NOISE REDUCTION IN CONTROL SIGNALS OF INDUSTRIAL SEWING MACHINES USING ADAPTIVE FILTERING

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Degree of Master of Science

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January 2022

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Thesis submitted in partial fulfillment of the requirements for the degree Master of Science in Electronics & Automation

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Dr. Chathuranga Weeraddana

ABSTRACT

Control signals of a typical industrial sewing machine are distorted when they are connected to the controller. Such distortions due to noise appear at the input port of the control signals and they are, in general, non-stationary signals. Furthermore, access to the controller of an industrial sewing machine is restricted. Therefore, such distortions cannot be attenuated using classical adaptive filters such as Wiener filters. In this dissertation, an adaptive algorithm is developed in order to solve this challenging problem. Here, an additive inverse of the distortion is generated and added to the control signals so that the distortion is significantly attenuated. In order to generate the additive inverse of the distortion, the Normalized Leas-Mean Square (NLMS) algorithm is employed as the adaptive algorithm with an external reference signal. In general, the error signal to the filter is the estimation of the signal, However, based on the nature of the adaptive filtering problem, the NLMS algorithm is formulated in a way that, the error signal to the filter is the difference between the noise signal and the estimated noise signal. The experimental results obtained with the control signals of a typical industrial sewing machine confirm that the proposed method effectively attenuates the distortion signal with fast convergence of the NLMS algorithm.

ACKNOWLEDGEMENT

I cannot express enough thanks to my advisors for their continued support and encouragement: Dr. Chamira U. S. Edussooriya and Dr. Chathuranga Weeraddana. I offer my sincere appreciation for the guidance and learning opportunities provided by you.

I would also like to thank the Director of Innovation, Dr. Chandika Wickramatillake, at my place of work, MAS Intimates. He gave me enormous support by granting me access to use the machinery and facilities.

My completion of this project could not have been accomplished without the support of my classmates, Dinushka Wijesuriya, and my colleague, Jayamini Ranaweera. Thank you for your support and ideas.

Finally, I must express my profound gratitude to my parents and my wife Nadeesha for providing me with unfailing support and continuous encouragement throughout my years of study. This accomplishment would not have been possible without them. Thank you.

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LIST OF ABBREVIATIONS

AC	Alternating Current
ECG	Electrocardiogram
EMI	Electromagnetic Interference
EMG	Electromyography
FFT	Fast Fourier Transform
FIR	Finite Impulse Response
I-O	Input-Output
LMS	Least Mean Square
NLMS	Normalized Leas-Mean Square
rpm	Revolution Per Minute
VFD	Variable Frequency Drive

LIST OF MATHEMATICAL OPERATOR NOTATIONS AND SYMBOLS

$e[n]$	Discrete-time error input signal
$E\{r\}$	Expected value of scalar r
h	window length of adaptive Wiener filter
N	Length of a signal
p	Adaptive filter order
T	Sampling period
$u[n]$	Discrete-time input signal of the external controller
$\mathbf{v}$	External reference input signal vector
$v(t)$	Continuous-time distortion of the input signal
$v[n]$	Discrete-time distortion of the input signal
$\hat{v}(t)$	Continuous-time estimated distortion of the input signal
$\hat{v}[n]$	Discrete-time estimated distortion of the input signal
$v_1(t)$	Continuous-time external reference input signal of the adaptive filter
$v_1[n]$	Discrete-time external reference input signal of the adaptive filter
$\mathbf{w}$	FIR adaptive filter coefficient vector
$x(t)$	Continuous-time input signal of the sewing machine
$x[n]$	Discrete-time input signal of the sewing machine
$\tilde{x}(t)$	Continuous-time distorted input signal of the sewing machine

$\tilde{x}[n]$	Discrete-time distorted input signal of the sewing machine
$\hat{x}[n]$	Discrete-time estimated input signal of the sewing machine
$\mathbf{x}^T$	Transpose of vector **x**
$z[n]$	Discrete-time input signal of the sewing machine
β	Normalized step size of the NLMS adaptive filter
Δv	Smallest voltage span of the input signal
ϵ	Small positive parameter used in NLMS algorithm
$\nabla\xi[n]$	Gradient of $\xi[n]$ with respect to **w**
$\xi[n]$	Mean square error
μ	step size of the LMS adaptive filter
ρ	Sample correlation coefficient

1 INTRODUCTION

Noise reduction is a very common technique in the electronics domain. It is used in many areas such as the design of control systems, image processing, audio signal processing, and signal transmission. In control system design and integration, noise free communication between systems on both analog and digital signals is crucial to perform satisfactorily.

In general, input signals are contaminated with noise. Therefore, to use these noise-contaminated signals as inputs to a system, noise filtering techniques must be used. The common way of applying noise filtering is in between the received signal and the input port of a control system. Lowpass filter [1, 2, 3], moving average filter [4, 5, 6], Wiener filter [7, 8], and least mean squares adaptive filter [7, 8, 9] are few examples of noise filtering techniques. These types of filters are used in applications such as image processing, Electrocardiogram (ECG) signal monitoring [10], sound engineering [11], and telecommunication [12]. For example, ECG signal contains mainly four types of noise components: baseline wander,power line interference, Electromyography (EMG) noise, and electrode motion artifacts [13, 14]. This type of noise must remove before feature extraction.

In controlling industrial sewing machines externally [15], the control signals are distorted heavily by noise, when connected to the sewing machine. The distortion is similar to the classic additive white noise, however the distortion is non-stationary. Furthermore, the distortion appears at the port of input of the control signal, and the effect of the distortion is significant for frequencies 50 Hz and above. Because the distortion signal is non-stationary, classical filters such as Wiener filter cannot be directly applied to reduce the distortion.

1.1 Contribution of the Dissertation

In this dissertation, the noise reduction of a control signal that is heavily distorted by noise when connected to an industrial sewing machines is considered. we consider the typical case where the access of controller of the sewing machine is restricted. In order to solve this challenging probelem, an adaptive algorithm is developed to distort the control signal in such a way that this added signal approximately follow the additive inverse of the distortion. In this case, the added signal adaptively cancel the distortion due to noise. In order to generate the replica of the distortion due to noise, NLMS algorithm is used as the adaptive algorithm, Here, based on the nature of the adaptive filtering problem, the error signal of the NLMS algorithm is formulated in a way that is different to the general formulation. In particular, the error signal to the filter is formulated as the difference between the noise signal and the estimated noise signal. The experimental results obtained with the control signals of a typical industrial sewing machine confirm that the proposed method effectively attenuate the distortion signal. Importantly, the proposed method is capable of attenuating the noise in a broadband signal despite a typical adaptive filter needs a narrow-band signal as an input.

1.2 Organization of the dissertation

In Chapter 2, the practical problem for the proposed method is discussed in detail. Input and output characteristics of the sewing machine, signal measurements, and characteristics of the signals are discussed in Chapter 3. In Chapter 4, the practical problem for the proposed method is discussed in detail. Input and output characteristics of the sewing machine, signal measurements, and characteristics of the signals are discussed in Chapter 5, the results of the proposed method are compared with the problem available. In the Chapter 6, the conclusion of the dissertation and the future works are described.

2 PROBLEM STATEMENT

2.1 Preliminaries

In order to increase the productivity and quality in apparel manufacturing in Sri Lanka the sewing industry is moving towards to automation. In this respect, many of the existing sewing machines are to be integrated with custom-made external controllers to automate the stitching process. In particular, inputs such as speed, foot-pressure, and thread trimming of the sewing machines are to be controlled by carefully designed external controllers.

According to the input specifications of the sewing machine, some of the inputs are inherently continuous-time and some are discrete-time. For example, usually the input signal *'speed'* is continuous-time and the input signals *'thread trimming'* and *'foot lifting'* are discrete-time.

Figure 2.1 depicts a general setting of the foregoing discussion, where $x(t)$ represents a continuous-time input signal and $z[n]$ represents a discrete-time input signal of the sewing machine. Depending on the type of the sewing machine, there can be many such input signals. Moreover, the external controller is driven by an input $u[n]$, which depends on many factors, such as fabric alignment to the needle point, sewing machine speed, and fabric availability, among others. This in turn enables a continual, yet a controlled stitching operation.

