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Comparison between stimulated EMG and natural EMG

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ABSTRACT

Comparison between Stimulated EMG and Natural EMG

by
Zak Belfki

The electromyograph (EMG) signal generated from a cat's jaw muscle in movement, is analyzed. After a series of experiments at UMDNJ, three major categories of EMG were recorded: rest EMG, biting EMG and hissing EMG.

The biting files contained a series of EMG collected in successive episodes. Power spectrum and statistical analysis were applied to the episodes. Each episode had approximately 43,000 samples. Results showed that these episodes had a similar spectrum with statistically the same mean and variance.

The hissing files were produced by electrical stimulation of the hypothalamus and contained EMG embedded in a stimulus artifact. The problem was to filter the stimulus out of the signal that contained hissing EMG for analysis. Unfortunately, the spectrum of the stimulus is within the bandwidth of the hissing EMG. Therefore we could not apply classical digital filtering techniques, and we had rather use adaptive filtering techniques. A suitable algorithm is the LMS algorithm because it is powerful and has a wide range of use. Moreover it is easy to use, and if used properly, it can give good results.

A conclusion was drawn that the response due to hissing is statistically different from the one due to biting. On the other hand, the spectra of the biting episodes are similar to each other.

COMPARISON BETWEEN
STIMULATED EMG AND NATURAL EMG

by
Zak Belfki

A Thesis
Submitted to the Faculty of
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This thesis is dedicated to
my wife Kristallia and my expected baby

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CHAPTER 1

BACKGROUND AND PHYSIOLOGY

1.1 Introduction

The objective of this work is to apply digital signal processing techniques to electromyograph signals. The first type of signal is biting EMG which is generated by having a cat chew on a stick. Five episodes of biting are recorded. The second type of signal is hissing EMG which is generated by stimulating the hypothalamus of the same cat. The EMG is detected from the same masseter muscle as for biting EMG. The stimulus artifact will be canceled adaptively using an LMS algorithm to extract the hissing EMG signal. We will assume that the cat's body is linear. We will apply spectrum analysis to both types of signals to analyze their powers at different frequencies.

The five episodes of biting EMG will be compared to each other, as well as comparing their average to the hissing EMG. To do this comparison we will apply statistical analysis to both types of signals.

1.2 Physiology

It is important to discuss some of the physiology involved in this work. The discussion will be brief, and will go over the relevant parts of the nervous system and the skeletal muscle, but if the reader wishes to know more about this subject can consult a physiology book such as [1].

The hypothalamus - is a tiny region of the diencephalon of the brain. It lies below the thalamus. The hypothalamus is crucial to homeostatic regulation and is a principal site for regulating the behavior essential to the survival of the individual and the species. The major functions of the hypothalamus are:

1. Regulation of anterior pituitary gland
2. Regulation of water balance
3. Regulation of autonomic nervous system
4. Regulation of hormones
5. Regulation of eating and drinking behavior
6. Regulation of reproductive system
7. Reinforcement and regulation of circadian rhythms

The peripheral nervous system - is the liaison between the parts of the body and the central nervous system (cns). This liaison consists of nerve fibers. The peripheral nervous system is divided into :

- I. Afferent division
- II. Efferent division

The efferent division is divided into two parts:

1. Somatic nervous system
2. Autonomic nervous system

The autonomic nervous system is divided into two parts:

- a. Sympathetic division
- b. Parasympathetic division

Efferent neurons carry signals (EMG) from the CNS to

muscles or glands.

Afferent neurons bring information from receptors to the CNS.

The somatic nervous system is made of all the nerve fibers going from the CNS to skeletal muscle cells.

The autonomic nervous system enervates all tissue besides the skeletal muscle. Some parts of the body that the autonomic nervous system controls are: heart, lungs, glands, liver, pancreas, etc. One interesting function of the autonomic nervous system is that it controls the muscle that causes hair to stand during emotional behavior. It is known that it is the sympathetic division that contracts this type of muscle. The autonomic nervous system is divided into two parts : **the sympathetic division** and **the parasympathetic division**. These two divisions are more likely to act opposite to each other; for example, if the one dilates a muscle, the other constricts it.

The muscle - There are three types of muscle: Skeletal muscle, smooth muscle, cardiac muscle.

The skeletal muscle is attached to bone. Depending on the released hormone or chemical in its fibers, the muscle can either dilate or constrict, this results in moving the bone attached to it.

1.3 Experiment

The experiment was done at UMDNJ New Jersey Medical school using the facilities of the Department of Neurosciences. The experiment is a very invasive one, where the cat had

permanent electrodes implanted into its hypothalamus sites from which the hissing behaviors could be elicited by stimulation. These electrodes are monopolar electrodes, coated with an insulator except at the tip. The electrical stimulation consisting of biphasic rectangular pulses (0.1-0.6 mA, 62.5 Hz, 2 ms/cycle duration) was generated by two independent Grass S88 stimulators and fed through stimulus isolation units to the cat. Pairs of 40 KOhms resistors in series with the cat approximated constant current conditions. The peak to peak current was monitored by a Tektronix 502A oscilloscope.

Three bipolar silver-silver chloride electrodes were placed on the masseter jaw muscle for EMG recordings. One electrode was used as a reference and the other two for two channels of data [see *figure 1.1* for experiment settings]. These electrodes had a distance of 10 - 15 mm between them. Hypothalamic behavior affective defense sites were identified and EMG recordings were made of the masseter muscle under the following conditions:

- 1) At rest
- 2) During forceful masticatory like activity (biting on a stick)
- 3) During affective defense behavior elicited by electrical stimulation at hypothalamic behavioral sites.

The first type of EMG is recorded in rest files, the second type is recorded in biting files and the third type is

recorded in hissing files.

The signal was passed through a Grass P511 preamplifier, sampled at 10,000 samples/sec. The gain was controlled manually and varied from 2,000 to 200. The signal was then stored in Asyst 3.0 data acquisition files after A-D conversion with the Metrabyte DASH16.

The next chapter will discuss the data in more detail.

