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Implementation of An Adaptive Filter on A Manifold Absolute Pressure (MAP) Sensor

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Abstract

This study proposes an adaptive filter based on a manifold absolute pressure (MAP) sensor in order to control automotive engines. The proposed adaptive filter, which is based on the least mean squares (LMS) algorithm, is intended to reduce the impacts of sensor noise and nonlinearity, which can result in false readings and a subsequent decline in engine performance. The filter can be used for long-term engine control applications because it is implemented on a model-based system and can adapt to changes in the sensor's properties over time. The suggested filter efficiently decreases sensor noise and increases the accuracy of MAP sensor readings, according to experimental data, which also indicate a roughly 10% rise in mean absolute percentage error (MAPE) compared to the standard lowpass filter. The filter's versatility also enables reliable operation under a variety of operating conditions and sensor characteristics. Additionally, the filter's signal-to-noise ratio (SNR) enhancement is almost 10% greater than that of a traditional lowpass filter, resulting in enhanced engine performance and fuel economy. Overall, the suggested adaptive filter appears to be a viable option for improving the performance of MAP sensors in automotive engine control applications.

Keywords: Signal processing, digital filtering, adaptive filtering, manifold absolute pressure

1. Introduction

Automotive engines rely on accurate and reliable sensor measurements to ensure optimal performance and fuel efficiency. The Manifold Absolute Pressure (MAP) sensor, which gauges pressure inside the engine's intake manifold, is one of the crucial sensors used in contemporary internal combustion engines (ICE) [1]. However, noise and nonlinearity in MAP sensors can result in inaccurate readings and decreased engine performance. Adaptive filtering techniques have been used in a number of recent studies on signal processing and control systems to address a variety of problems. [2] is focused on Adaptive Filter design for Electrocardiogram (ECG) signal noise removal in order to obtain noiseless and pure embryo signals. During acquisition and transmission, various noise sources frequently contaminate ECG signals. To remove noise from the desired ECG signals and ultimately obtain noiseless and pure embryo signals, the researchers use the well-known Least Mean Square (LMS) algorithm as an adaptive filtering technique. The study offers a potential remedy to improve the accuracy and clinical applicability of ECG data in healthcare settings by showcasing promising results in noise reduction. The creation of a model-free adaptive filter with the goal of reducing actuator wear in engineering systems is the subject of [3]. Actuator wear is a common problem that shortens system lifespan and degrades performance. The proposed model-free approach successfully addresses uncertainties in system dynamics and model parameterization to address this problem. As a result, actuator wear is successfully mitigated, and the reliability and longevity of control systems are improved.

In this paper, an implementation of the proposed Adaptive Filter using the LMS algorithm on a MAP sensor is suggested. The filter is implemented on a model-based system to enable real-time operation and is intended to reduce the effects of sensor noise and nonlinearity. The filter is suitable for use in long-term engine control applications because its adaptability ensures robust performance over a variety of operating conditions and sensor characteristics. The recommended filter successfully reduces sensor noise and raises the accuracy of MAP sensor data, which enhances engine performance and fuel efficiency as measured by an improvement in Signal to Noise Ratio (SNR) [2]. Overall, this research offers a promising method for improving the performance of MAP sensors in applications involving automotive engine control.

Internal combustion engine supercharging has been used for a long time to increase engine power output, but a new trend is emerging to comply with fuel consumption and emission control. Increasing the mean effective pressure is the most preferred way to increase power output by providing air or a combination of air and fuel under pressure that is greater than atmospheric pressure. By increasing density, the engine's power output will rise

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as a result [1]. To adjust the fuel and air pressures in the intake manifold of automotive engines, accurate and reliable sensor measurements are crucial, and the existence of a MAP sensor is a must. This sensor measures the pressure inside the engine's intake manifold, providing critical information to the engine control system to optimize fuel injection and air intake, ultimately ensuring optimal performance and fuel efficiency. Without the accurate readings from the MAP sensor, the engine control system would not be able to adjust the fuel and air pressures to the appropriate levels, leading to reduced engine performance and fuel efficiency, and potentially causing damage to the engine over time. Therefore, the MAP sensor plays a vital role in the operation and performance of modern automotive engines, making its accuracy and reliability a top priority for engine manufacturers and designers.