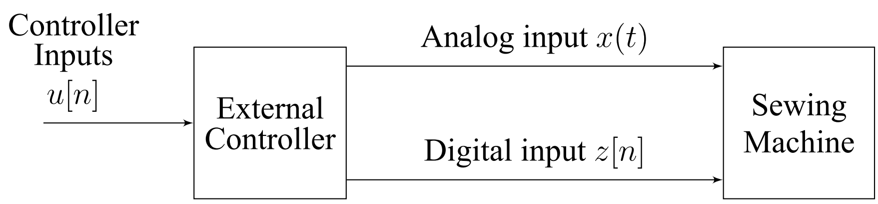
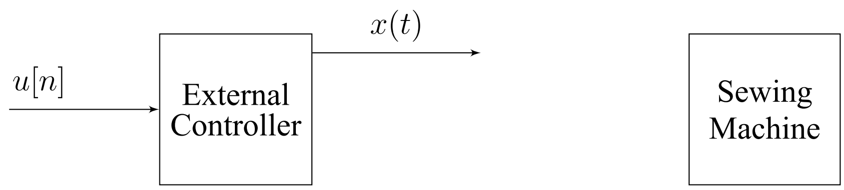


Figure 2.1: Basic type of input to external controller and sewing machine.

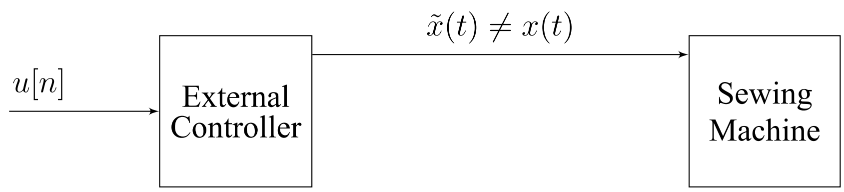
However, it turns out that a *direct coupling* of the external controller and the sewing machine fails to yield the desired operation as we will highlight in the next section.

2.2 Main problem

Usually discrete-time signals (e.g., $z[n]$) are less susceptible to external interference [1]. Nonetheless, in the case of continuous-time signal $x(t)$, the sewing machine is not responding as anticipated. This in turn suggests the existence of an inevitable signal distortion that underlies the unanticipated respond of the sewing machine. Thus, in this study, we place a greater emphasis on the *continuous-time signal* inputs of the sewing machine.



(a) Before Coupling the External Controller and the Sewing Machine.



(b) After Coupling the External Controller and the Sewing Machine.

Figure 2.2: Coupling External Controller to the Sewing Machine.

Without loss of generality, we assume system with only one input signal $x(t)$, see Figure 2.2. Of course, when there are more than one input signals, those are separately handled. Let $x(t)$ denote the intended input signal to the sewing machine [Figure 2.2a]. However, when the physical contact of input $x(t)$ and the sewing machine is established as depicted in Figure 2.2b, the input undergoes an undesired distortion. Thus, instead of the intended signal $x(t)$, a distorted input signal is $\tilde{x}(t)$ is present at the input port of the sewing machine. Consequently, the requisite automation of the stitching process is impeded.

[1] Such a phenomenon is not fortuitous and is an intrinsic property of discrete signals.

Figure 2.3 shows the disparity between $x(t)$ and $\tilde{x}(t)$ by using *real measurements*. More specifically, the samples of $x(t)$ and $\tilde{x}(t)$ are plotted, where $x[n] = x(nT)$ and $\tilde{x}[n] = \tilde{x}(nT)$ with $T = 0.002$ s. The figure shows that there is a significant difference between the signal $x(t)$ and $\tilde{x}(t)$, which in turn mutilate the sewing process. However, in industrial sewing involving *best quality garments*, *precision* matters and deviations of the input signal $x(t)$ from $\tilde{x}(t)$ beyond specified design limits are impermissible. Therefore, investigating mechanisms of minimizing the distortions are of crucial importance, especially from a business point of view.

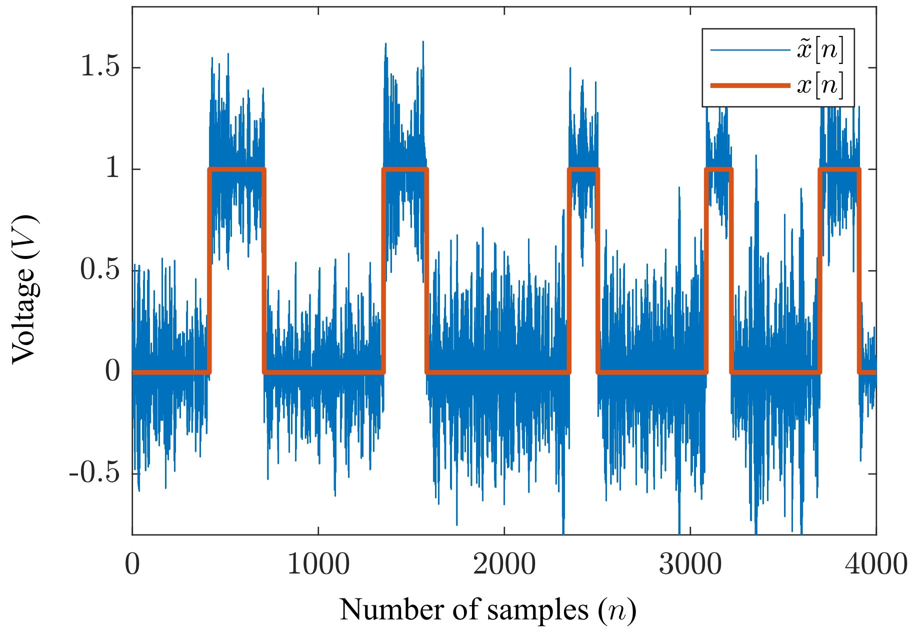


Figure 2.3: The measured signal $x[n]$ before connecting to the sewing machine and $\tilde{x}[n]$ after connecting to the sewing machine.

The main problem in this project is to:

1. analyse the distortion and investigate potential sources of it,

2. mathematically model the underlying distortion phenomenon,

3. find a mechanism to eliminate the distortion.

3 BACKGROUND STUDY

In this section, we first discuss the input-output characteristics of a sewing machine and the attendant consequences that are to be carefully considered during the design. Then signals at our disposal are identified to proceed with subsequent design stages. Characteristics of the available signals are discussed and analyzed. This in turn can be greatly useful when making proper choices of available techniques for our design.

3.1 I-O characteristics of the sewing machine

Figure 3.1 shows the sewing machine speed response with the input signal $x(t)$. The response for increasing $x(t)$ and that for decreasing $x(t)$ are clearly different. In fact there is an inherent *hysteresis*. The figure suggests that the Input-Output (I-O) characteristics follows a *piece-wise-exponential* form, whether or not the input $x(t)$ is increasing or

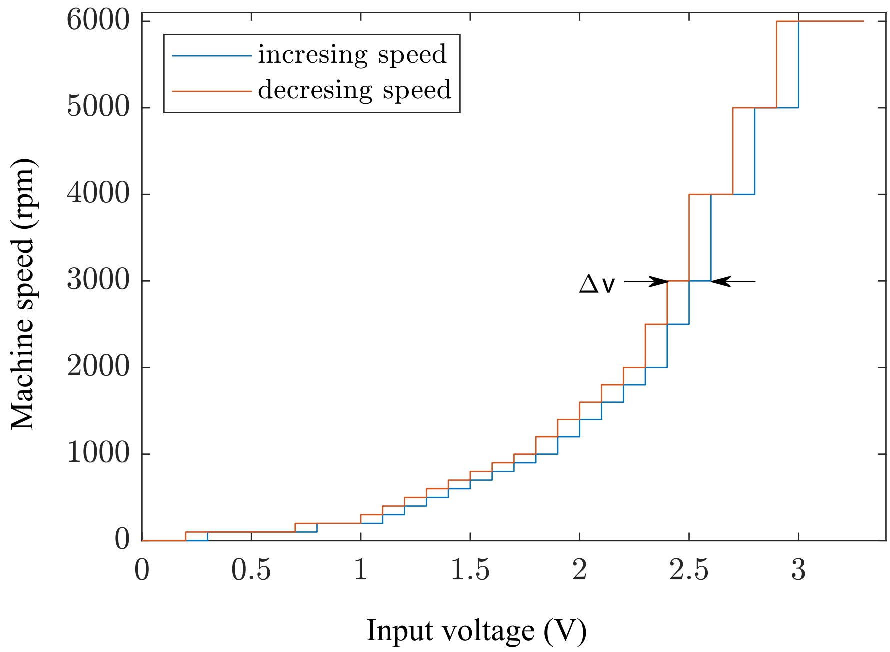


Figure 3.1: Machine speed vs input signal $x(t)$.

decreasing.