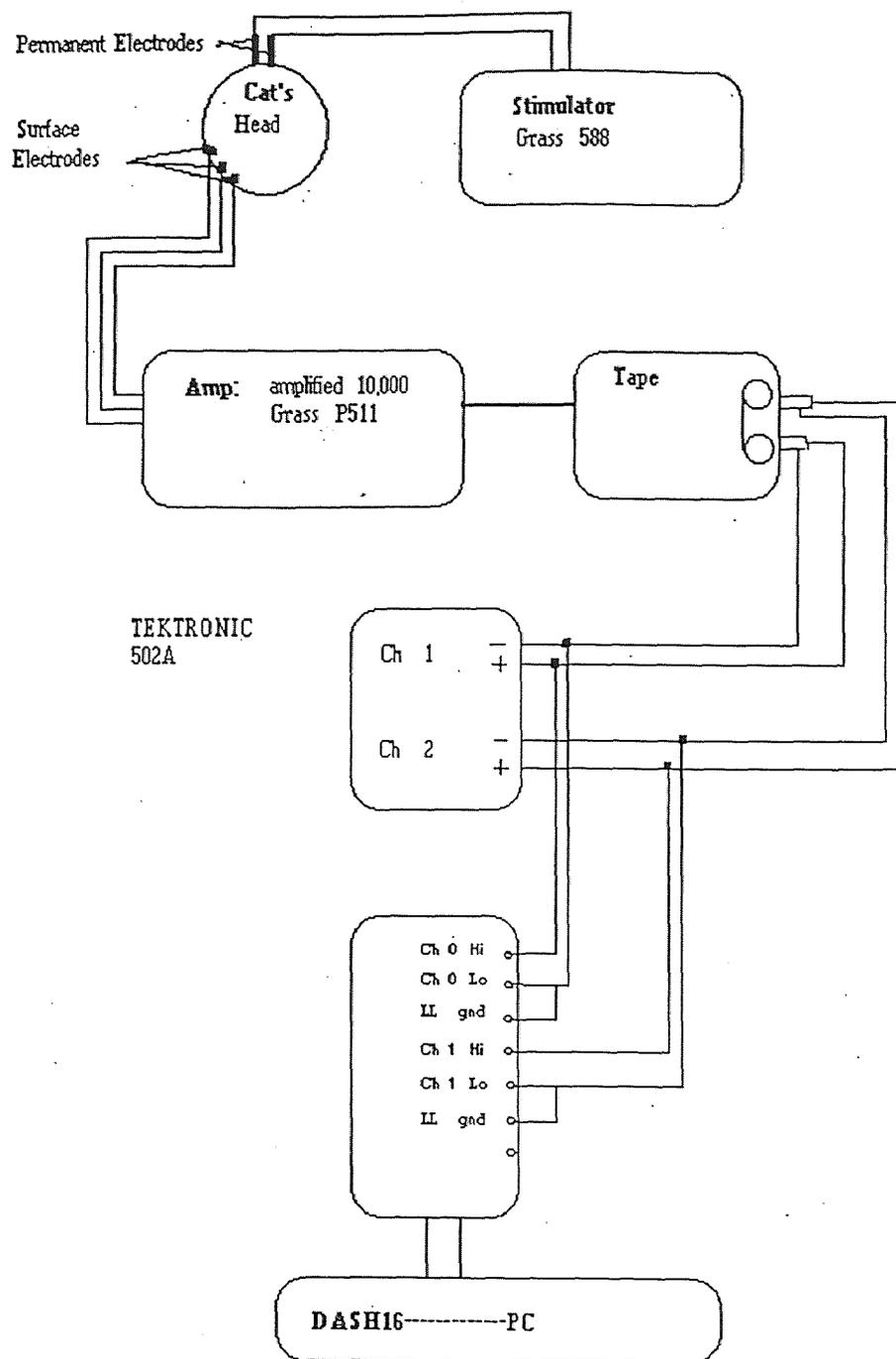


Figure 1.1. Experiment settings

CHAPTER 2

THEORY

2.1 Introduction

This chapter contains the theory applied to the EMG signal analysis. The outcome of the experiment is three categories of EMG:

1. EMG Rest
2. EMG Biting
3. EMG Hissing

The third category of EMG is called hissing EMG because the EMG produced by modulating the hypothalamus of the cat is provoking a low jaw muscle masticatory activity, whereas the biting EMG had more activity because the cat was actually biting on a stick. This was demonstrated by observing the signals on the Tektronix oscilloscope used in the experiment. This will be fully discussed in chapter 3.

The files that contained the hissing EMG were corrupted by the stimulus artifact used to modulate the hypothalamus. In other words, when the hypothalamus is stimulated, this stimulus goes through the entire body of the cat.

The system consisting of the stimulus, cat and EMG acquisition is modeled in a very simple way in *figure 2.1*

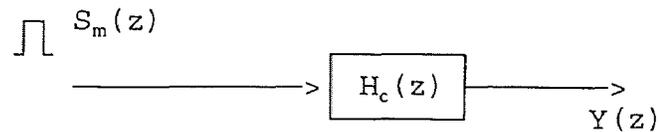


Figure 2.1. Simple model of the system

where $S_m(z)$ is the input stimulus signal in the z domain, $H_c(z)$ is the transfer function of the system, taken as the entire body of the cat, and $Y(z)$ is the output from the jaw muscles. The output $Y(z)$ is defined as:

$$Y(z) = H_c(z)S_m(z)$$

$$y(t) = h_c(t)*S_m(t)$$

The system is a time varying system, and the coefficients of the transfer function are functions that characterize the body of the cat.

One of the reasons that the stimulus is present with the hissing EMG is that the square wave used to stimulate the hypothalamus goes through the entire body of the cat and gets modified by it. Therefore, the hissing files contained EMG embedded in stimulus. In order to analyze this EMG we need to isolate it from the stimulus signal. One approach is to find a model that characterizes the cat body, and use it to model the stimulus. We will not follow this approach in this work.

Another way is to use classical digital filtering techniques to filter the stimulus artifact, i.e. a low-pass, high-pass or band-pass filter. This approach is not satisfactory, because the bandwidth of the stimulus is within the bandwidth of the EMG, so by using digital filtering techniques, a lot of information from the EMG signal would be lost and we would not be able to cancel the stimulus artifact completely. Examining all these options, we are left with adaptive filtering techniques. We need a filter that will adapt to each frequency of interest quickly.

A suitable algorithm is the LMS algorithm because it is powerful and has a wide range of use. Moreover, it is easy to use and usually gives good results. To understand how the LMS algorithm works and whether or not we can use it, we will first discuss the theory of adaptive filtering.

2.2 Concept of LMS Algorithm

The key difference between adaptive signal processing methods and the classical signal processing techniques is that we are now dealing with time-varying digital systems [2], [3]. Our general system is now as illustrated in *figure 2.2*.

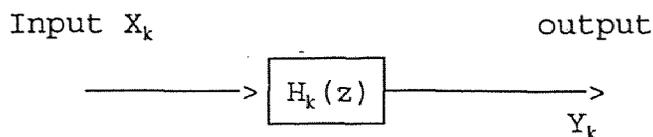


Figure 2.2. Block diagram of time-varying digital system

where $H_k(z)$ denotes a time-varying transfer function.

The system is assumed to be linear, and the characteristics of the transfer function $H_k(z)$ change, or adapt, according to signal conditions. An adaptive algorithm is the equation or set of equations used to adjust the coefficients of $H_k(z)$.

To better understand adaptive filtering, we will examine an example:

Suppose we have a broad-band signal corrupted by power line frequency interference. The classical approach would be to use a notch filter centered at 60 Hz, the nominal line frequency. Since the interfering frequency may in reality deviate from 60 Hz, this filter will attenuate the interference by different amounts as the frequency varies. A better solution in this case is to use an adaptive filter capable of tracking the line frequency and keeping the notch centered on the incoming interference.