A type of MAP sensor, which is made of semiconductor piezo resistance. Its primary operating principle is the piezoresistive effect of semiconductors, as depicted in Figure 1. It consists of a pressure converter and a composite integrated circuit for signal amplification.

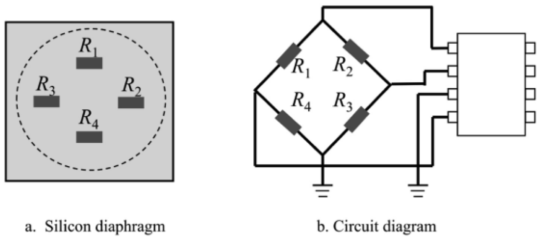

Figure 1. *Schematic of Manifold Absolute Pressure Sensor [4]*

Noise is present to variable degrees in practically all surroundings, and there are numerous varieties of noise, the most identifiable of which is Acoustic Noise, which occurs from moving, vibrating, or colliding sources. Electromagnetic noise may be found at all frequencies, including radio frequencies, whereas Processing Noise is caused by the processing of signals, such as quantization noise in digital coding or missing data packets in digital data transfer networks. A random white noise will be added and then a denoising technique, which is digital filtering, will be applied in order to clean up the noisy signal.

Using a limited number of data, the power spectrum (PS) of a signal in the temporal domain describes how the signal's power is distributed across various frequencies. The signal's frequency-domain form is frequently easier to examine than its time-domain counterpart. Several signal processing applications, including noise removal and system identification, rely on frequency-specific signal alterations. The purpose of power spectral estimation is to estimate a signal's power spectrum from a succession of time samples. Fourier transform methods, such as the Welch method and the filter bank approach, are used to estimate the power spectrum [5].

The signal can be entirely retrieved from noise if the spectra of the signal and noise do not overlap. Figure 2 depicts an example of a noisy signal with different signal and noise spectra. The signal and noise occupy separate parts of the frequency spectrum in this case, and a low-pass filter may be used to denoise the signal. Although, Figure 2(b) depicts a more common example in which the signal and noise spectra overlap. It is difficult to distinguish the signal from the noise in these instances. Nonetheless, using a filter approach can reduce the influence of noise to some amount. [3].

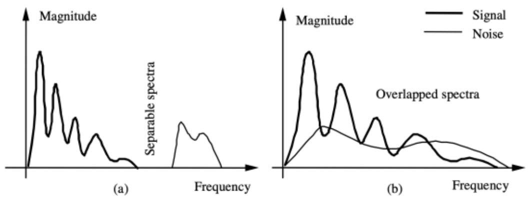

Figure 2. *Separability of a Signal*

Unit-delay elements, multipliers, and adders make form a digital FIR filter, sometimes referred to as a tapped-delay line filter or a transversal filter. The length of the impulse response is dependent on the amount of delay elements which is also called filter order. It is represented by M in Figure 3 depicts a filter made up of delay elements represented by the unit-delay operator z^{-1}. The delay elements operate on the input signal and produce delayed versions of it. The multipliers multiply the tap inputs by coefficients known as tap weights, resulting in a weighted sum of delayed inputs. The adders sum the outputs of the multipliers to produce the overall response of the filter. The Eq. (1) is a representation of the filter's output. It is important to notice that complex conjugation is indicated by the asterisk, and that complex valued inputs and tap weights are expected.