The exponential nature of the I-O characteristics stipulates tight constraints on the distortion $v(t)$ at high rpm levels, where [1]

$$v(t) = \tilde{x}(t) - x(t). \tag{3.1}$$

In other words, in either case, $x(t)$ is increasing or $x(t)$ is decreasing, for a fixed distortion in $x(t)$, the higher the rpm level is, the higher the relative rpm error. As a result, when the sewing machine is operating at high rpm levels, in either case, $x(t)$ is increasing or $x(t)$ is decreasing, effects of distortions of $x(t)$ can become more stringent on the pre-planned stitching operation.

In general, the *machine speed control program* specified by $x(t)$ for a given stitching task is neither increasing nor decreasing. In particular, the related $x(t)$ can be increasing in some segments and decreasing in others. In this respect, the intrinsic hysteresis of the I-O characteristic plays a key role when determining effects of the distortions of $x(t)$.To see this, let Δv denote the *smallest* voltage span in which the 'increasing speed' and 'decreasing speed' are equal, see Figure 3.1. The parameter Δv provides the minimum range over which $x(t)$ can be changed without changing the machine speed. Roughly speaking, if the distortion $v(t)$ [see (3.1)] is within $\pm\Delta v/2$, then the effects of the distortion is annulled by the hysteresis itself.

The foregoing discussion suggests that only *large* values of distortions $v(t)$ that are not handled by hysteresis can mutilate significantly the assigned stitching task. Thus, adequate measures are to be taken to keep the distortion $v(t)$ at requisite low levels.

3.2 Signal measurements

The nature of the distortion $v(t)$ can either be deterministic or non deterministic, which is to be carefully understood. To this end, we rely on measurements of the underlying phenomenon.

[1] Compare with Figure 2.3.

Of course, the signal $x(t)$ is available and can be used whenever required, either in real-time or offline [compare with Figure 2.2a]. According to Figure 2.2b, the signal $\tilde{x}(t)$ is also available, whereby the distortion $v(t)$ given in (3.1) can be computed and even stored for offline processing.

It is worth pointing out that the system configuration in Figure 2.2b is futile because the intended signal $x(t)$ is no longer available at the input port of the sewing machine. Nonetheless, it is useful for determining the nature of the distortion $v(t)$, which is pivotal for subsequent design steps.

The two signals $x(t)$ and $\tilde{x}(t)$ are measured by using a digital oscilloscope. In particular, we use GW Instek GDS-1152A-U digital oscilloscope to measure the signals. The oscilloscope has a 4000 data point length memory for each channel. Due to technical limitations of the measuring equipment, a sampling rate of 500Hz is used. Thus, the signals are captured for a period of 8 seconds. The resulting discrete-time signals are also stored for offline analysis. Recall that the measured signals are shown in Figure 2.3.

3.3 Characteristics of signals $x(t)$ and $v(t)$

The external controller output $x(t)$ is a *piece-wise constant* signal. The minimum width of a constant piece is 0.5 s and the maximum width can go up to 20 s. Since $x(t)$ is a sum of rectangular pulses, it is not a *bandlimited* signal. Amplitudes levels of $x(t)$ varies from $0V$ to 3.3 V with the *slew rate* of 2.5 V/μ s.

Before using the collected data signals $x[n]$ and $\tilde{x}[n]$ for any simulation or analysis, it is important to check roughly the nature of the collected data. Therefore, first a basic *Fast Fourier Transform (FFT)* analysis of $x[n]$ is conducted, where the signal is treated as deterministic.

According to the Figure 3.2, $x[n]$ has low frequencies with high magnitudes. The frequencies higher than $100Hz$ have magnitude lower than $-60dB$. This is technically expected because $x[n]$ is a sequence of samples that corresponds to a sum of rectangular pulses [16].

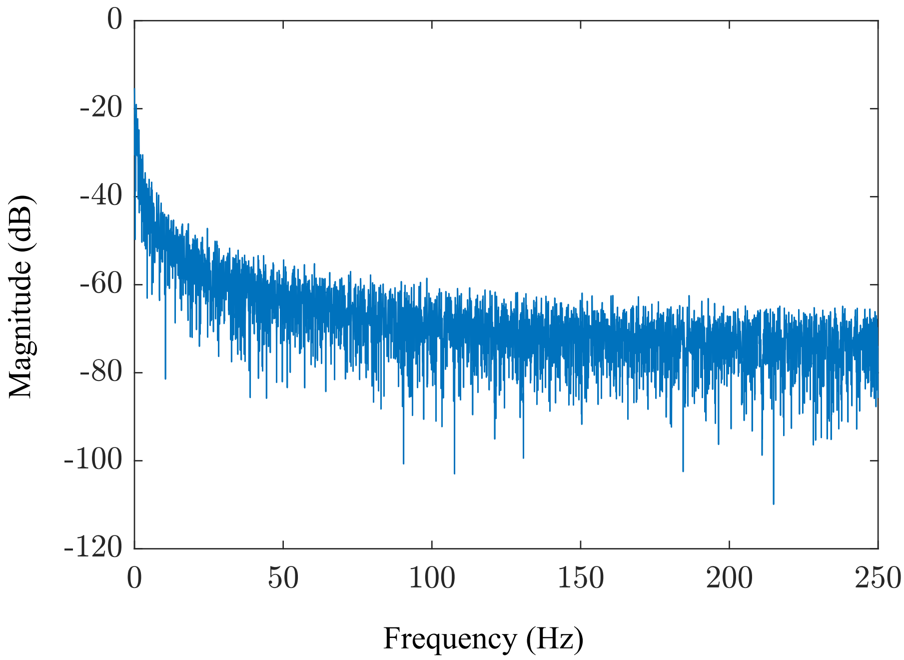


Figure 3.2: FFT of $x[n]$.

Further, it is important investigate the characteristics of the distortion $v[n] = v(nT)$ where $T = 0.002$ s, [see (3.1)]. Assuming $v[n]$ is deterministic, a basic FFT computation is conducted. Figure 3.3 depicts the magnitude spectrum of $v[n]$. Figure shows that the distortion is on the order of -60 dB or more throughout the considered frequency range. This suggests that the distortion $v[n]$ appears to be similar to the classic additive white noise. By comparing Figure 3.2 and Figure 3.3, we clearly see that the effect of $v[n]$ on $x[n]$ is significant especially for frequencies around 50 Hz or above. This suggests the possibility of suppression of the underlying distortion by using a low pass filter with a bandwidth of approximately 50 Hz. However, such a method does not apply, because the resulting system is again of the form shown in Figure 2.2b. Note that the magnitude seems to increases approximately linearly with increasing frequency. We believe this is mainly due to aliasing.

The preceding FFT computation presumes the deterministic nature of $v[n]$, which may not be true in reality. One may assume that $v[n]$ is random. Therefore, some statistical tests are also conducted to check the stationarity or nonstationarity of $v[n]$. These tests rely on a single *sample function* of the underlying discrete-time random process.

According to the test results, from a statistical point of view, it turns out that $v[n]$ is a *non-stationary* discrete-time random process. Details of the tests are deferred to Appendix A.