2.3 Operation of the Least-Mean-Square Algorithm

The operation of the LEAST-MEAN-SQUARE (LMS) Algorithm is

descriptive of a feedback control system. Basically, it consists of a combination of two basic processes:

1. Adaptive process, which involves the automatic adjustment of a set of tap weights.
2. A filtering process, which involves:
 - a. forming the inner product of a set of tap inputs and the corresponding set of tap weights emerging from the adaptive process to produce an estimate of a desired response.
 - b. generating an estimation error by comparing this estimate with the actual value of the desired response. The estimation error is in turn used to actuate the adaptive process, thereby closing the feedback loop.

See *figure 2.3.1* and *figure 2.3.2*.

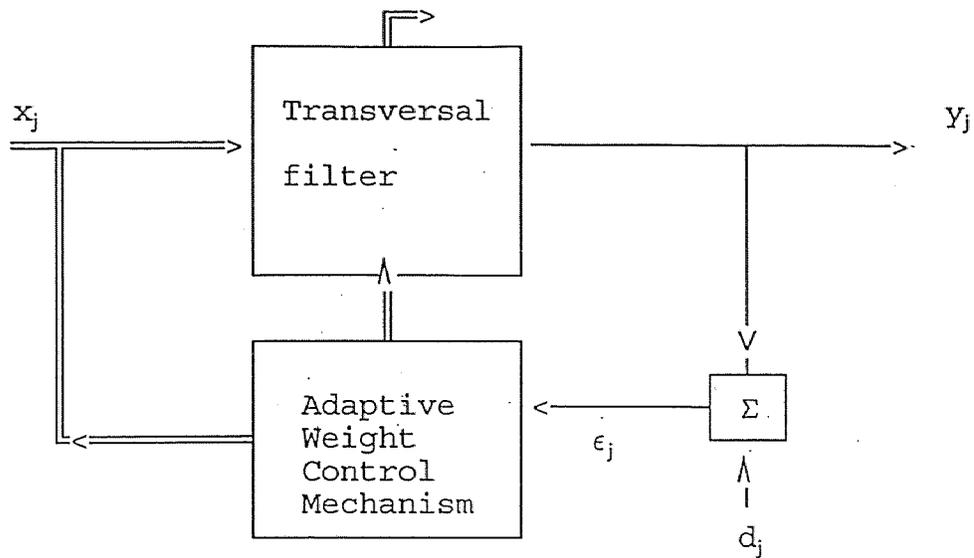


Figure 2.3.1. Adaptive process

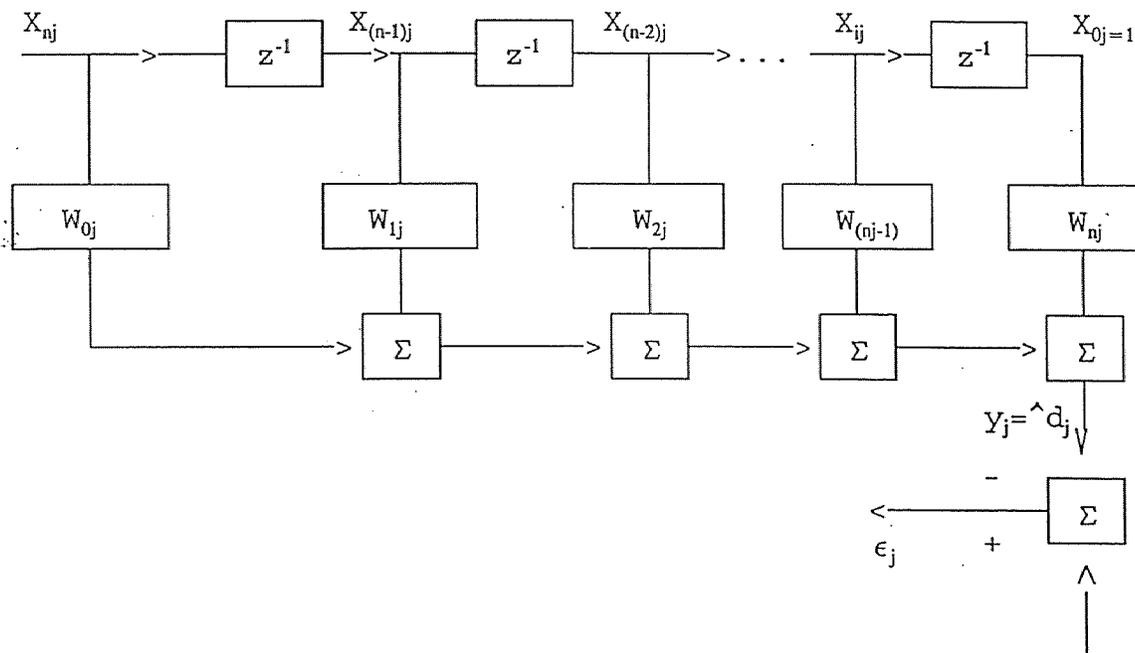


Figure 2.3.2. Transversal filter

The transversal filter is an FIR filter consisting of three basic elements: a unit-delay element, a multiplier, and an adder.

The number of delay elements used in the filter determines the duration of its impulse response.

$x_{nj}, x_{(n-1)j}, \dots, x_{0j}$ form the elements of the tap input vector X_j .

The tap weights $w_{0j}, w_{1j}, \dots, w_{nj}$ form the elements of the tap weight vector W_j .

The output y_j from *figure 2.3* is equal to the inner product of the two vectors X_j and W [2].

$$y_j = X_j^T W = W^T X_j \quad (2.1)$$

Note: equation (2.1) can be derived from the difference equation of the transversal filter.

Difference equation :

$$y_j = \sum_{j=0}^L w_j(n) x_{(n-j)} \quad (2.2)$$

Let \hat{d}_j be is an estimate of the desired response d_j , $y_j = \hat{d}_j$

The error ϵ_j is defined as the difference between the desired response and the estimate coming out of the filter:

$$\epsilon_j = d_j - \hat{d}_j = d_j - y_j = d_j - X_j^T W = d_j - W^T X_j \quad (2.3)$$

The signal x_j is input to the transversal filter and interacts with the weights w_j to cancel the correlated signal which is the stimulus present in the desired response d_j . Based on this configuration, the LMS output will be the error ϵ_j . In other words ϵ_j is the hissing EMG provided that the LMS algorithm converges.

The algorithm is developed by calculating ϵ_j^2 , taking its expected value and minimizing the result.

$$\epsilon_j = d_j - W^T X_j \quad (2.4)$$

Note that W and X_j are vectors whereas d_j and ϵ_j are scalars.

Squaring both sides of equation (2.4) :

$$\epsilon_j^2 = d_j^2 - 2d_j X_j^T W + W^T X_j X_j^T W \quad (2.5)$$

Taking the expected value of both sides of equation (2.5) [2]

$$J = E[\epsilon_j^2] = E[d_j^2] - 2E[d_j X_j^T W] + E[W^T X_j X_j^T W] \quad (2.6)$$

J is defined in equation (2.6) and called the cost function.

We assume that the filter input and the desired response are single realizations of jointly wide-sense stationary stochastic processes, both with zero mean.

