB), similar to Combination 2.
- The convergence time slightly increases to 111 samples, suggesting a slightly longer convergence compared to Combination 2.

Combination 4 ($\mu = 0.01$, $M = 50$):

- The algorithm fails to converge, resulting in a non-convergence outcome.
- The SIR achieved is 4.68 dB, indicating some separation between the signal and interference components, although less than in Combinations 2 and 3.
- The negative SIR improvement (-0.14 dB) suggests that the algorithm struggles to effectively suppress interference.

Combination 5 ($\mu = 0.1$, $M = 70$):

- Similar to Combination 4, the algorithm fails to converge, resulting in a non-convergence outcome.
- The achieved SIR is 2.01 dB, indicating weaker separation between the signal and interference components compared to other combinations.
- The negative SIR improvement (-2.81 dB) further highlights the challenges in interference suppression.

Overall, the results suggest that the choice of algorithm parameters significantly impacts the algorithm's performance. Higher values of μ generally lead to better SIR and faster convergence, while larger values of M may result in non-convergence and decreased performance.

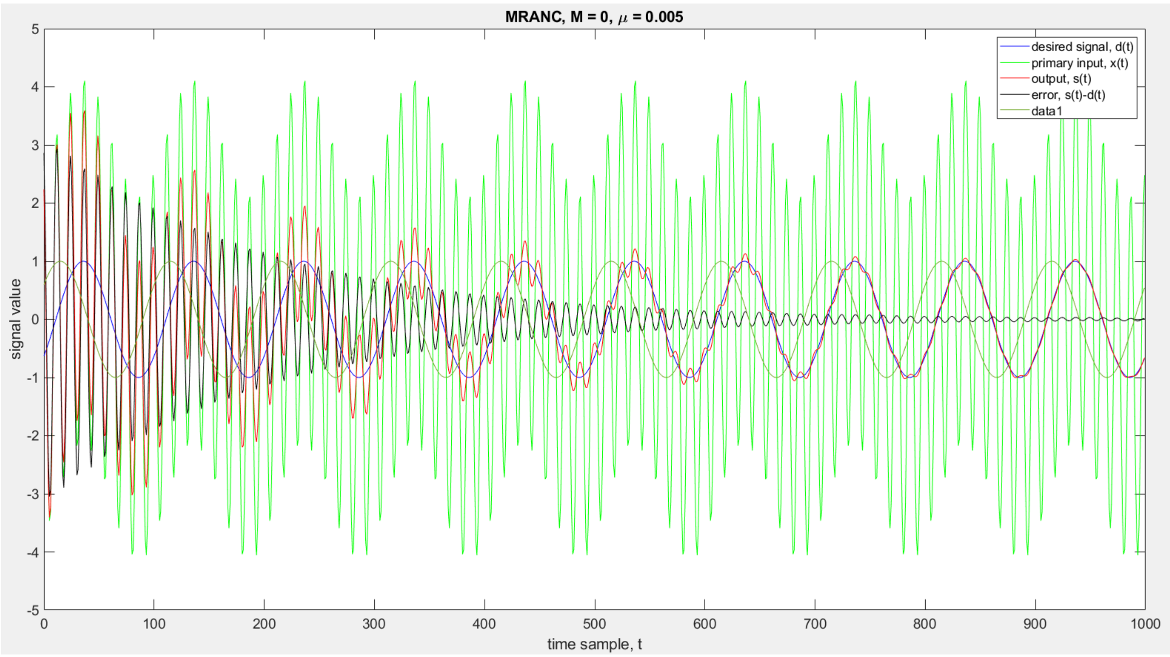

Figure 1: Ploting: M=0, mu = 0.005

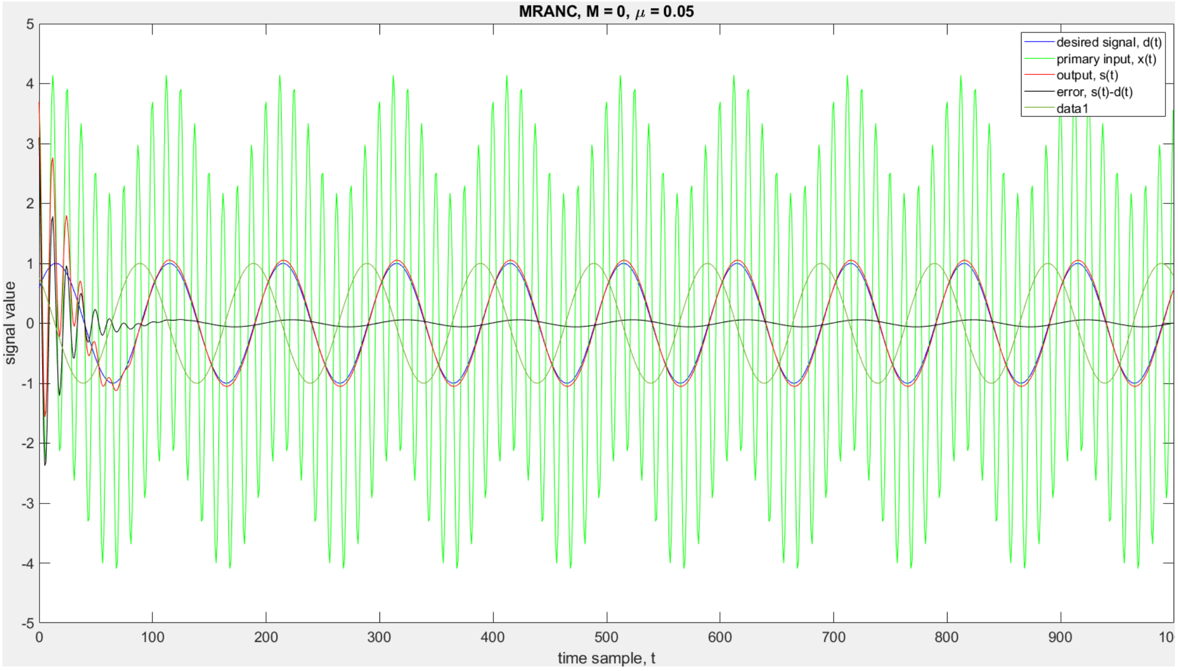

Figure 2: Ploting: M=0, mu = 0.05