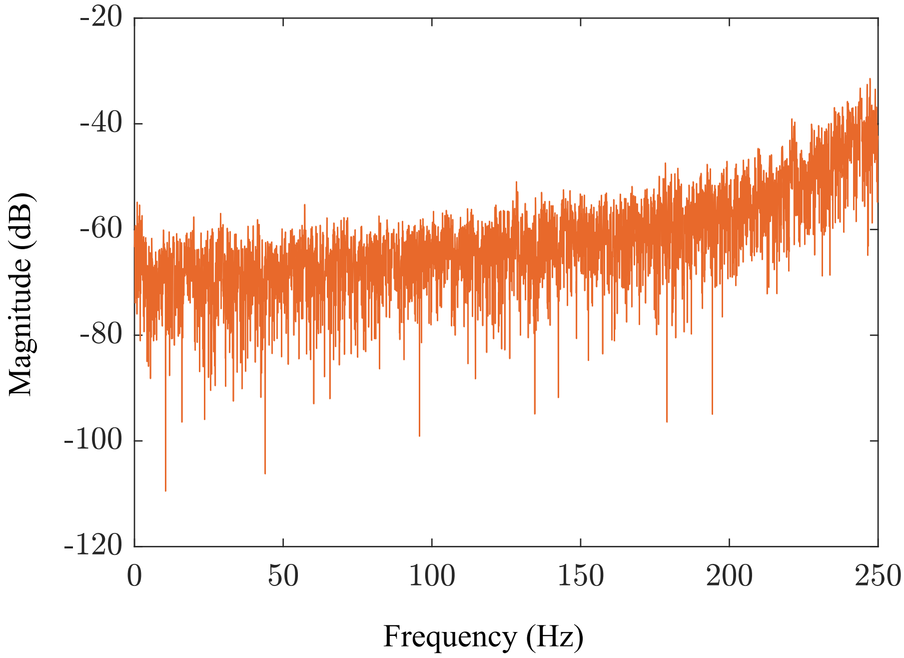


Figure 3.3: FFT of $v[n]$.

4 MATHEMATICAL MODELING AND SOLUTION APPROACH

In this chapter, first a mathematical model is developed to capture the essence of the problem discussed in section 2.2. Then a solution approach is devised based on the mathematical model of the problem.

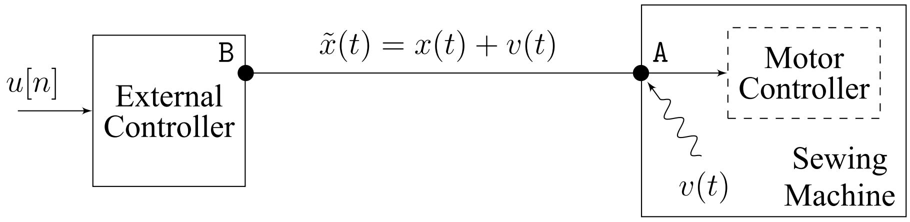
4.1 Mathematical modeling

The main challenge is that the access to the sewing machine is restricted. The only point where the access is given is the input port of the sewing machine. Therefore, we have to be cautious here, because whatever the distortion suppression circuitry we may design, it is to be interfaced between the output port of the external controller and the input port of the sewing machine.

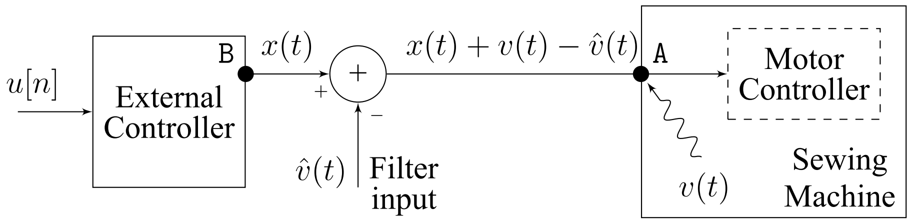
Let us start by comparing Figure 2.2a and Figure 2.2b. Note that the desired signal $x(t)$ is distorted as soon as it is connected to the input port of the sewing machine. To further scrutinize the situation we consider the setup drawn in Figure 4.1. Let us first connect the the *output port* `B` of the external controller and the *input port* `A` of the sewing machine by a conductor `BA`. According to the preceding discussion in section 2.2, $\tilde{x}(t)$ is the signal available at any point in `BA`. Moreover, from (3.1), we have that $\tilde{x}(t) = x(t) + v(t)$.

The above conditions suggest the configurations depicted in Figure 4.1a and 4.1b. The motor controller is introduced as a separate module enclosed in the sewing machine, whose input is directly connected to the port `A`. More importantly, the distortion $v(t)$ is always *induced* at the input port `A` of the sewing machine whether or not `B` and `A` are connected. Note that the symbol ● at port `A` represents the point at which the distortion $v(t)$ is *induced* to the system. It is worth pointing out that the symbol ● is *not an*

(a) Before coupling the external controller and the sewing machine.



(b) After coupling the external controller and the sewing machine.



(c) Coupling the external controller and the sewing machine with noise cancelling.

Figure 4.1: Mathematical modeling of the problem.

adder that isolates the conductor BA and the conductor from A to the input of the motor controller. In fact, both the conductor BA and the conductor from A to the input of the motor controller have the same potential.

Intuitively, we would argue that the induced distortion can be annulled by simply modifying the output signal $x(t)$ of the external controller to be $x(t) - v(t)$. More specifically, the following modification is to be performed:

$$x(t) \leftarrow x(t) - v(t). \tag{4.1}$$

However, in practice the signal $v(t)$ is not available. Nevertheless, one might seek for an estimate $\hat{v}(t)$ of $v(t)$, based on which the modification (4.1) is realized, at least approximately, i.e.,

$$x(t) \leftarrow x(t) - \hat{v}(t). \tag{4.2}$$

A potential modeling to realize (4.2) is depicted in Figure 4.1c. Note that if the output of the adder is not connected to the input port `A`, the adder output is trivially $x(t)-\hat{v}(t)$. However, the distortion *induced* at the input port `A` of the sewing machine results in the signal $[x(t)-\hat{v}(t)]+v(t)$ at the input of the motor controller, see Figure 4.1c. Thus, the distortion $v(t)$ suppression problem reduces to a problem of computing in real-time, a signal $\hat{v}(t)$ that bears a "close resemblance", in some sense, to $v(t)$.

4.2 Solution approach

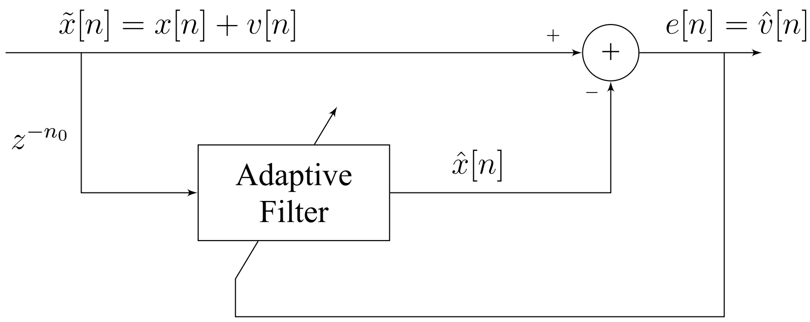
Based on the mathematical model that developed in section 4.1, it turns out that, non of the *classical filters* are applied to suppress the distortion. The main disadvantage of such filters in this application is, the estimate the noise signal $v(t)$ is not obtainable.

According to the experiment conduct for $v[n]$ in Appendix A, it was observed that, the underlying distortion $v(t)$ is a non-stationary. Hence, the *Wiener filter* is also not applicable in this context, because Wiener filters are applied only for stationary signals [7]. Therefore one of the promising method is going for adaptive filtering.

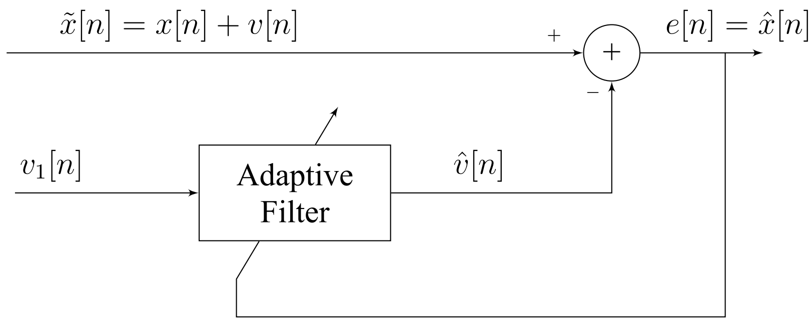
With respect to the adaptive noise cancelling, there are two configurations [7].

1. Adaptive noise canceller without a reference signal, See Figure 4.2b.
2. Adaptive noise canceller with a reference signal, See Figure 4.2a.