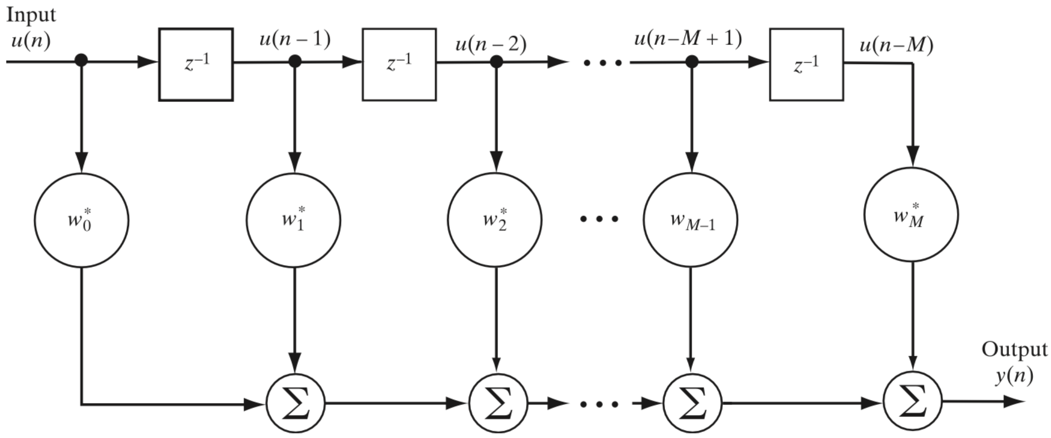

Figure 3. *Finite Impulse Response (FIR) Filter*

$$y(n) = \sum_{i=0}^{M} w_k^* u(n - k) \tag{1}$$

The Eq. (1) is representation of convolution sum since the process of convolution takes the impulse response of the filter, represented by w_k^*, and combines it with the filter input, represented by $u(n)$, to produce the filter output, represented by $y(n)$ [6].

Conventional digital filters such as a lowpass filter, or even a finite impulse response (FIR) may not be appropriate for accurate results due to their static structure. On contrary, recursive filters are better choices due to their dynamic structure. A type of recursive filter, which is adaptive filter, will be used to filter a noisy signal in this paper.

The concepts "signal" and "noise" are similar. The waveform that is of interest is typically referred to as the signal, and the remainder as the noise. The SNR is frequently used to calculate the relative amounts of signal and noise in a waveform. The SNR is often expressed in decibels (dB), where:

$$SNR = 20\, log \frac{Signal}{Noise} \tag{2}$$

RMS amplitude is the unit of measurement for signal and noise values [2].

2. Adaptive Filter

A system created to gather details about a specified quantity of interest from noisy data is commonly referred to as an estimator or filter [6]. There are two types of filters: digital and analog. Digital signals with discrete temporal components are processed by digital filters. The internal structure and parameters of time-invariant filters are fixed, and if they are linear, the output signal is a linear function of the input signal [7].

The Wiener Filter is a type of linear filter that can effectively remove noise from a signal, but its design requires prior knowledge of the statistical characteristics of the signal and noise, such as power spectral densities and cross-correlation functions. However, in real-world scenarios, this information may be incomplete or unavailable, making it challenging to design the Wiener Filter optimally. To address this issue, the "estimate and plug" procedure can be used, which involves estimating the statistical parameters of the signal and noise from the available data and then using these estimates to design the filter. However, this approach requires significant computational resources, making it unsuitable for real-time applications.

To overcome these limitations, an Adaptive Filter can be used. This filter is self-designing, meaning it can adjust its parameters based on the input data without requiring prior knowledge of the statistical characteristics of the signal and noise. The filter operates using a recursive algorithm that updates the filter coefficients in real-time, starting from a set of predetermined initial conditions. In a stationary environment, the adaptive filter converges to the optimum Wiener solution in a statistical sense, meaning that the filter coefficients approach the optimal values that would be obtained with complete knowledge of the signal and noise statistics. In a nonstationary environment, where the statistical characteristics of the input data may change over time, the adaptive filter can track the time variations by continuously updating the filter coefficients. However, this capability relies on the assumption that the variations in the input data statistics are sufficiently slow. If the variations are too rapid, the adaptive filter may not be able to track them accurately. Overall, the adaptive filter offers an effective and practical solution for removing noise from signals in real-time applications where prior knowledge of the signal and noise statistics may be incomplete or unavailable [6, 7, 8].