We obtain:

$$J = \sigma_j^2 - 2E[d_j X_j^T]W + W^T E[X_j X_j^T]W \quad (2.7)$$

where $\sigma_j^2 = E[d_j^2]$

We define the vector P as the cross-correlation between the desired response d_j and the vector X_j :

$$p = E[d_j X_j] = E[d_j x_{0j}, d_j x_{1j}, \dots, d_j x_{nj}] \quad (2.8)$$

We also define the cross-correlation Matrix R as the expected value of the inner product of the input vector by its transpose.

$$R = \begin{bmatrix} r(0) & r(1) & \dots & r(n) \\ r^*(1) & r(0) & \dots & r(n-1) \\ \cdot & \cdot & \dots & \cdot \\ \cdot & \cdot & \dots & \cdot \\ \cdot & \cdot & \dots & \cdot \\ r^*(n) & r^*(n-1) & \dots & r(0) \end{bmatrix} \quad (2.9)$$

where r is the autocorrelation function defined as:

$$r[n, n-k] = E[x_{nj}x_{(n-k)j}] \quad k = 0, \pm 1, \pm 2, \dots \quad (2.10)$$

R is a symmetric positive n by n matrix.

Combining equations: (2.7), (2.8), and (2.9), we obtain:

$$J = \sigma_j^2 - 2PW + W^TRW$$

The cost function is a hyperparabolic surface shaped like a bowl. The function is never negative. (see figure 2.4)

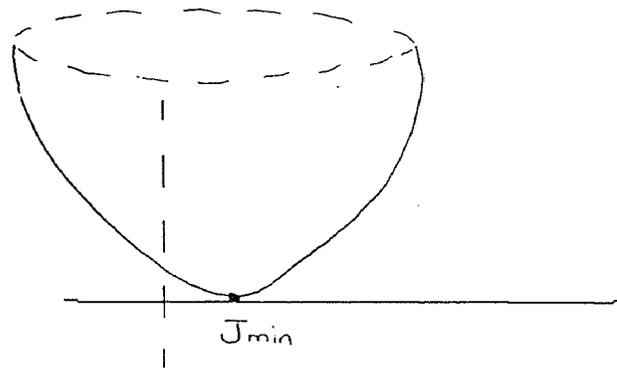


Figure 2.4 cost function J

To find the minimum of the function J we need to take the derivative, equate to zero and solve for the minimum value. Applying the gradient operator ∇ to the cost function J we obtain the gradient vector:

For the cost function J to attain its minimum value, all the elements of the gradient vector $\nabla(J)$ must be simultaneously equal to zero,

$$\nabla(J) = \begin{bmatrix} \partial J / \partial w_0 \\ \cdot \\ \cdot \\ \cdot \\ \partial J / \partial w_n \end{bmatrix}$$

$$\nabla(J) = 0$$

$$\nabla(J) = -2P + 2RW$$

$$\partial J / \partial W = \partial / \partial W (\sigma_d^2 - 2P^T W + W^T R W)$$

$$\partial J / \partial W = 0 - 2P^T + (\partial W^T / \partial W) R W + W^T R (\partial W / \partial W)$$

$$\nabla(J) = -2P + 2RW$$

$$\nabla(J) = 0 \Rightarrow -2P + 2RW = 0 \Rightarrow$$

$$\Rightarrow RW = P \quad (2.12)$$

$$\text{or } W^* = R^{-1}P$$

which is the Wiener-Hopf equation [2].

Although R is a $n \times n$ square matrix, it is very difficult to find its inverse, due to the lengthy input data vector x_j .

One way of solving this equation is to approximate R or R^{-1} .

The other way is to approximate the gradient ∇ . We will see that the LMS algorithm is based on this approximation.

The technique utilized by the LMS algorithm to update the coefficients is based on the METHOD OF THE STEEPEST DESCENT, described in vector notation as follows:

$$W_{j+1} = W_j - \mu \nabla_j$$

where $W_j = [w_0(j), w_1(j), \dots, w_n(j)]^T$ (2.13)

and μ is a parameter that controls the rate of convergence. From equation (2.13) we see that the coefficient updates are proportional to the negative gradient ($-\nabla_j$) of the performance surface.

When ∇_j is known at each step of the adaptive process, the adjustment always results in a better filter. In addition, once the MMSE solution is found, the gradient reaches zero, and the coefficients will be at their optimal value.

From equation (2.10) and equation (2.11), we have:

$$\nabla = \begin{bmatrix} \partial J / \partial w_0 \\ \cdot \\ \cdot \\ \cdot \\ \partial J / \partial w_n \end{bmatrix} = \begin{bmatrix} \partial E / \partial w_0 [\epsilon_j^2] \\ \cdot \\ \cdot \\ \cdot \\ \partial E / \partial w_n [\epsilon_j^2] \end{bmatrix}$$

$$\nabla = \partial E[\epsilon_j^2] / \partial \vec{w}_j \quad [2.14]$$

$$\begin{aligned}
\nabla(J) &= \begin{bmatrix} \partial J / \partial w_0 \\ \cdot \\ \cdot \\ \cdot \\ \partial J / \partial w_n \end{bmatrix} \\
&= \begin{bmatrix} \partial E[\epsilon_j^2] / \partial w_n \\ \cdot \\ \cdot \\ \cdot \\ \partial E[\epsilon_j^2] / \partial w_n \end{bmatrix} \\
&= \partial E[\epsilon_j^2] / \partial W
\end{aligned}$$

In order to estimate the gradient ∇ , we have to estimate the error $E[\epsilon_j^2]$ by omitting the expected value [2] [3]

$$\begin{aligned}
\hat{\nabla} &= \partial \epsilon_j^2 / \partial w_j \\
&= 2\epsilon_j \partial \epsilon_j / \partial w_j \\
&= 2\epsilon_j \partial (d_j - y_j) / \partial w_j \\
&= -2\epsilon_j X_j \quad (2.15)
\end{aligned}$$

$\hat{\nabla}$ is the estimate of ∇ , and $\epsilon_j = d_j - y_j$

Combining equations (2.15) and (2.13) we obtain:

$$W_{j+1} = W_j + 2\mu\epsilon_j X_j \quad (2.16)$$

Equation (2.16) is the LMS algorithm equation and μ is the parameter of stability and convergence. We have to choose μ , so that the following two forms of convergence are satisfied:

1. *Convergence in the mean*, which means that the expectation of tap-weight vector $w(n)$ approaches the (optimum) Wiener solution w_0 as the number of iterations n approaches infinity.

2. *Convergence in the mean square*, which means that the final (steady-state) value $J(\infty)$ of the mean-squared error is finite [2].

The recursive equation (2.16) tells us that given an input vector X_j , a desired response d_j and by selecting the right μ , we can implement the LMS algorithm assuming w_0 is initialized to zero. Therefore, the convergence parameter μ plays an important role in determining the performance of the adaptive system.

We recall that we are using the instantaneous error ϵ_k^2 in the gradient instead of the mean value $E[\epsilon_k^2]$. A single update of the weight vector W_j could contain a considerable error. Thus a large μ could result in a fast adaptive process (might never converge), and if μ is too small, the coefficient vector adaptation is very slow.

The algorithm can be used in a stationary or non-stationary environment.