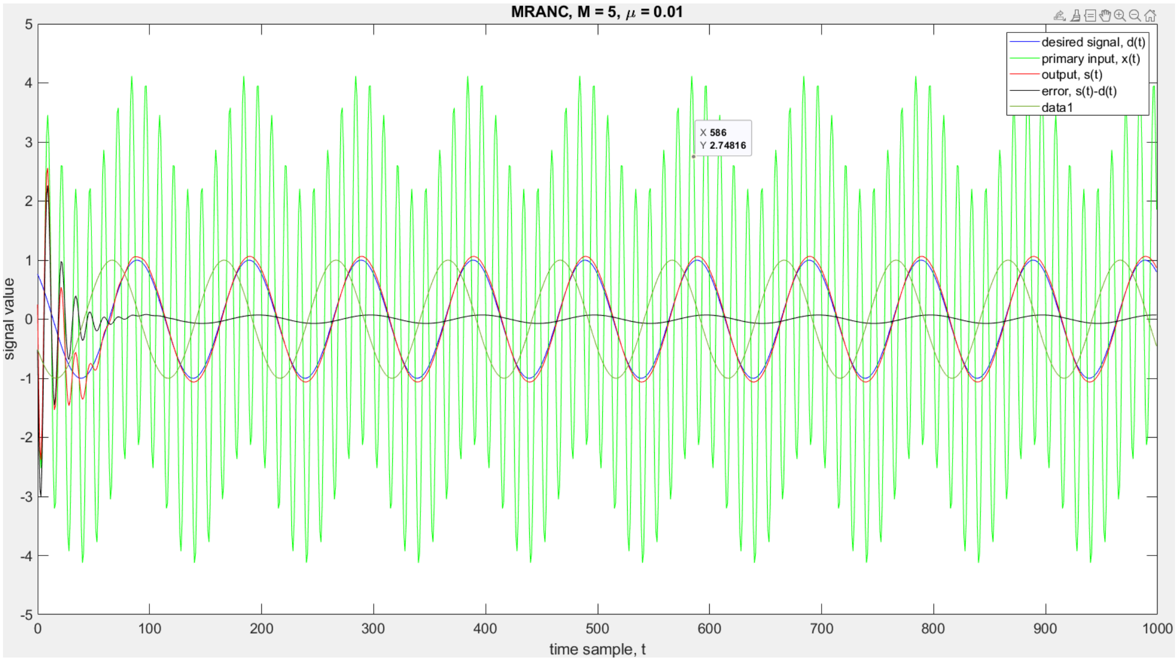

Figure 3: Ploting: M=5, mu = 0.01

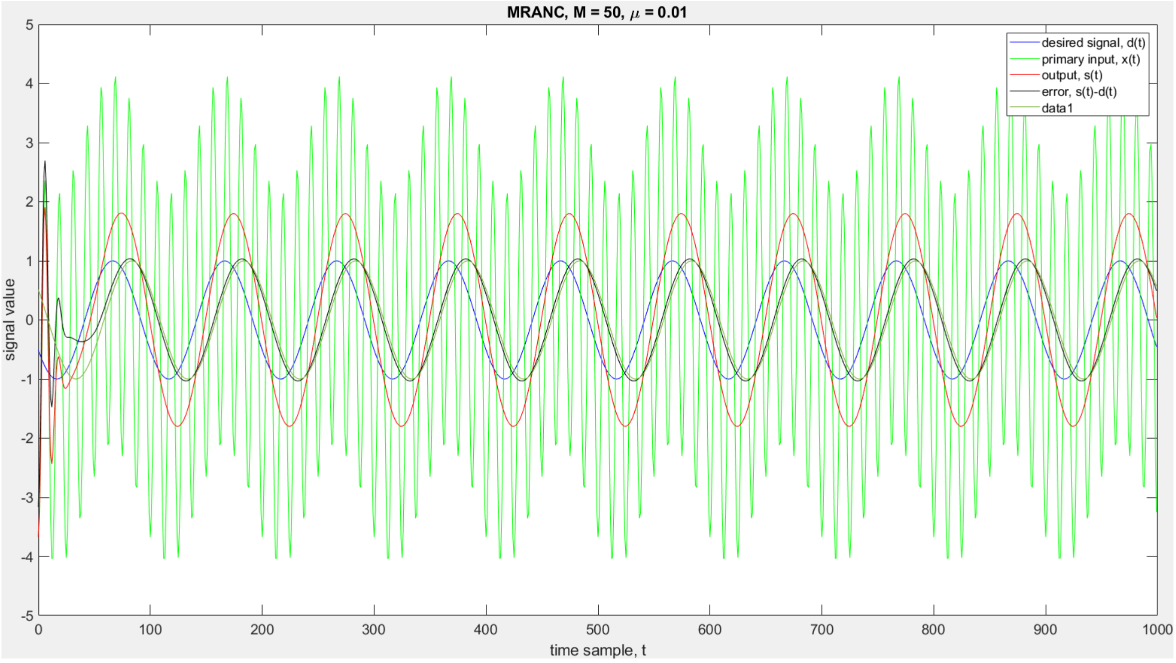

Figure 4: Ploting: M=50, mu = 0.01

1.2 Effects of desired signal leakage into the reference signal. Assume that the reference signals are contaminated by a component of the desired signal attenuated by 10 dB relative to the desired signal power contribution to the primary input. Repeat Exercises 5 and 6 of the course. What can be concluded about the effect of contamination on the algorithm's performance?

Table 2: Effects of Algorithm Parameters

Combination	μ Value	M Value	SIR (dB)	SIR Improvement (dB)	Convergence Time (samples)
1	0.005	0	2.39	-2.43	Non Convergence
2	0.05	0	8.68	3.86	Non Convergence
3	0.01	5	8.80	3.98	Non Convergence
4	0.01	50	-4.91	-9.73	Non Convergence
5	0.1	70	NaN	NaN	Non Convergence

The table 2 displays the effects of algorithm parameters under the condition of contamination in the reference signals.

Combination 1 ($\mu = 0.005$, $M = 0$):

The achieved SIR is 2.39 dB, indicating a moderate level of separation between the desired signal and interference components. However, the SIR improvement is negative (-2.43 dB), suggesting that the algorithm struggles to suppress interference effectively.

Unfortunately, the algorithm fails to converge, resulting in a non-convergence outcome. Combination 2 ($\mu = 0.05$, $M = 0$):

The achieved SIR is 8.68 dB, which represents a substantial improvement over Combination 1. The SIR improvement is positive (3.86 dB), indicating some success in interference suppression. Nevertheless, the algorithm fails to converge, similar to Combination 1. Combination 3 ($\mu = 0.01$, $M = 5$):

The achieved SIR remains high at 8.80 dB, comparable to Combination 2. The SIR improvement is positive (3.98 dB), indicating effective interference suppression. Unfortunately, the algorithm fails to converge. Combination 4 ($\mu = 0.01$, $M = 50$):

The SIR drastically drops to -4.91 dB, indicating poor separation between the desired signal and interference components. Moreover, the SIR improvement is highly negative (-9.73 dB), suggesting severe degradation in performance. As expected, the algorithm fails to converge. Combination 5 ($\mu = 0.1$, $M = 70$):

Due to NaN (not a number) values, the SIR and SIR improvement cannot be determined for this combination. Nonetheless, the algorithm fails to converge, consistent with previous combinations. Overall, the results demonstrate the significant impact of contamination on the algorithm's performance. Higher values of μ and M exacerbate the challenges posed by contamination, leading to degradation in SIR, negative SIR improvement, and failure to converge.