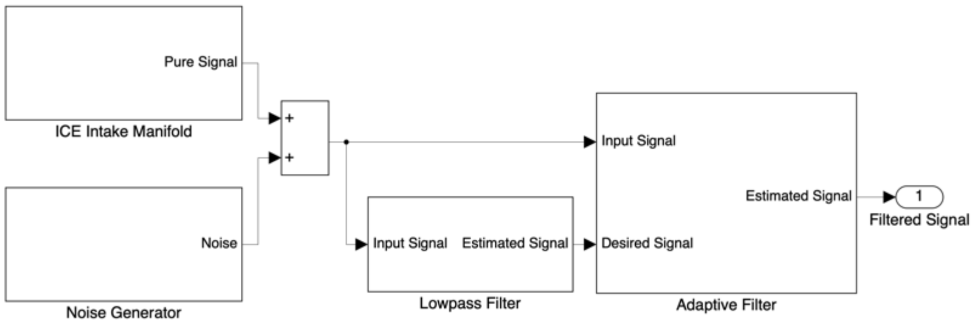

Figure 4. *Signal Processing Schematic of Adaptive Filtering*

Pure Signal is representing the ideal theoretical sensor response of intake manifold pressure without any noise. Noise is generated by using Uniform Random Number block in Simulink which gives a uniformly distributed random signal. Noise is added to this signal before summing it up with pure signal. This sum will be called as MAP sensor data. Noisy signal is the input of adaptive filter, desired signal is lowpass filtered signal and the output is filtered signal as shown in Figure 4.

To meet the performance requirement, the settings of the adaptive filters are continually changing (time variable).

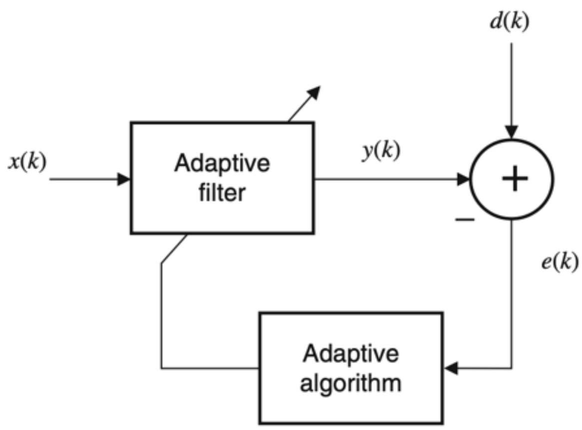

Figure 5. *Adaptive Filter Configuration [7]*

In Figure 5, the error between the filtered signal and the desired signal can be calculated as

$$e(k) = d(k) - y(k) \tag{3}$$

It is intended to closely resemble the desired signal, d(k), by using an adaptive filter to analyze the input signal, x(k). An error signal is created by subtracting the filtered signal, y(k), from the intended signal, d(k).

Due to a variety of characteristics, the LMS algorithm is often used in adaptive filtering. Its appeal stems mostly from its cheap computing complexity, shown convergence in stationary situations, unbiased convergence towards the Wiener solution, and steady behavior even when implemented with finite-precision arithmetic.

The resultant gradient-based approach, which minimizes the mean squared error, is referred to be the least-mean-square (LMS) algorithm, and its equation is shown below:

$$w(k+1) = w(k) + 2^{*}\mu^{*}e(k)^{*}x(k) \tag{4}$$

Where $w(k)$ is a set of adaptive filter coefficients. The convergence factor, which is μ, chosen from a range to assure convergence [7, 9].

The performance of a filter in a certain context can be measured by either the normalized cumulative squared error or the mean-squared error (MSE), which are equivalent metrics. The equation of MSE is: [10]

$$\frac{1}{n}\sum_{t=1}^{n}(x_t - \hat{\chi}_t(Y^t))^2 \tag{5}$$

$\hat{\chi}_t(Y^t)$is the causal estimator of x_t based on the noisy observation Y^t.

MMSE is an abbreviation for Minimum Mean Square Error. MMSE is used to calculate the difference between the original and filtered signals in such a way that the expected value of the square of the difference is minimized.

In practical applications, the MMSE can be used to compare different filtering algorithms or to optimize the parameters of a given filter. A lower MMSE value indicates better performance and higher accuracy of the filter in reproducing the original signal [6].