Let us try to unravel first, how the 1st model of the adaptive noise canceller be applied to our problem (see Figure 4.2a). Even though, the adaptive filter needs a zero mean input signal, with some minor modifications, it can be used with piece-wise constant signals [17]. Recall that the ultimate goal of using the adaptive filter is to generate a reasonable estimation $\hat{v}[n]$ of the noise signal $v[n]$. The adaptive filter output in the 1st model generates a reasonable output. Note that filter input is to be $x[n]+v[n]$ which is available only in an offline setting with adequate measurements. However, in an real time implementation, which is the case of our problem, $x[n]+v[n]$ is not available. In this context, together with the technicalities intrinsic to the 1st model, It turns out that the filter if not directly applicable (See Figure 4.3). However, 2nd model can be slightly



(a) Adaptive noise canceller without a reference.



(b) Adaptive noise canceller with a reference signal.

Figure 4.2: Adaptive noise canceller models.

modified to handle the situation even in the real time setting. It is worth pointing out that the 2nd model relies on an additional signal $v_1[n]$, which is to be correlated with $v[n]$. To proceed with the design, we must first explore a method to capture such a signal if any. Then we must verify correlation properties.

4.3 Capturing of $v_1[n]$ and verification for correlation

Few experiments were conducted to design a mechanism to capture continuous time signal $v_1(t)$. Experiments suggest that the noise can be generated due to Electromagnetic Interference (EMI)[1]. If there is an electromagnetic field disturbing the control signal $x(t)$, the same interference must also disturbs other conductors placed sufficiently close to the sewing machine. Thus a simple sensor schematic shown in Figure 4.4 is used to capture $v_1(t)$. A real image of the sensor is shown in Figure 4.5[2]. The sensor is placed

[1] Note that the EMI can be generated due to Alternating Current (AC) servo motors and Variable Frequency Drive (VFD)s [18].

[2] 1K resistor and 15 turns with 8mm diameter 1.044mm^2 copper coil was used for the sensor.

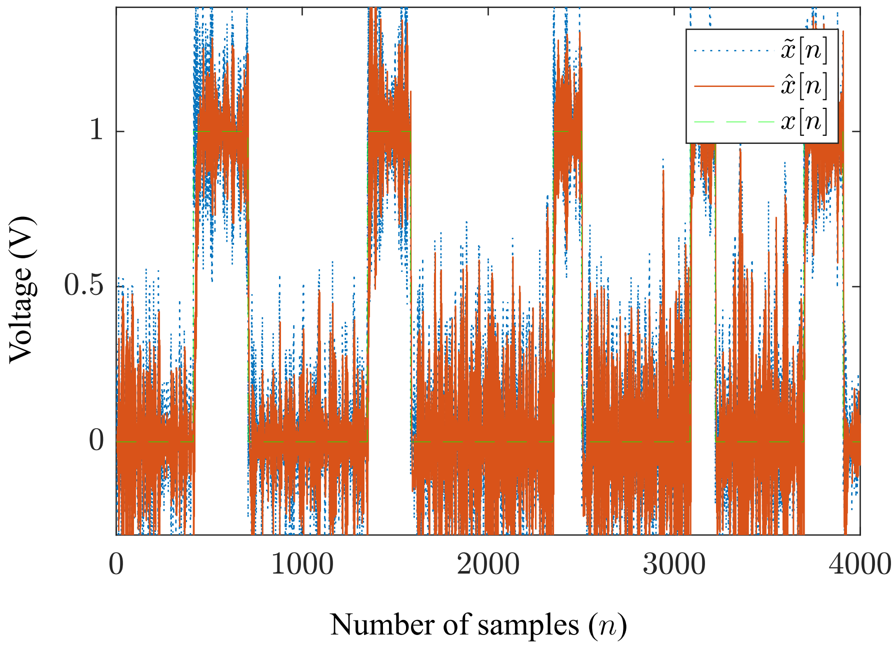


Figure 4.3: Output of the adaptive filter without reference.

close to the input port `A` of the sewing machine (refer Figure 4.1). Then the induced voltage $v_1(t)$ is recorded by using a digital oscilloscope. Figure 4.6 shows the signal $v_1[n] = v_1(nT)$ and $\tilde{x}[n] = \tilde{x}(nT)$ with $T = 0.002$s.

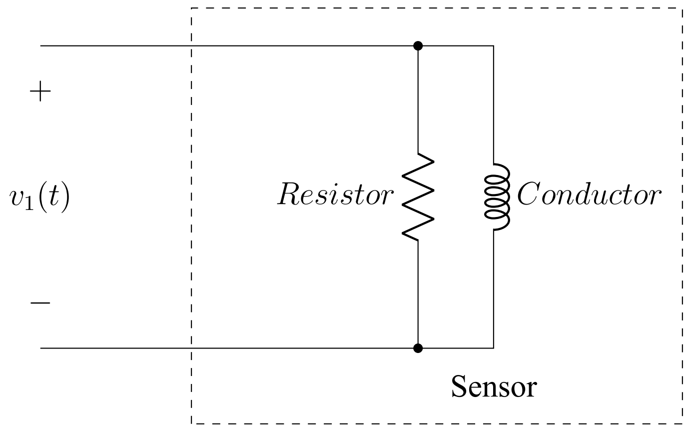


Figure 4.4: Sensor used to measure $v_1(t)$.

The sample correlation coefficient ρ between $\tilde{x}[n] - x[n]$ is computed. It turns out that $\rho = -0.2$, which suggest a *negative week correlation* between the signals. See Appendix B for details.

Figure 4.5: Implemented noise sensor.

Therefore, with satisfying the requirements of secondary sensor input signal for adaptive filter, we proposed that the 2nd model of the adaptive noise canceller would be solve the problem discussed in section 2.2.

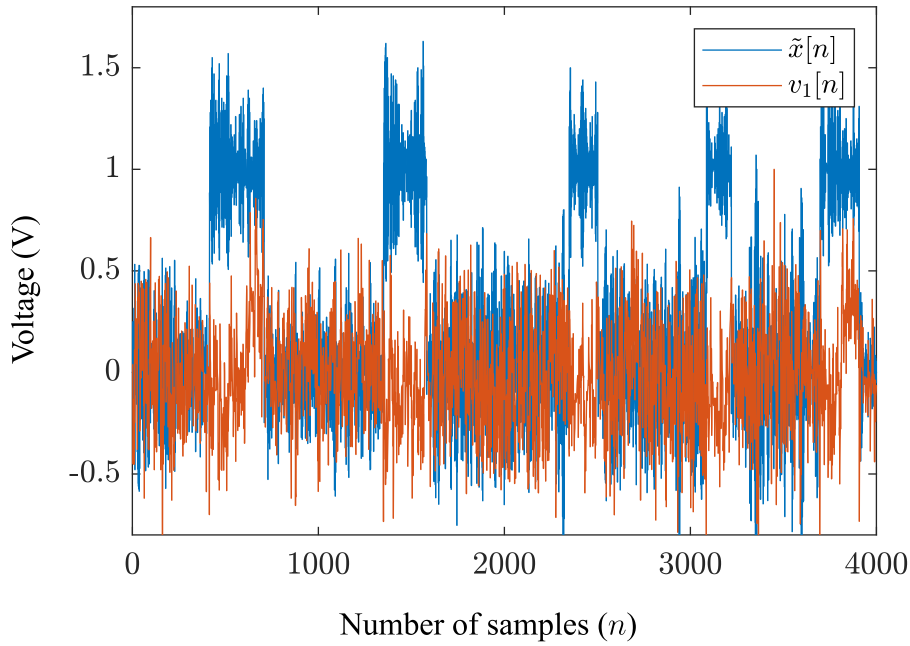


Figure 4.6: Secondary sensor input $v_1[n]$ and $\tilde{x}(t)$.

4.4 Proposed method

The slightly modified adaptive filter with reference needs two inputs:

1. the sensor input signal $v_1[n]$,
2. an appropriately chosen error signal $e[n]$.

Signal $v_1[n]$ has already been captured by using the sensor circuit, see Figure 4.5. The error signal $e[n]$ is calculated as $e[n] = v[n] - \hat{v}[n]$ [9, 7] Where $\hat{v}[n]$ is the output of the proposed adaptive filter. Figure 4.7 shows the proposed adaptive filter implementation.