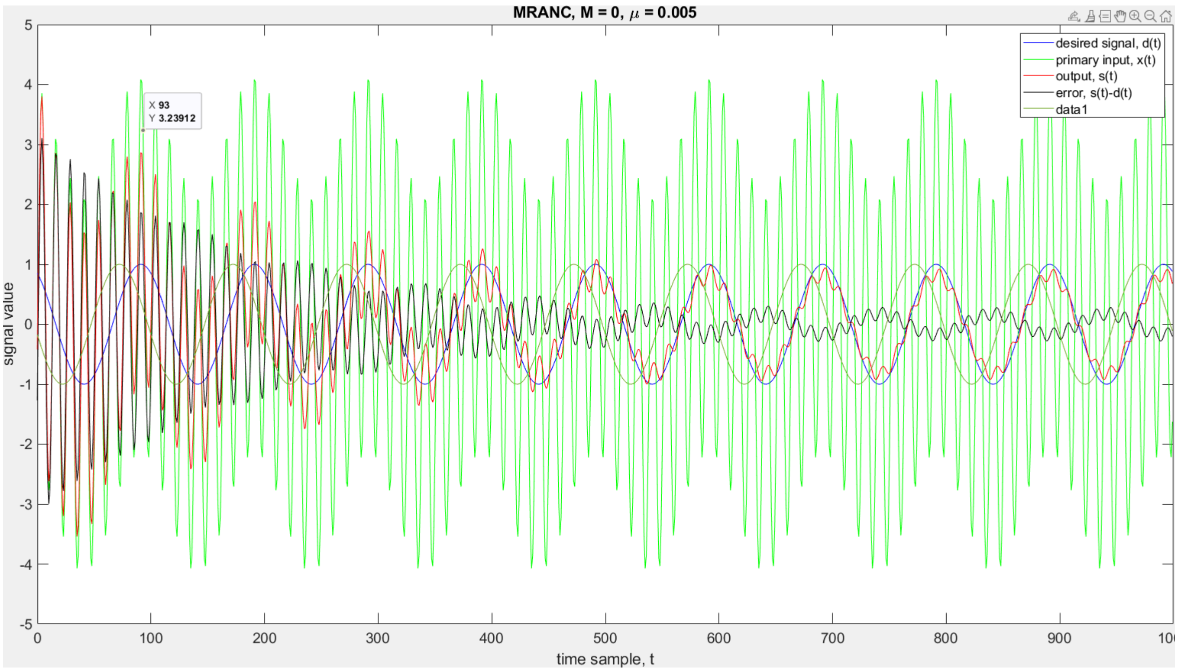

Figure 5: Ploting: M=0, mu = 0.005

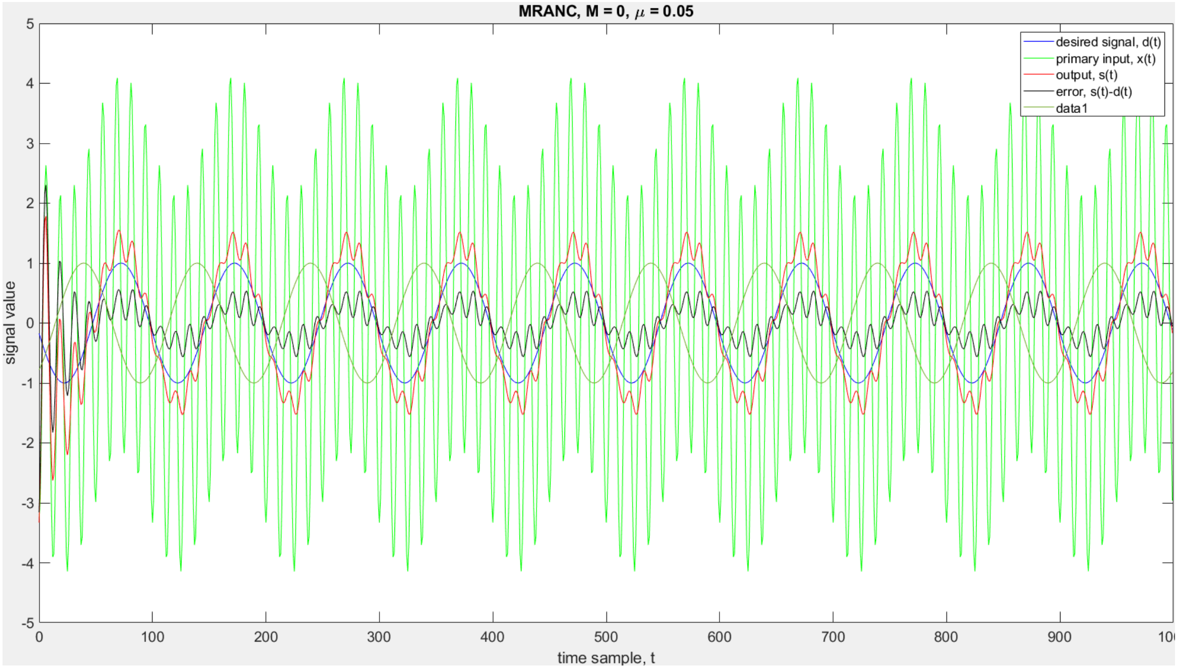

Figure 6: Ploting: M=0, mu = 0.05

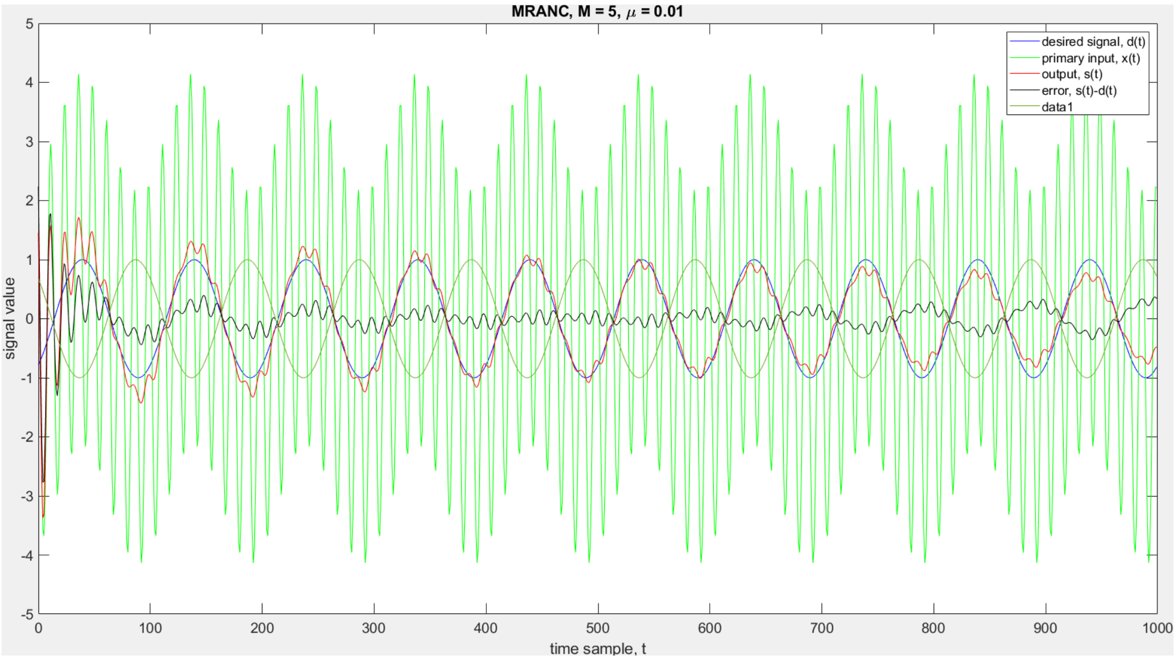

Figure 7: Ploting: M=5, mu = 0.01

2. Fetal ECG extraction

In this experiment, the primary input comprises both fetal ECG (FECG) and maternal ECG (MECG) components obtained from the abdominal leads, while the reference

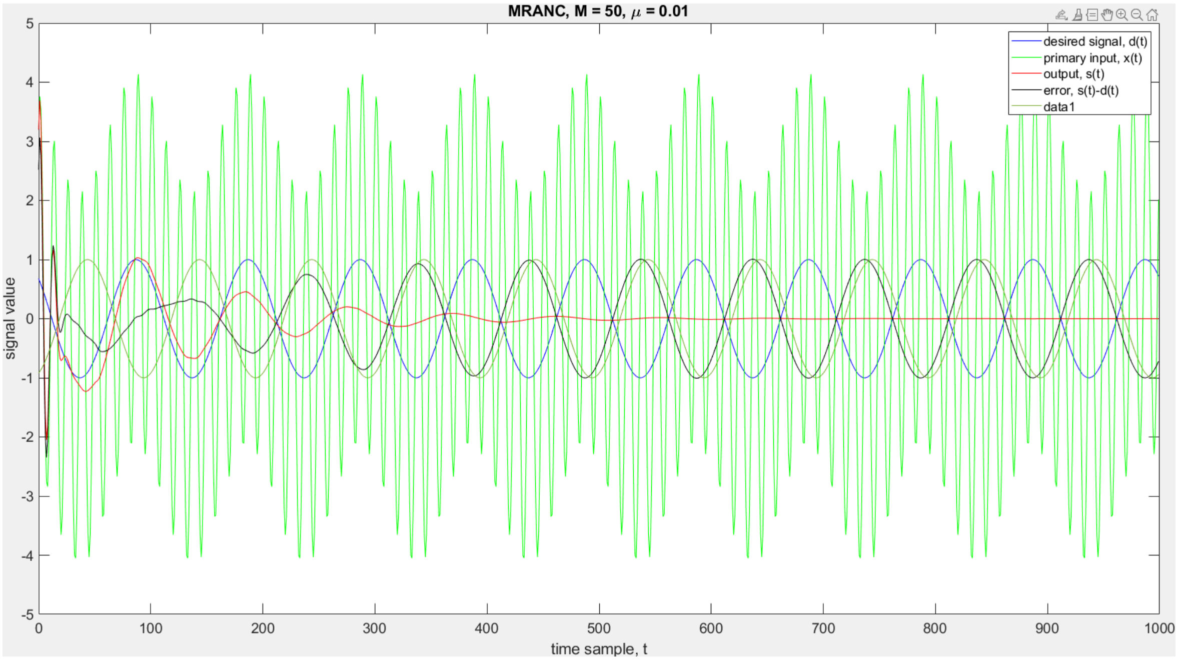

Figure 8: Ploting: M=50, mu = 0.01

signals consist solely of the MECG component recorded from the thoracic leads. The goal is to eliminate the MECG interference from the primary input signals, thereby isolating the FECG component.

As depicted in 9, the primary input exhibits greater irregularity and oscillation compared to the output signal. The output signal appears more regular with fewer peaks. This observation underscores the effectiveness of the algorithm in isolating the FECG signal from MECG interference in each abdominal primary lead. Notably, the removal of peaks is evident in the figure, further validating the success of the cancellation process.