Mean Absolute Percentage Error (MAPE) is another performance metric that can be used to evaluate the accuracy of a digital filter. MAPE measures the average percentage difference between the actual values of a signal and the predicted values produced by the filter. It is commonly used in time series forecasting and other applications where the accuracy of predictions is critical. It was the major metric in the M-competition. Absolute percentage errors (APE) are referred to as the mean, or MAPE. Let A_t and F_t stand for the true and expected values, respectively, at data point t. Thus, MAPE is described as follows:

$$MAPE = \frac{1}{N}\sum_{t=1}^{N}\left|\frac{A_t - F_t}{A_t}\right| \tag{6}$$

N denotes the number of data points. That should be multiplied by 100 to be more precise [11].

3. Results

The Lowpass filter uses two parameters which are the cut-off frequency and minimum stopband attenuation As depicted in Table 1. The adaptive filter uses three parameters as initial conditions which are μ, N, and ε as shown in Table 2. These parameters are step size, filter order, and a small constant to prevent division by zero. Parameter optimization is done by using Parameter Estimator Toolbox in Simulink. The toolbox uses an MSE algorithm to optimize the initial parameters. As a result, the initial parameters are:

Table 1. *Lowpass Filter Parameters.*

Cut-off Frequency	Attenuation (dB)
24.5186	524.32

Table 2. *Adaptive Filter Parameters.*

μ (Step Size)	N (Filter Order)	ε (Small Const.)
0.05	20	0.001

By using MATLAB Simulink, the noise of the MAP sensor data is removed with the help of an adaptive filter, and the plots are shown in Figure 6.

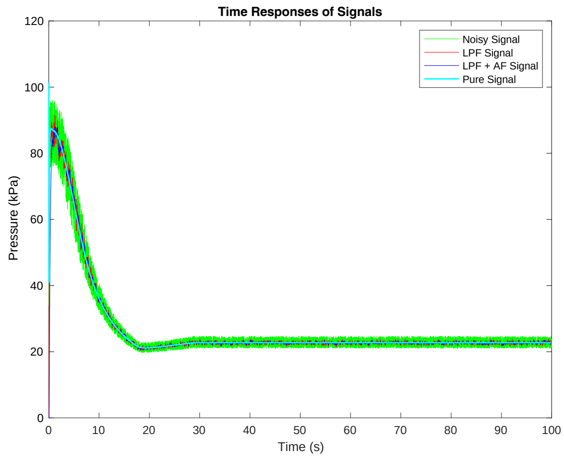

Figure 6. *Time Response of Noisy and Filtered Signal*

The error plot in Figure 7 generated from the adaptive filter implementation on the MAP sensor provides valuable insights into the filter's performance. The error plot shows a significant reduction in the magnitude of the error over time as the filter adapts to the changing signal. The error values gradually decrease, indicating that the filter effectively reduces sensor noise and improves the accuracy of MAP sensor readings.

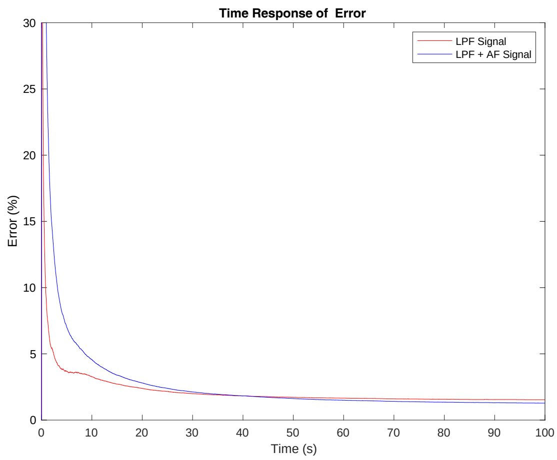

Figure 7. *Time Response of Error*

The MAPE errors of the Lowpass and Adaptive filters provide valuable insights into the performance of the two filters. In the Table 3, the MAPE error of the Lowpass filter is measured at 4.176, indicating a moderate level of error in the filter's ability to mitigate sensor noise and nonlinearity. On the other hand, the MAPE error of the Adaptive filter is measured at 3.762, indicating a lower level of error and thus superior performance compared to the Lowpass filter. This result suggests that the Adaptive Filter is more effective at reducing sensor noise and improving the accuracy of MAP sensor readings, leading to improved engine performance and fuel efficiency. Overall, the MAPE error results demonstrate the effectiveness of the proposed Adaptive filter implementation on the MAP sensor, outperforming the Lowpass filter in terms of accuracy and performance.