It has been shown that the stable range of μ is :

$$0 < \mu < 1/\lambda_{\max} \quad (2.17)$$

where λ_{\max} is the largest eigenvalue of the correlation matrix R.

From equation (2.18):

$$\chi(R) = \frac{\lambda_{\max}}{\lambda_{\min}} \leq \frac{S_{\max}}{S_{\min}} \quad [2] \quad (2.18)$$

where $\chi(R)$ is the eigenvalue spread, and S_{\min} , S_{\max} are minimum and maximum power spectral density, respectively.

From equations (2.17) and (2.18), we can say that μ depends on the input signal power.

We will proceed with the normalized value of μ :

$$\mu_N = \mu / (L+1) \sigma^2, \quad (2.19)$$

where $L+1$ is the number of the filter lags, and σ^2 is the input signal power x_j .

If we substitute this normalized value into equation (2.16) we can show that: $0 < \mu < 1$.

The input signal power can be estimated by :

$$\hat{\sigma}^2_j = \alpha x_j^2 + (1-\alpha) \hat{\sigma}^2_{j-1} \quad (2.20)$$

where x_j is the current input sample, and α is a factor that determines the stationarity of the input signal and it is called the forgetting factor.

α is defined in the range: $0 < \alpha < 1$.

This estimate enables operation in nonstationary environment, since α can be selected to reduce the influence of past input samples. That is the reason for the name "forgetting factor".

As a general guideline, updating the input signal power via equation (2.20) amounts to forgetting the past value of x_j and using the new one.

Therefore, we implement the LMS algorithm as follows:

$$W_{j+1} = W_j + \frac{2\mu\epsilon_j x_j}{(L+1)\hat{\sigma}_j^2} \quad 0 < \mu \leq 1 \quad (2.21)$$

$$\hat{\sigma}_j^2 = \alpha x_j^2 + (1-\alpha)\hat{\sigma}_{j-1}^2 \quad 0 < \alpha < 1$$

The LMS program is written in Fortran77 (see Appendix).

CHAPTER 3
DATA MANAGEMENT

3.1 Data Collection

As it was mentioned in chapter 1, three types of data were collected:

- i Rest;
- ii Biting;
- iii Hissing;

We collected 8 files as follows:

Test1.prn;
Test2.prn;
Test3.prn;
Test4.prn;
Test5.prn;
Test6.prn;
Test7.prn;
Test8.prn;

Test1.prn, test2.prn, test8.prn contained biting with no stim, whereas test3.prn, test4.prn, test5.prn, test6.prn, test7.prn contained hissing EMG with stim. All files contained rest EMG in, either a pre-stim rest episode or post stim rest episode.

The biting files contained masticatory-like activity packaged in episodes. We will analyze these episodes of biting EMG to investigate the correlation between them, and we will apply spectrum analysis, and digital filtering techniques to further analyze these episodes. On the other hand we will apply adaptive filtering techniques to the hissing files.

3.2 Tabulation of Results

TABLE 3.1 Experiment layout

| FILE | | | |
|--------|------------|----------------------------|---------------------------|
| SIZE | TAPE INDEX | DATA RECORDED | NOTES |
| | FROM - TO | | |
| 20 sec | Test1.Dat | Biting - no stim | gain = 2,000 |
| 391 K | 0 - 51 | | filters: .1 Hz, 30 KHz |
| | | | 60 Hz filter in |
| 35 sec | Test2.Dat | Biting - no stim | Same as above |
| 684 K | 60 - 143 | 5 episodes with | |
| | | Rest in between | |
| 18 sec | Test3.Dat | Stim EMG response | gain = 2,000 |
| 352 K | 150 - 188 | Start 5 sec before stim | Same as above |
| | | Stim for 5 sec end | |
| | | 5 sec poststim | |
| 18 sec | Test4.Dat | 5 sec before stim | gain = 2,000 |
| 352 K | 195 - 236 | stim until hiss | |
| | | 5 sec poststim | |
| 23 sec | Test5.Dat | Same as above | gain = 1,000 |
| 450 K | 240 -293 | | |
| 21 sec | Test6.Dat | Same as above | gain = 500 |
| 411 K | 300 - 350 | | |
| 22 sec | Test7.Dat | Same as above | gain = 200 |
| 430 K | 360 - 414 | | |
| 40 sec | Test8.Dat | Biting - no | gain = 2,000 |
| 782 K | 420 - 514 | Stim, 5 episodes | |

The first column of the table is the size of the file in binary format (unpacked) and its duration in seconds.

The second column is the index of the tape where the data is stored.

The third column shows comments about the type of EMG stored. The fourth column shows the gain of the amplifier which varied from 2,000 to 200, it also shows that the data is band-pass filtered from .1 Hz to 30 kHz.

Since the files are very large (sampling frequency : 10,000 samples per second), a large memory and storage are needed.

3.3 Data Processing

The Metrabyte DASH16 comes with software called STREAMER.EXE, which allows you to collect data from an interfaced device, with up to 8 channels.

We sampled the data at a rate of 10,000 Hz because we want to obey the sampling theorem in which the sampling frequency must be at least twice as fast as the highest frequency in the signal.

After determining the size of the file, we use streamer to collect the data from the tape to the PC in MS-DOS environment. At this point the files (test1 through test8) are stored in BINARY format. Although some of the programs used in this work read files in BINARY, the files were converted to ASCII format in order to load them into MATLAB.

MATLAB is a very nice and powerful software package that will be used for the data analysis.

We used UNPACK.EXE to convert data from BINARY to ASCII format.

The command :

```
C:UNPACK TEST2.DAT,TEST2.PRN,0-50000/B/DAS16
```

converts the file test2.dat into 50,000 ASCII format samples and stores them in the file test2.prn.

Note that the extension .DAT will be used for BINARY files, whereas as the extension .PRN will be used for ASCII files.

The program UNPACK.EXE is unpacking file sizes up to 50,000 samples only. This limitation forces us to split the files into 50,000 samples each. One of the largest files (test8.prn) contains 800,000 samples.

CHAPTER 4

DATA ANALYSIS

4.1 Introduction

The main focus of the analysis is to compare biting EMG produced by making a cat bite on a stick to EMG produced by the cat's jaw muscle activity during emotional behavior responses elicited by electrical stimulation at hypothalamic sites.

To do this comparison, we need to analyze the biting EMG collected in test2.prn, and extract hissing EMG collected in test5.prn by using the LMS algorithm discussed theoretically in chapter 2. The hissing EMG is then analyzed and compared to the biting EMG using spectrum analysis.

This chapter will be divided in three parts:

1. Biting EMG Analysis
2. Hissing EMG Analysis
3. Comparison

4.2 Biting EMG

Biting EMG is collected in test2.prn as described in Chapter 3. The file contained about 350,208 samples (see table 3.3.2 in the appendix), but only 250,000 samples are of interest, the remaining samples containing rest EMG and noise. There are five episodes of biting EMG in these 250,000 samples.

Since the data is sampled at 10,000 samples per second,

the duration of the episodes are about 25 seconds total. The plots of the episodes are in *figures 4.1.1* and *4.1.2*.