In the 10, in the Welch estimate of Power Spectral Density (PSD), we notice a discernible trend between the spectra of the primary input and output signals. Initially, there's a clear disparity in their spectra. However, as the frequency exceeds 25 Hz, the spectra of both signals begin to converge and exhibit greater similarity.

This convergence implies that the adaptive cancellation process effectively mitigates or removes the interference present in the primary input signal, especially at lower frequencies. Consequently, the spectral characteristics of the output signal progressively resemble those of the primary input signal as the frequency rises. This alignment signifies successful interference cancellation, resulting in a cleaner output signal that closely mirrors the original primary input signal at higher frequencies.

In summary, the convergence of spectra beyond 25 Hz reflects the efficacy of the adaptive cancellation algorithm in isolating the desired signal components from interference. This leads to enhanced spectral similarity between the primary input and output signals at higher frequencies.

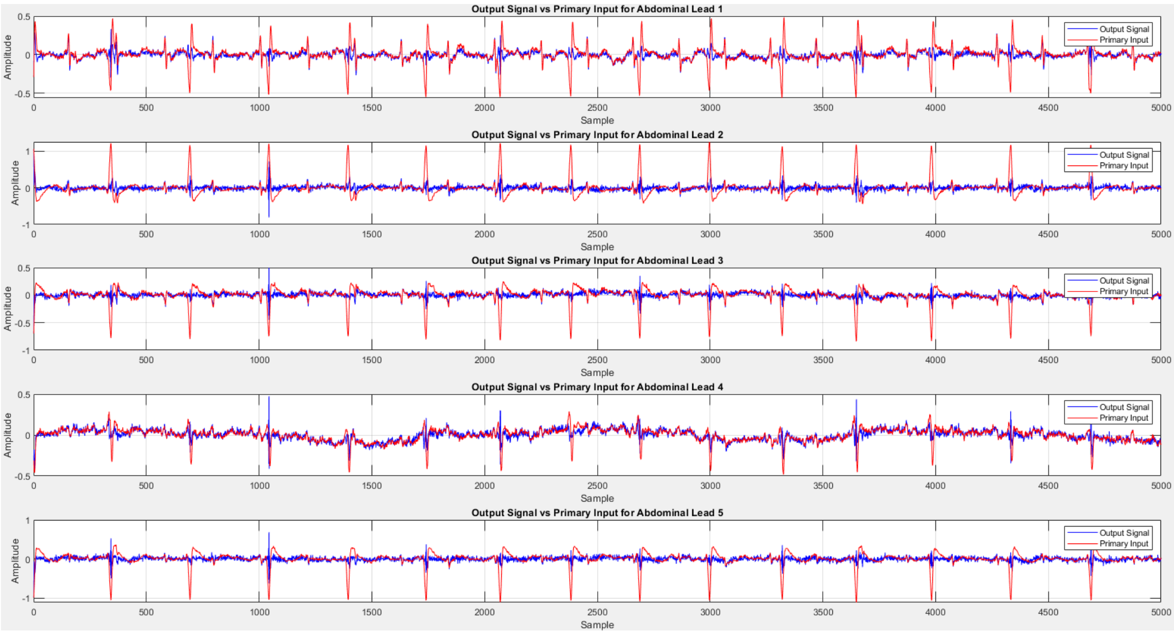

Figure 9: Ploting: Output Signal vs Primary Input (5 Leads)