Table 3. *MAPE Values for MAP Signal.*

Filter	MAPE (%)

LPF	0.00
LPF + AF	1.14

The Power Spectrum of the Noisy and Filtered MAP Signal is depicted in Figure 8 as a consequence of the adaptive filter's recursion method. When the least mean square method is used, the filter cancels out the noise.

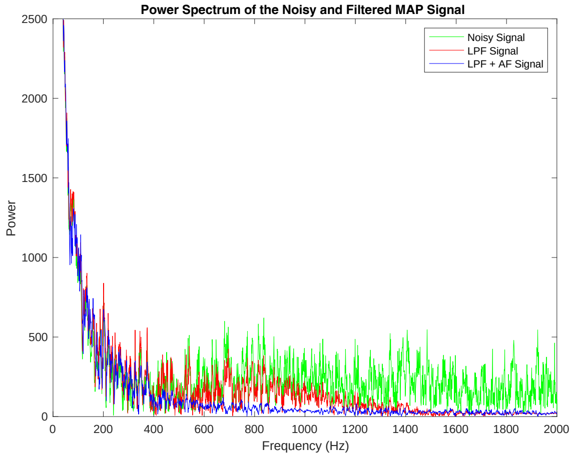

Figure 8. *Power Spectrum of the Noisy and Filtered MAP Signal*

Prior to filtering, the SNR was measured at -0.2641 as shown in the table, indicating that the noise in the signal was higher than the signal itself. However, after implementing the adaptive filter, the SNR increased to 35.2807, indicating a significant improvement in the quality of the signal. The adaptive filter SNR improvement is %10 higher than that the lowpass filter. This increase in SNR demonstrates that the filter effectively mitigates the effects of sensor noise and nonlinearity, leading to improved accuracy in MAP sensor readings. Overall, the SNR results provide strong evidence for the effectiveness of the proposed adaptive filter implementation on the MAP sensor in reducing sensor noise and improving the accuracy of MAP sensor readings.

Table 4. *SNR Values for MAP Signal.*

Filter	Noisy SNR	Filtered SNR	Improvement
LPF	-0.2641	32.1169	32.3810
LPF + AF	-0.2641	35.2807	35.5448

4. Conclusion

The adaptive filter implementation suggested in this study offers a potentially effective method for improving the functionality of MAP sensors in automotive engine control applications. The proposed adaptive filter implementation on a MAP sensor based on the LMS algorithm offers a promising solution for enhancing the performance of MAP sensors in automotive engine control applications. The filter is effective in overcoming the problems caused by sensor noise and nonlinearity, which may lead to more precise readings, better engine performance, and increased fuel efficiency. The MAPE results of the Lowpass and Adaptive filters demonstrate that the Adaptive filter outperforms the Lowpass filter in terms of accuracy and performance. The filter is a useful tool for long-term engine control applications because its adaptability ensures consistent performance under various operating conditions and sensor characteristics. The effect of the filter is also demonstrated by using the SNR algorithm, where the adaptive filter significantly improves the SNR compared to the lowpass filtered signal. This study makes a significant contribution toward improving MAP sensor measurements in automobile engines, which is essential for improving performance and minimizing environmental impact.

Declaration of Interest

The authors declare that there is no conflict of interest.

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Author Contributions

The following authors affirm their contributions to the paper: Muhammet Furkan Özata, Ali Sertkaya, İlkay Erdeniz; data collection: Ali Sertkaya, İlkay Erdeniz; data analysis and interpretation: Muhammet Furkan Özata, Ali Sertkaya; draft manuscript preparation: Muhammet Furkan Özata, Ali Sertkaya. All authors examined the findings and approved the final paper version.

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