From the plot of *test2.prn*, we can see the five episodes of biting EMG consisting of a series of bursts with rest EMG in between distorted with low frequency noise (probably due to motion artifact).

The first episode was collected with a delay (about 2.5 seconds). In other words, biting occurred 2.5 seconds before turning on the switch to collect the data. Therefore we will disregard episode one. The episodes have 2-3 seconds between them, and have a duration of approximately 4 seconds each. To compare the four episodes, we need to maintain the same number of samples in each episode, keeping in mind that we should not overlap any of them.

The power spectrum of biting contained high power components below 10 Hz and very low power components above 1000 Hz. For this reason, we determined that the data should be filtered by a Butterworth band-pass filter with a lower cutoff frequency of 10 Hz and an upper cutoff frequency of 1,000 Hz.

[see bandpass filter design in the appendix].

4.3 Biting EMG - Episodes Selection

As we said before, *test2.prn* is broken into six files of 50,000 samples each. These files are filtered one by one through the band-pass filter as if they were part of one long file and plotted using Matlab. (see *figure 4.2.1* to *4.2.6*).

From this filtered plot, we can estimate (in "number of samples" sense) the episodes without overlapping, and we can see that they have rest EMG between them of approximately 2 to 3 seconds. We can also see that they have seven major bursts of EMG with an approximate periodic occurrence with a period of $\approx .5$ sec. Note also that the last plot in *figure 4.2.6* (test25.prn) has more activity than the others.

From these investigations, we selected the episodes as follow:

$$E_2 = [\text{test21}(22\text{K}:50\text{K}); \text{test22}(2:15\text{K})]$$

$$E_3 = [\text{test22}(24\text{K}:50\text{K}); \text{test23}(2:17\text{K})]$$

$$E_4 = [\text{test23}(36\text{K}:50\text{K}); \text{test24}(2:29\text{K})]$$

$$E_5 = [\text{test24}(45\text{K}:50\text{K}); \text{test25}(2:38\text{K})]$$

where E_2, E_3, E_4, E_5 , represent the episodes respectively.

This notation is in n by 1 matrix form.

Since test2.prn is split into six files, the episodes contain samples from two consecutive files, for example, E_2 : episode 2 starts from sample number 22 of test21.prn (50,000 samples) ends at 50,000 and then starts again at sample number 2 of test22.prn (50,000 samples) and ends at sample 15,000. The other episodes are selected in the same way.

These episodes are plotted in *figure 4.3.1 to 4.3.4*) then filtered throughout the band-pass filter designed previously and plotted in *figure 4.4.1 to 4.4.4*)

4.4 Hissing EMG - ADAPTIVE FILTERING

In the previous chapter, we discussed the theory of adaptive filtering, and in particular, the LMS algorithm. We are going to apply this theory to our data: test5.prn to cancel the stim and analyze the hissing EMG.

We will use part of the file test5.prn as a reference signal (this part contains stim only) to cancel the stim present in the part that contains the hissing EMG.

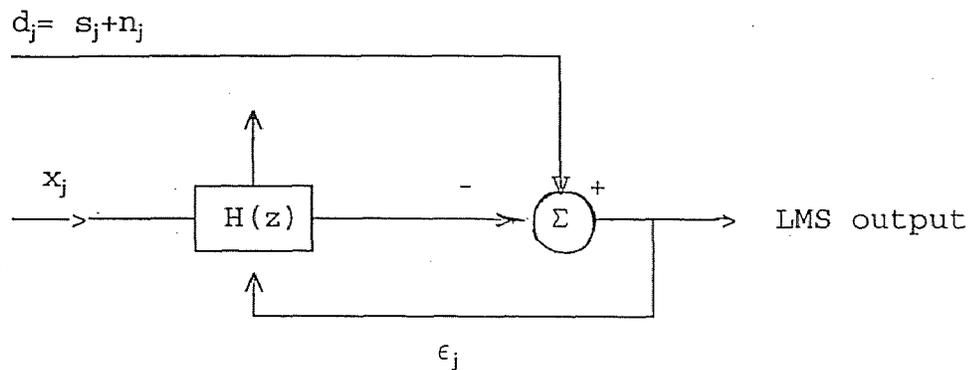


Figure 4.7.1 LMS algorithm structure

In figure 4.7.1, d_j is the desired response, (in our case, the part that contains stim and hissing EMG), $d_j = s_j + n_j$, s_j is the hissing EMG and, n_j is the stim signal $x_j = n_j$, is the input signal to the adaptive filter and it is the part that contains stim only. Since we are using x_j to cancel n_j , present in d_j , then the error ϵ_j is our output. The error signal ϵ_j is continuously fed back to the adaptive control to be updated, depending on the number of lags used. $\epsilon_j = d_j - x_j$.

We will assume that the signal $x_j = n_j$ is uncorrelated to the s_j .

We must split test5 into these configured signals. The desired response and the reference signal are plotted on *figure 4.7.2, and figure 4.7.3*

LMS algorithm [see program # 4]

The algorithm requires the use of the input signal (sm01.prn) power.

We will assume that this signal is wide-sense stationary and has zero mean and that the best estimate of its power is equal to $\hat{r}(0)$ without the expected value.

$$\hat{r}(0) = \sum_{i=0}^n x_i^2$$

where n is the length of sm01.prn which is 6050.

See program # 2 for computing input power.

The convergence of the LMS algorithm to the best estimate of ϵ_j depends on the choice of μ . The algorithm also depends on L , the number of lags and the parameter α . We will run the program for different values of these parameters.

The outputs of the LMS algorithms are called resp(i).prn with $i = 1, 2, 3, \dots$

From chapter 2, we know that $0 < \mu < 1$. α is a parameter called the forgetting factor. When $\alpha = 0$, it assumed that the signals are stationary, and since we want to be as close as possible to stationarity, the parameter α should be in the

range of .01.

We should note that if we had the exact stimulus present in the hissing EMG as a separate signal, the output of the LMS would be an ideal case.

The outputs respi.prn of the LMS algorithm are generated by varying the three parameters α , μ , and L (see *figure 4.7.4 through figure 4.7.7*). In *figure 4.7.4*, we can identify from the plot of the desired response that the hissing EMG has an amplitude between -.05 and .05. Therefore a good estimate of the hissing EMG should be in the same range. *Figure 4.7.3* tells us that the reference signal used to cancel the stim is made of spikes occurring in a periodic pattern and a periodic noise that looks like 60 Hz power line noise but is not because during the experiment a 60 Hz notch filter was used. Also, this periodic signal is present in all the test5.prn file, and since it is present in the reference and the desired response signals, the LMS algorithm will cancel it. We investigated the value of μ that will maintain stability and convergence. And the best value of μ is .15, we can see in *figure 4.7.7* for $\mu = .2$ the algorithm does not converge. We also note that by increasing L from 4 to 18 we obtain a better and sharper output as in *figure 4.7.5*. We used $r(0)$ as an estimate for the input signal power by assuming zero mean and stationarity. and when the samples are incremented during the iteration, this input signal power is updated to a better estimate using equation (2.20) from chapter 2.

$$\hat{\sigma}_j^2 = \alpha x_j^2 + (1-\alpha) \hat{\sigma}_{j-1}^2 \quad (2.20)$$

As a conclusion of this part of the analysis, we can say that resp40 in *figure 4.7.5* is a good estimate of the hissing EMG.