Note that the implementation is different to the commonly use configuration of the adaptive filters. In particular, the input signal to adaptive filter is often going to be distorted signals or the noise plus the intended signal. The output is the estimate of the desired signal. In contrast, our proposed adaptive filter gets as the input the desired signal $x[n]$ itself. The out put of the filter in fact a distorted signal which is connected to port `A` of the sewing machine, see Figure 4.7. Further, the estimated signal $\hat{x}[n]$ of the desired signal $x[n]$ is the error input $e[n]$ to the commonly used adaptive filters. In our proposed adaptive filter gets error signal $e[n] = v[n] - \hat{v}[n]$ where $v[n]$ is the noise signal and $\hat{v}[n]$ is the estimated noise signal generated by the proposed adaptive filter.

Specifically suppose that, $x[n]$ and $v[n]$ are real-valued, uncorrelated zero mean processes [7, p. 496]. The mean-square error can be expressed as:

$$E\{e^2[n]\} = E\{\left(v[n] - \hat{v}[n]\right)^2\}. \tag{4.3}$$

Thus, the output of the adaptive filter $\hat{v}[n]$ is the minimum mean-square estimation of $v[n]$.

When implementing the proposed method, NLMS adaptive filter is used and the weight vector $(\mathbf{w}_n)$ update equation is:

$$\mathbf{w}_{n+1} = \mathbf{w}_n + \beta \frac{\mathbf{v}_n}{\epsilon + \|\mathbf{v}_n\|^2} e[n] \tag{4.4}$$

as derived in Appendix C

Here, β is the *normalized step size* with $0 < \beta < 2$ and ϵ is a small positive number. $\mathbf{v}_n$ and $\mathbf{w}_n$ are p-vectors defined as:

$$\mathbf{v}_n = \Big[v_1[n], v_1[n-1], v_1[n-2], \ldots, v_1[n-p-1]\Big]^T,$$

$$\mathbf{w}_n = \Big[w[1], w[2], w[3], \ldots, w[p]\Big]^T.$$

The algorithm for the proposed method is outlined as shown in Algorithm 1.

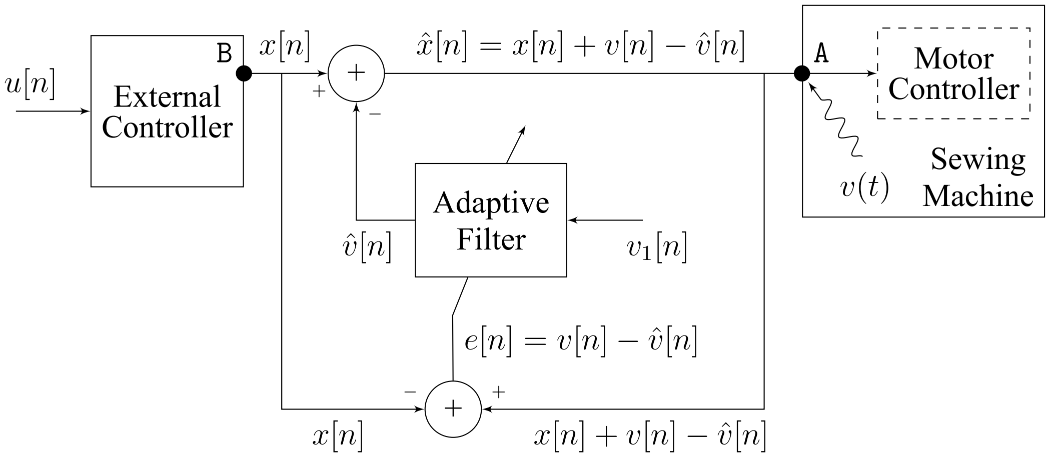


Figure 4.7: Proposed system configuration.

Algorithm 1 NLMS algorithm for noise cancellation.

Parameters: p = filter order , β = normalized step size

Initialization: $\mathbf{w}_0 = 0$, a real p-vector

Computation: For $n = 1, 2, 3, \ldots$

1: $\hat{v}[n] = \mathbf{w}_n^T \mathbf{v}_n$

2: $\hat{x}[n] = \tilde{x}[n] - \hat{v}[n]$

3: $e[n] = \hat{x}[n] - x[n]$

4: $\mathbf{w}_{n+1} = \mathbf{w}_n + \beta \dfrac{\mathbf{v}_n}{\epsilon + \|\mathbf{v}_n\|^2} e[n]$

5 RESULTS

In generating the results of the proposed system [see Figure 4.7], there are two main parameters to be chosen:

1. normalized step size β,
2. filter order p.

The 'best' β and p values for Algorithm 1 is computed by using a grid search where, β is taken from the set $\mathcal{B} = \{0.10, 0.15, 0.20, \ldots, 2.00\}$ and p is taken from the set $\mathcal{P} = \{10, 11, 12, \ldots, 100\}$.

For each (β, p) pair, the Algorithm 1 runs from $n = 1$ to N where, N is the total length of offline signal $x[n]$[1].Then we compute the error e_p associated with each $p \in \mathcal{P}$ as follows:

$$e_p = \min_{\beta \in \mathcal{B}} \left[\frac{1}{N} \sum_{n=1}^{N} \left\| \hat{v}_{p\beta}[n] - v_1[n] \right\|_2^2 \right], \tag{5.1}$$

where $\hat{v}_{p\beta}$ is the estimated v_1 with specified β and p.

Figure 5.1 shows the e_p vs p plot. Note the best performance in terms of e_p is obtained when $p = p^\star = 64$. In this respect best β, $\beta^\star$:

$$\beta^\star = \arg\min_{\beta \in \mathcal{B}} \left[\frac{1}{N} \sum_{n=1}^{N} \left\| \hat{v}_{p^\star\beta}[n] - v_1[n] \right\|_2^2 \right]. \tag{5.2}$$

Thus, $(\beta, p) = (\beta^\star, p^\star)$ is chosen as the best pair fro the proposed adaptive filter. In particular, we have $(\beta^\star, p^\star) = (1.5, 64)$.

The output of the proposed adaptive filter is shown in Figure 5.2. Note that, above chosen filter parameters $(\beta^\star, p^\star)$ is used in this case. It can be noticed that, initially

[1]When doing this we used an offline computation together with measurements of length $N = 4000$.

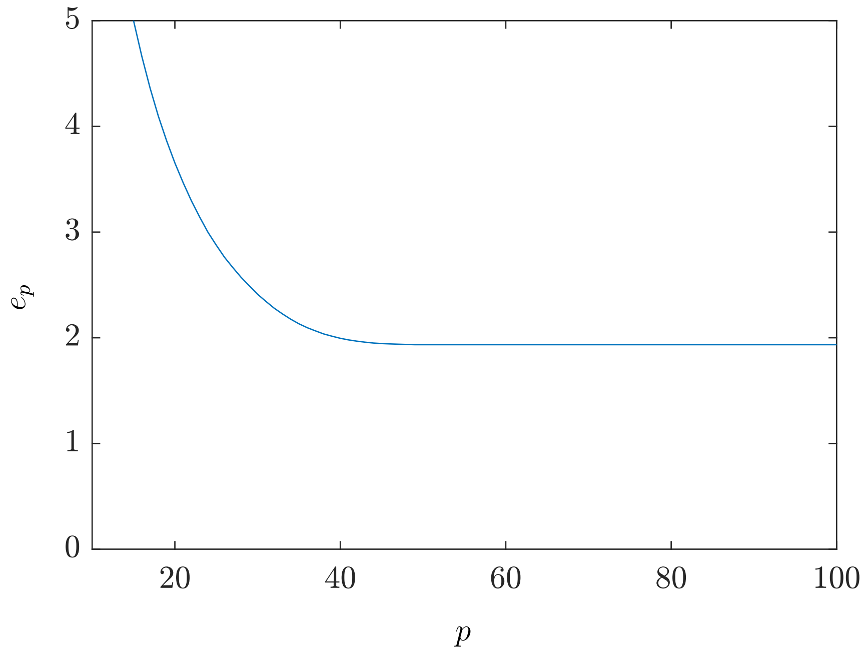


Figure 5.1: e_p **vs** p **curve using proposed adaptive filter for offline data set.**