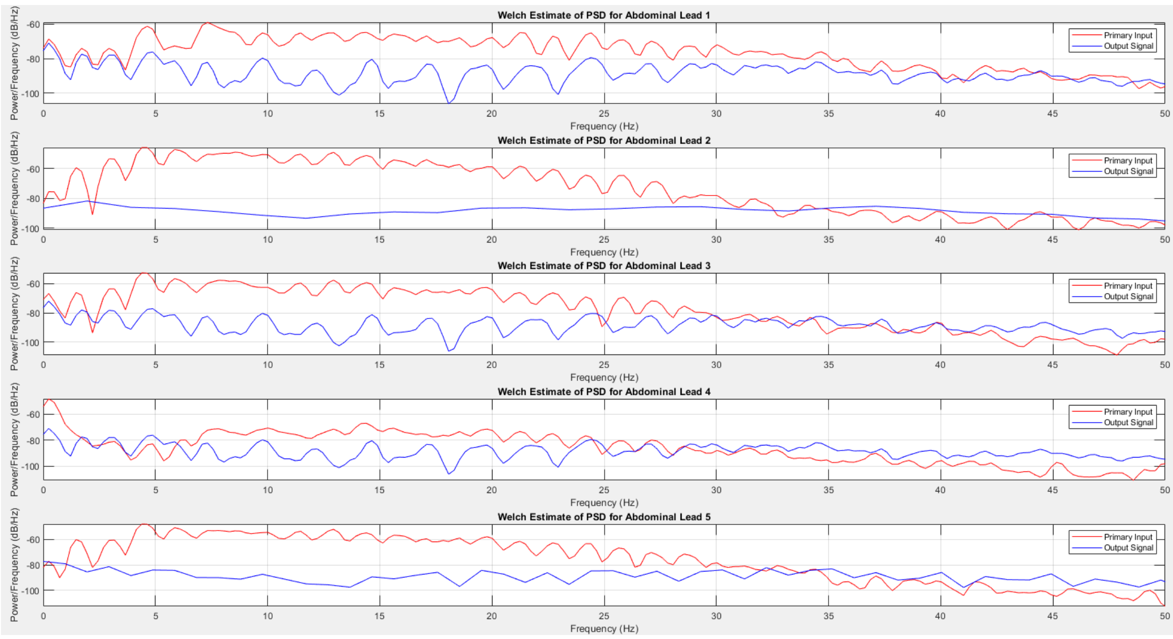

Figure 10: Ploting: Welch Estimate of PSD (5 Leads)

3. Atrial activity extraction — single patient

3.1 In the AF dataset analyzed in assignment 1.2, consider the precordial leads V1–V6 of the recorded ECG (Xva) from the first patient. These signals were recorded from the precordial (chest) region. Plot the 6-lead record. Check that the atrial activity is more clearly present in lead V1.

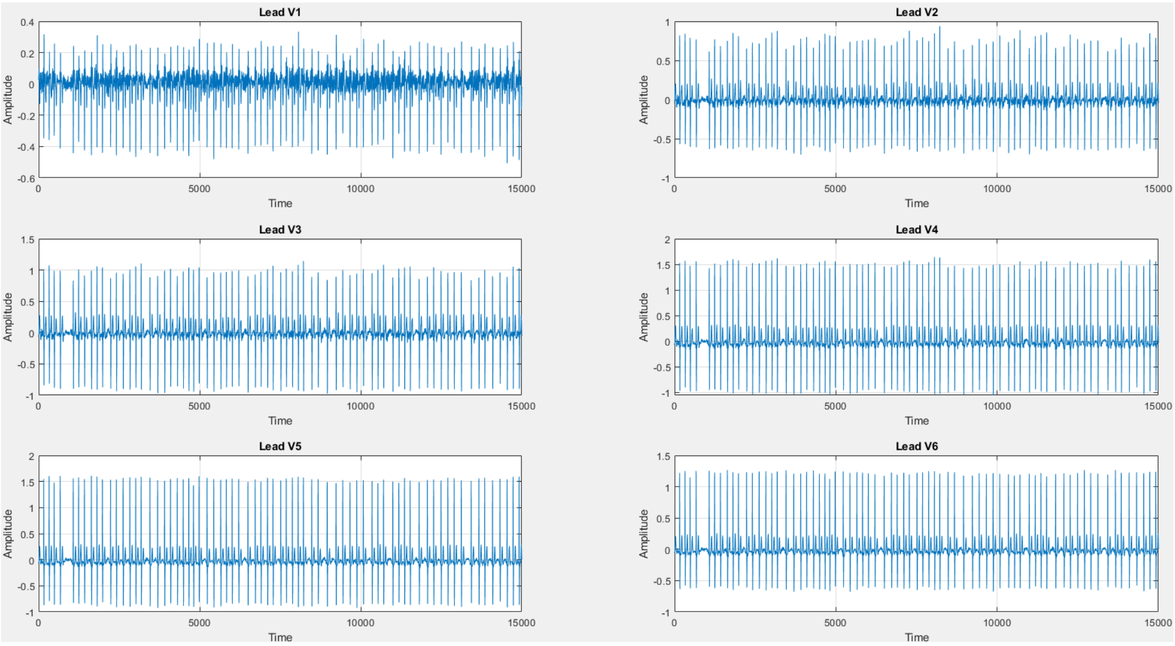

Figure 11: Ploting: 6-lead record

As depicted in Figure 11, it's noticeable that lead 1 exhibits more pronounced oscillations compared to the other leads, which appear relatively closer in terms of oscillatory behavior. This observation raises the question of whether atrial activity may be more prominent in lead 1 compared to the other leads.

3.2 Carry out the adaptive cancellation of the QRST complex taking V1 as primary input and V2–V6 as reference signals. Assume a mixture without time dispersion (M = 0). Evaluate the signal estimation quality: Plot and compare the primary signal and the filter output signal. Plot and compare the frequency spectrum (Welch method) of the primary input and the output signal between 0 et 50 Hz. Consider only the output signal samples after convergence of the adaptive algorithm. The DF and SC parameters were introduced in assignment 1.2. Compute these performance indices on the output signal after convergence. Compare with the spectral parameters of the atrial activity signals provided in matrix Xa, obtained by the spatio-temporal cancellation (STC) method in experiment 1.2.