4.5 Spectrum Analysis

Examining the power spectral density of a signal has many powerful applications, such as the ability to define the frequency range with the highest power (or the area with the highest power). Another application is the median frequency shift. Work was done to show that this frequency shift particularly to the left was interpreted as a sign of fatigue. Nevertheless, it is not the purpose of our work to investigate the median frequency shift.

Another application is the ability to identify dominant peaks (frequencies) in random noise. This task involves some effort and sometimes it is not possible to be realized. One difficulty lies in the resolution of the spectrum. When the resolution is good, it is possible to detect peaks that are close to each other, but when the resolution is poor, two close peaks can appear as one. Therefore if we are trying to detect a signal embedded in random noise, we might miss some of its components or we might not be able to detect any of its components at all.

Using computers to calculate the power spectrum of a signal is actually estimating it because computers are digital and

work with discrete non-continuous signals only.

The estimation of power spectrums [8] is divided into two major parts:

- 1- The Classical Spectral Estimation
- 2- The Modern Spectral Estimation

1- The classical methods include Correlation methods PSD Estimation, and Periodogram PSD Estimations(Danill Periodogram, Bartlett Periodogram, Welch Periodogram). The use of classical methods require trade-offs in an effort to produce statistically reliable spectral estimators of highest possible resolution with a finite amount of data samples. Trade-offs among data windowing, lag windowing, time domain averaging, and frequency-domain averaging are required to balance the need to reduce sidlobes, and to insure appropriate spectral resolution.

2-Modern spectrum estimators which estimate AR parameters only from available sample data, do not require windowing. Therefore we will not have the problems introduced by controlling a window with the data samples, but there is another trade-off paid for a higher resolution [8]. We will not investigate these methods any further because in our work we used the classical method, using the Fast Fourier Transform (FFT) to calculate the power spectrum.

4.5.1 Power Spectrum of biting EMG

We will take an FFT (Fast Fourier Transform) of the episodes and calculate their power spectrum using:

$$Y_2(k) = \sum_{n=0}^{N-1} y_2(n) e^{-2\pi kn/N}$$

$$PY_2 = Y_2 \cdot Y_2^*$$

where Y_2 is an FFT of an episode y_2

and, Py_2 is the power Spectrum of y_2 .

[See program # 2 in the appendix for FFT and power spectrum calculation]

We should note that the power spectrum is a function of the amplitude squared versus frequency whereas the FFT is a function of amplitude versus frequency.

The episodes have 43,000 samples each. The next higher power of two is $2^{16} = 65536$. Therefore each sequence [episode] will be padded with 22536 zeroes.

The power spectrum plots of the four episodes E_2 , E_3 , E_4 , E_5 , are in *figure 4.5.1 to figure 4.5.4*.

Note that all data is filtered at 60 Hertz component, which is due to the 60 Hz notch filter used during the experiment. We can note also, that there is no DC component and nothing below 10 Hz due to the band-pass filter used to filter the data from 10 Hz to 1,000 Hz.

4.5.2 Power Spectrum of hissing EMG

Using program # 1, we can estimate the power spectrum of

sm01, reference signal, sr01: desired response and resp40: hissing EMG, see *figure 4.7.10*.

The power spectrum of the reference signal and the desired response signal (see *figure 4.7.8 and 4.7.9*) are very close to equal to each other, therefore, we can say that all the frequencies that we see are mainly due to stim. The power spectrum of hissing EMG(resp40) does not have those frequencies, this is another supporting factor that resp40 is a good estimate of the power spectrum of the hissing EMG. By the same token the power spectrum of resp40 is clearly different from the power spectrum of the episodes. [compare *figure 4.7.10* to any of *figures 4.5*].

These conclusions are based on visual examination of the spectral plots and on the physiological characterization as discussed in chapter 1. In order to further investigate this conclusion, statistical analysis was performed and will be described in the next section.

4.6 STATISTICAL ANALYSIS

In this section, we will apply statistical tests to the four episodes of biting EMG and hissing EMG power spectra. The tests will tell us whether or not they have same mean and variance.

To avoid dealing with large numbers in applying statistical analysis to episode spectra, we will normalize each power spectrum by dividing it by its maximum squared amplitude. We will consider hissing EMG as episode number 1,

with P_{y1} as its power spectrum. Although this episode does not have the same number of samples as the biting episodes its power spectrum has the same number of FFT points because, recall that we padded the hissing episode with zeros to maintain the same length of FFT for all the episodes.

Notation:

P_{y1} : is the power spectrum of hissing EMG, and will be considered as episode 1.

P_{y2} : is the power spectrum of episode 2 - biting EMG.

P_{y3} : is the power spectrum of episode 3 - biting EMG.

P_{y4} : is the power spectrum of episode 4 - biting EMG.

P_{y5} : is the power spectrum of episode 5 - biting EMG.

As noted earlier Episode 5 has more activity; this is shown also in its power spectrum with a higher power.

Next we will evaluate the episodes variances and standard deviations.

Notation:

$P_{Y_{2n}}$: normalized power spectrum of P_{y2} (2nd episode).

$$P_{Y_{1n}} = [P_{Y_1}] / m_1$$

$$P_{Y_{2n}} = [P_{Y_2}] / m_2;$$

$$P_{Y_{3n}} = [P_{Y_3}] / m_3;$$

$$P_{Y_{4n}} = [P_{Y_4}] / m_4;$$

$$P_{Y_{5n}} = [P_{Y_5}] / m_5;$$

The following table summarizes variances, standard deviations and means of each power spectrum using the following formulas [4]:

The mean μ and variance σ of a discrete RV is defined by:

$$\mu = E[X] = \frac{\sum_i x_i}{N}$$

$$\sigma^2 = E[(X-\mu)^2] = \sum_i \frac{(x_i - \mu)^2}{N-1}$$

σ is the standard deviation defined by:

$$\sigma = \sqrt{\sigma^2}$$

See program # 2 in the Appendix for calculating these parameters]

TABLE 4.1 Statistical calculations

| Normalized Power Spectrum | Parameters | | |
|---------------------------|------------|---------------|----------|
| | Mean | Std Deviation | Variance |
| Py _{2n} | .0061 | .0353 | .0012 |
| Py _{3n} | .0060 | .0331 | .0011 |
| Py _{4n} | .0067 | .0374 | .0014 |
| Py _{5n} | .0061 | .0325 | .0011 |
| Average | .0062 | .0395 | .0012 |
| Py _{1n} | .0031 | .00231 | .000563 |

As we can see from table 4.1, the means and variances of the four biting EMG spectra are very close to each other, but this is not a sufficient condition to imply that all spectra are the same. We still have to apply statistical tests before we can draw any conclusion. We also note that the mean and variance of episode 1 which is hissing EMG spectra is far off from the others.