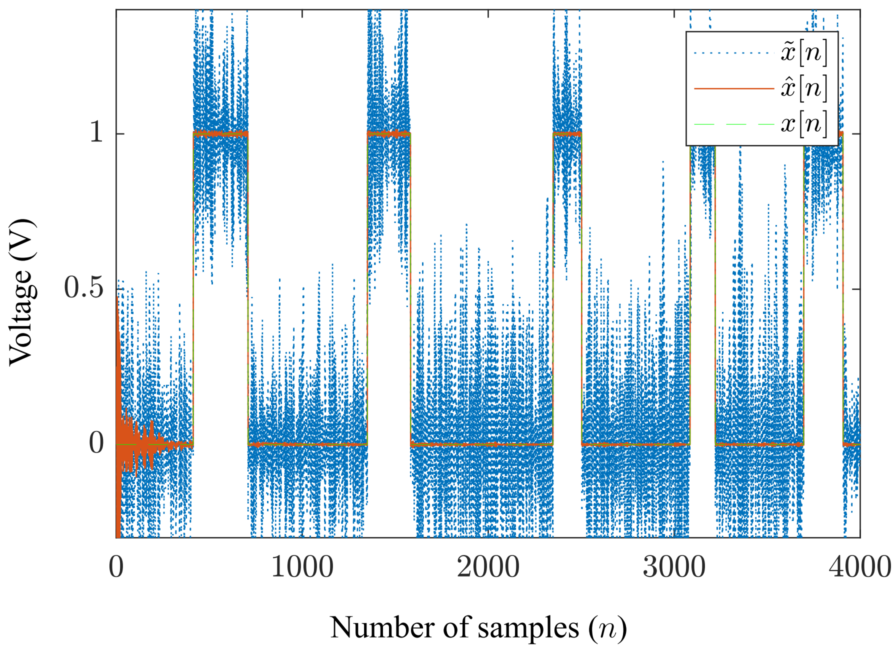


Figure 5.2: Optimum Proposed adaptive filter output.

around 300 samples are taking to converge the filter coefficients to the optimum vales. Therefore, the time taken for this set of samples (0.6 seconds) can be considered as initial training time of the filter. During this period of time, the external controller output $x(t)$ can be set to 0V for eliminate the unexpected behaviour of the sewing machine.

Figure 5.3 shows a case where the desired input $x[n]$ to the sewing machine is maintained at 1V, that correspond a rpm of 200. The solid horizontal lines indicates the upper and lower voltage values within which the sewing machine machine speed is remains intact.

Results show that the input to the sewing machine can change over a significant range of voltage values, if there is no mechanism to suppress the distortion, see the variation of $\tilde{x}[n]$ in the figure. More specifically $\tilde{x}[n]$ changes from 0.6V to 1.3V resulting changes in the rpm values from $100, 200, 300, 400$ and 500, back and forth. Therefore results emphasise the necessity of a carefully designed adaptive filter for maintaining a precision sewing process. In this respect our proposed setup with the adaptive filter appears to playing a crucial role for maintaining a steady sewing process.

Results show that the proposed adaptive filter steadily maintains the $\hat{x}[n]$ at the value very close to the intended input $x[n] = 1$V. For comparison, we have also plotted the input due to the classic adaptive Wiener filter for filter order $p = 20$ and window length $h = 100$. Result shows that the adaptive Wiener filter can not track the input at the desired level 1V. For other filter orders and different window sizes, the same behavior was observed. Results further show that the input level of the adaptive Wiener filter can cause the rpm values to change rpm values from 0 to 700, a transition that should never be allowed if precision sewing is to be performed.

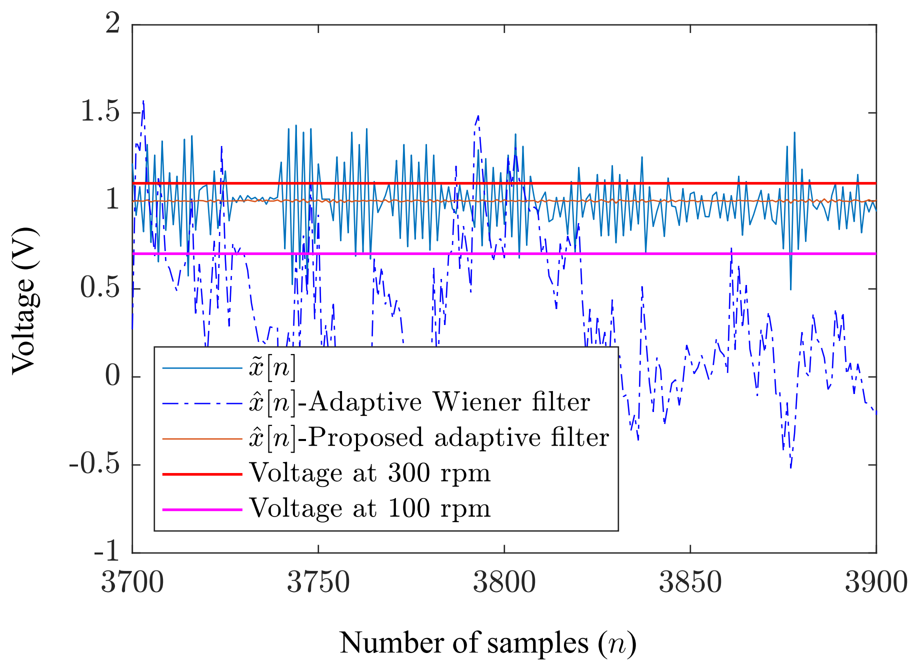


Figure 5.3: Optimum proposed adaptive filter output comparison with boundary voltages.

6 CONCLUSION AND FUTURE WORK

An adaptive algorithm is developed to attenuate the distortion of control signals of typical industrial sewing machines. Here, an additive inverse of the distortion is adaptively generated and added to the control signals so that the distortion is attenuated. Because of restricted access to the controller, the adaptive algorithm using NLMS is formulated in such a way the error signal of the proposed adaptive algorithm is generated as the difference between the noise and the estimated noise by the NLMS adaptive filter whereas the error signal of the general formation takes the form estimated input signal. The experimental results obtained with the control signals of a typical industrial sewing machine confirm that the proposed method effectively attenuates the distortion signal with fast convergence of the NLMS algorithm.

Future work includes the implementation of the proposed adaptive algorithm in hardware for experimental validation. Furthermore, the secondary sensor which was used to capture the external reference signal can be improved to get a strong correlated signal with the distortion.

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A STATIONARY CHECK OF THE NOISE SIGNAL

There are different methods in testing the stationary of a time series. In this chapter, two types of test,

1. Summary statistics
2. Statistical test

will be conducted.

A.1 Summary Statics

As a ground rule, time series data set must not have a time dependant structure such as trend, seasonal effects. Therefore, referring to the Figure A.1, at present, the $\tilde{x}[n]-x[n]$ does not show any time dependent structure. Further, in summary statistic test, the

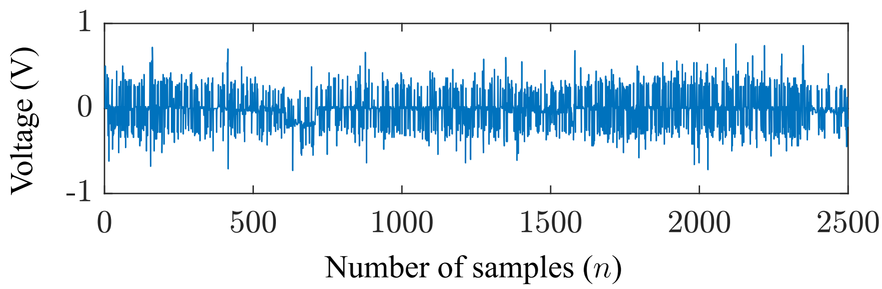

Figure A.1: $\tilde{x}[n]-x[n]$ **signal.**

change of mean and variance with time is tested [19]. In fact, this is a quick and sanity check. In time series test for stationarity, the typical method is to split the time series data into two or more segments and check for the variation of statistical parameters of each segment. Since the signal $\tilde{x}[n]-x[n]$ is associated with two voltage levels of $x[n]$, the time series was spitted based on voltage level. The sample mean and sample variance of each segment is calculated as shown in Table A.1

Table A.1: Sample mean and sample variance of $\tilde{x}[n] - x[n]$ associated with voltage level of $x[n]$.