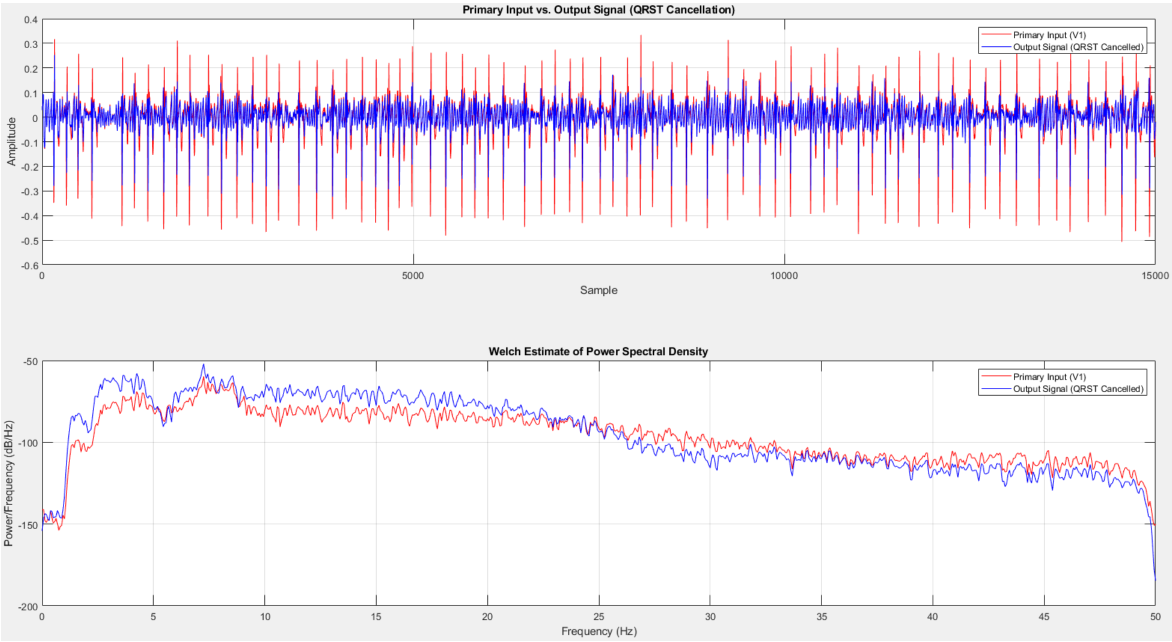

Figure 12: Ploting: Output signal samples after convergence of the adaptive algorithm

SC, DF after convergence	**(Xa) SC, DF**
7.2500, 0.5270	7.5350, 0.7563

Table 3: Example of a 2x2 table.

Upon examination of Figure 12, it becomes evident that the output signal demonstrates a reduction in the number of peaks compared to the primary signal. This reduction in peaks indicates a smoother waveform in the output signal, suggesting effective removal or attenuation of unwanted noise components by the algorithm.

The increased regularity observed in the output signal's waveform further supports the notion of signal cleaning by the algorithm. The algorithm's ability to produce a smoother and more regular output signal signifies its efficacy in isolating and extracting the desired components while suppressing interfering noise.

Overall, the adaptive cancellation algorithm appears to have successfully enhanced the signal quality by reducing noise and improving the clarity of the primary signal.

4. Atrial activity extraction — full database

4.1 Repeat experiment 2.3 for the full patient dataset. When evaluating performance (part 3), just compute spectral parameters DF and SC without plotting results.

Table 4: Summary Statistics for Dataset Xa and Xva

	Dataset Xa			**Dataset Xva**		
Feature	**Mean**	**Median**	**Std. Dev.**	**Mean**	**Median**	**Std. Dev.**
df	6.7146	6.7188	0.85778	4.1317	3.6875	1.673
sc	0.66794	0.69562	0.10888	0.45647	0.44978	0.075614
Feature	**Min**	**Max**	**IQR**	**Min**	**Max**	**IQR**
df	4.875	8.4375	1.0781	1.7812	11.5625	1.2891
sc	0.18798	0.83214	0.11038	0.31662	0.68524	0.099872
Feature	**Skewness**	**Kurtosis**	**Skewness**	**Kurtosis**		
df	0.00075521	2.4386	1.7384	7.0412		
sc	-1.712	7.2504	0.53452	3.1044		

The statistical comparison of datasets Xa and Xva provides insights into the differences in the distribution of features between the two datasets. Here's a summary of the key findings:

Dataset Xa (df) vs. Dataset Xva (df):

- Dataset Xa exhibits higher mean and median values compared to Xva, indicating a shift towards higher values.
- Xva has a higher standard deviation, maximum value, interquartile range, skewness, and kurtosis, suggesting a wider spread and greater variability in the data compared to Xa.

Dataset Xa (sc) vs. Dataset Xva (sc):

- Similar to df, Xa shows higher mean and median values for sc compared to Xva.
- Xa also demonstrates higher standard deviation, maximum value, interquartile range, skewness, and kurtosis, indicating greater variability and deviation from normal distribution compared to Xva.

  Conclusion:

- Dataset Xa generally exhibits higher values across all statistical measures compared to Xva for both df and sc features.
- The higher variability and spread observed in Xva suggest a wider range of values and potentially more diverse patterns compared to Xa.