Sample range	Associated voltage of $x[n]$ (V)	Sample Mean	Sample Variance
$1 - 400$	0	$+0.0012$	0.0539
$420 - 700$	1	-0.0031	0.0497
$720 - 1340$	0	-0.0020	0.0431
$1360 - 1560$	1	$+0.0084$	0.0669
$1600 - 2320$	0	$+0.0024$	0.0937
$2360 - 2500$	1	$+0.0060$	0.0358
$2520 - 3070$	0	$+0.0023$	0.0987
$3090 - 3215$	1	$+0.0078$	0.0264
$3231 - 3690$	0	-0.0001	0.1255
$3700 - 3900$	1	$+0.0068$	0.0374

The changes in the values of either mean or variance is negligible. But in each case, rate of change between adjacent sample ranges is significant. For example, Consider the 1st sample mean associated with $0V$ over the sample range $1 - 400$ and the sample mean associated with $1V$ over the range $420 - 700$. The rate of change of sample mean is 258%. The sample variance also shows a similar behavior. Therefore, the signal $x[n] - \tilde{x}[n]$ appears to processing some non-stationarity properties.

A.2 Statistical test

The statistical test makes stronger inferences about the stationarity of time series. Among number of statistical test, one of the widely used *Augmented Dickey-Fuller* test [20].

Based on the ρ-value of the test, stationarity or non-stationarity of the time series is decided. In perticuler, the time series can be classified as follow:

1. ρ-value $> 0.05 \implies$ the time series is non-stationary,
2. ρ-value $\leq 0.05 \implies$ the time series is stationary.

The resultant ρ-value for the sample data $v[n]$ is 0.08, which in turns classify $v[n]$ as a non-stationary process.

B CORRELATION BETWEEN $v[n]$ and $v_1[n]$

The sample correlation coefficient r is a measurement that indicate the connection between relative moments of two variables. The value of r is between -1.0 and $+1.0$. The case $r = -1$ represents the perfect negative correlation, $r = 1$ represents the perfect positive correlation, and $r = 0$ indicates no correlation between two random variables.

There are several methods for computing empirically the correlation coefficient, such as Pearson, Kendall, and Spearman. The *Pearson* correlation is the most commonly used one. This measurement has an ability to capture the direction and the strength of linear relationship between two random variables [21] characterized by r and p-value, respectively. The r value of the Pearson test represents sample correlation between two random variables. The p-value is used to determine probability of null hypothesis is true. Finally the decision is determined based on a threshold level of the p-value, as follows:

1. p-value $\leq 0.05 \implies$ the correlation is statically significant,
2. p-value $> 0.05 \implies$ the correlation is not statically significant.

The correlation coefficient(r) between $v[n]$ and $v_1[n]$ is -0.2. This suggests that the $v[n]$ and $v_1[n]$ has very week negative correlation. The p-value of the test is almost identical to 0. Therefore, according to the Pearson test, the correlation between $v[n]$ and $v_1[n]$ is statistically significant.

C NLMS ALGORITHM

Content of this chapter based on [7, Chapter 9]. In the proposed adaptive filter (see Figure 4.7), The error signal to the adaptive filter $e[n]$ is:

$$e[n] = v[n] - \hat{v}[n]. \tag{C.1}$$

Here, the Finite Impulse Response (FIR) adaptive filter output $\hat{v}[n]$ can be expressed as:

$$\hat{v}[n] = \mathbf{w}_n^T \mathbf{v}_n \tag{C.2}$$

where, $\mathbf{v}_n$ and $\mathbf{w}_n$ are p-vectors defined as $\mathbf{v}_n = \Big[v_1[n], v_1[n-1], v_1[n-2], \ldots, v_1[n-p-1]\Big]^T$ and $\mathbf{w}_n = \Big[w[1], w[2], w[3], \ldots, w[p]\Big]^T$. From (C.1) and (C.2) , we have $e[n] = v[n] - \mathbf{w}_n^T \mathbf{v}_n$. The mean square error $\xi[n]$ of $e[n]$ is given by

$$\begin{aligned} \xi[n] &= E\big\{e^2[n]\big\} && \text{(C.3)} \\ &= E\big\{\big(v[n] - \mathbf{w}_n^T \mathbf{v}_n\big)^2\big\}. && \text{(C.4)} \end{aligned}$$

Note that $\xi[n]$ is quadratic in $\mathbf{w}_n$.

FIR adaptive filter coefficient vector $\mathbf{w}_n^\star$ that minimizes $\xi[n]$, i.e.,

$$\mathbf{w}_n^\star = \arg\min_{\mathbf{w}_n} \xi[n]. \tag{C.5}$$

However, computing (C.5) for each n is impractical, and therefore a method based on *steepest descent* is typically considered.

In the steepest descent algorithm for FIR adaptive filter coefficient computation, the following update is considered:

$$\mathbf{w}_{n+1} = \mathbf{w}_n - \mu \nabla \xi[n], \tag{C.6}$$

where, $\nabla \xi[n]$ is the gradient of the ξ with respect to $\mathbf{w}_n$ and μ is a step size of the update. More specifically, from (C.3) and (C.4), $\nabla \xi[n]$ is given by

$$\begin{aligned}
\nabla \xi[n] &= \nabla E\big\{\big(v[n] - \mathbf{w}_n^T \mathbf{v}_n\big)^2\big\} && \text{(C.7)}\\
&= E\big\{\nabla\big(v[n] - \mathbf{w}_n^T \mathbf{v}_n\big)^2\big\} && \text{(C.8)}\\
&= E\big\{2\big(v[n] - \mathbf{w}_n^T \mathbf{v}_n\big)\nabla(-\mathbf{v}_n^T \mathbf{w}_n)\big\} && \text{(C.9)}\\
&= E\big\{2\big(v[n] - \mathbf{w}_n^T \mathbf{v}_n\big)(-\mathbf{v}_n)\big\} && \text{(C.10)}\\
&= -2E\big\{e[n]\mathbf{v}_n\big\}. && \text{(C.11)}
\end{aligned}$$

Thus, the steepest descent algorithm becomes

$$\mathbf{w}_{n+1} = \mathbf{w}_n + \mu E\big\{e[n]\mathbf{v}_n\big\}, \tag{C.12}$$

where the scalar 2 is (C.11) is absorbed in μ without loss of generality.

In practical application, the value of $E\big\{e[n]\mathbf{v}_n\big\}$ is generally unknown. Therefore, it is typically replaced with an estimation $\hat{E}\{\cdot\}$ of the mean $E\{\cdot\}$, where

$$\hat{E}\big\{e[n]\mathbf{v}_n\big\} = \frac{1}{L}\sum_{l=0}^{L-1} e[n-l]\mathbf{v}_{n-l} \tag{C.13}$$

and L is the number of samples.

By replacing $E\big\{e[n]\mathbf{v}_n\big\}$ of (C.12) by the sample mean $\hat{E}\big\{e[n]\mathbf{v}_n\big\}$ given in (C.13), the steepest decent algorithm becomes

$$\mathbf{w}_{n+1} = \mathbf{w}_n + \frac{\mu}{L}\sum_{l=0}^{L-1} e[n-l]\mathbf{v}_{n-l}. \tag{C.14}$$

A special case of (C.14) is obtained when $L = 1$, and is known as Least Mean Square

(LMS) algorithm. The LMS algorithm simply has the following form:

$$\mathbf{w}_{n+1} = \mathbf{w}_n + \mu e[n]\mathbf{v}_n. \tag{C.15}$$

In the case LMS algorithm, the value of μ is to be carefully chosen [7, p. 512]. A commonly used variant of (C.15) is the normalized LMS algorithm which is given by

$$\mathbf{w}_{n+1} = \mathbf{w}_n + \beta \frac{e[n]}{\epsilon + \|\mathbf{v}_n\|^2}\, \mathbf{v}_n, \tag{C.16}$$

where, β is the normalized step size with $0 < \beta < 2$ and ϵ is a small positive number.