We will define three types of distributions that will be used in our statistical analysis, these distributions are: the Chi-Square Distribution, the "Student's" t-distribution and the F-distribution [5] [6].

a) Chi-square distribution

Suppose y_1, y_2, \dots, y_v are independent random variables each distributed normally with 0 mean and variance 1. Let χ^2 (chi-square) be the sum of their squares.

The random variable:

$$\chi^2 = y_1^2 + y_2^2 + \dots + y_v^2$$

has probability density function:

$$f[\chi^2] = \frac{1}{2^{v/2} \Gamma(\frac{v}{2})} e^{-\chi^2/2} (\chi^2)^{\frac{v}{2}-1} \quad \text{for } 0 \leq \chi^2$$

v is called degree of freedom

$v = \text{number of experiment} - 1.$

b) The "student's" t-distribution

If Z has a normal distribution with 0 mean and variance 1, and V is distributed as χ^2 with ν degrees of freedom and Z and V are independent, then the random variable

$$t = \frac{Z}{\sqrt{V/\nu}}$$

has the probability density function

$$f(t) = \frac{1}{\sqrt{\nu\pi}} \frac{\Gamma(\frac{\nu+1}{2})}{\Gamma(\frac{\nu}{2})} \left(1 + \frac{t^2}{\nu}\right)^{-(\nu+1)/2} \quad \text{for } -\infty < t < \infty$$

c) F-distribution.

The F-distribution is the distribution of the random variable F which is defined as:

$$F = \frac{\frac{U}{v_1}}{\frac{V}{v_2}}$$

where U and V are independent variables distributed as χ^2 with ν_1 and ν_2 degrees of freedom, respectively. The probability density function of F is given by:

$$f(F) = \frac{\Gamma\left(\frac{\nu_1 + \nu_2}{2}\right)}{\Gamma\left(\frac{\nu_1}{2}\right)\Gamma\left(\frac{\nu_2}{2}\right)} \left(\frac{\nu_1}{\nu_2}\right)^{\frac{\nu_1}{2}} \frac{F^{\frac{\nu_1-2}{2}}}{\left(1 + \frac{\nu_1}{\nu_2}F\right)^{(\nu_1 + \nu_2)/2}}$$

These distributions are utilized by their values provided in tables in the Appendix of reference [6].

4.6.1 Comparison of means

For comparing the means of the episode spectra, we will use the "student's" t-test [6].

First we will compare the biting EMG spectra: Py_2 , Py_3 , Py_4 , Py_5 . Their four means are:

$$\bar{X}_2 = .0061$$

$$\bar{X}_3 = .0060$$

$$\bar{X}_4 = .0067$$

$$\bar{X}_5 = .0061$$

$$\bar{X}_{avg} = .0062$$

Since $\bar{X}_2 = \bar{X}_5$, we need to compare only three means:

$$\bar{X}_2 = .0061, \bar{X}_3 = .0060, \bar{X}_4 = .0067$$

First we compare

$$\bar{X}_2 \text{ to } \bar{X}_{avg}$$

The t-distribution has a bell shape curve almost like a normal distribution, see figure 4.6.1, 4.6.2.

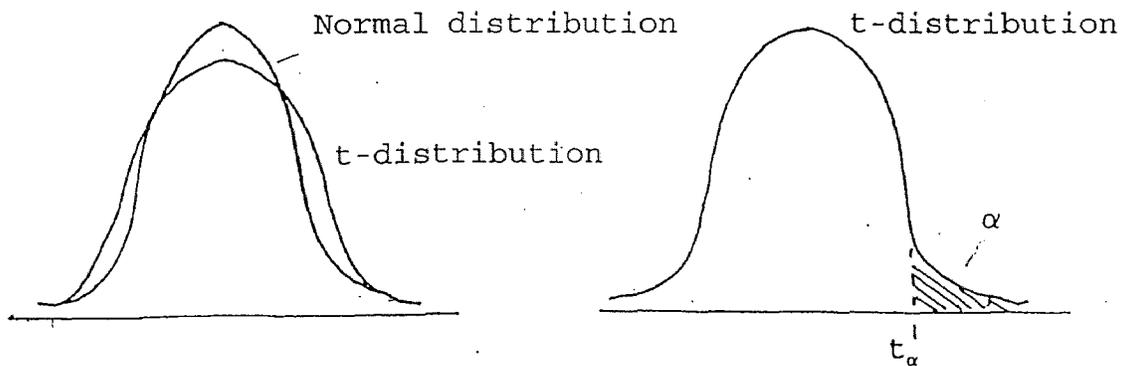


Figure 4.6.1. Normal, and Figure 4.6.2. t-distribution
t-distribution

Using the average of the mean:

$$\bar{X}_{avg} = .0062$$

we will test for null Hypothesis:

$$\bar{X}_2 = \bar{X}_{avg}$$

$$\bar{X}_3 = \bar{X}_{avg}$$

$$\bar{X}_4 = \bar{X}_{avg}$$

The test simply tells you to use this equation

$$t = \frac{\bar{X} - \mu}{\frac{S}{\sqrt{N}}}$$

to calculate the value of t, and compare this value with the one from the table in appendix of reference [6]. If the value of t computed is less than the one from the table, then it is possible to conclude that the means are equal.

μ is the average of the mean:

$$\bar{X}_{avg} = .0062$$

\bar{s} : sample variance, we will use the average of that variance from table 4.1 : $\bar{s} = .0012$.

N is number of FFT point: 65536 which is the length of the episode spectra.

The degree of freedom is $N-1 = 65535$.

$$\text{For } \bar{X}_2 = .0061, \quad t_2 = \frac{.0061 - .0062}{.0012\sqrt{65536}} = -.000325$$

t_2 : distribution for X_2 is symmetric: we can use the positive value of $t_2 = .000325$.

From the table since N is a very large number, we can use the value of infinity : $t_{.005} = 2.576$

$t_{.005}$: the probability that t_2 will exceed $t_{.005}$ is .005, or .5 percent of the area under F distribution lies to the right of $t_{.005}$.

It is clear that $t_2 < t_{.005}$

The same procedure will follow for x_3, x_4

$$\text{For } \bar{X}_3 = .006, \quad t_3 = \frac{.006 - .0062}{.0012\sqrt{65536}} = .000651$$

therefore, $t_3 < t_{.005} = 2.576$

$$\text{For } \bar{X}_4 = .0067, \quad t_4 = \frac{.0064 - .0062}{.0012\sqrt{65536}} = .000651$$

therefore, $t_4 < t_{.005}$

Since all t_2, t_3, t_4 are less than $t_{.005}$ we can conclude by the t-test that all the means can be equal to their average:

$$\bar{X}_{avg} = .0062$$

Next we need to compare the mean of episode 1 spectra with the average mean of the other four.

From the table : $t_{.005} = 2.576$ with a degree of freedom equal to infinity.

Hypothesis :

$$\bar{X}_1 = \bar{X}_{avg}$$

Where $\bar{X}_1 = .0031$; $\bar{X}_{avg} = .0062$

$$t_1 = \frac{.0062 - .0031}{\sqrt{\frac{(.0012)^2}{65536} + \frac{(.00053)^2}{65536}}}$$

$$t_1 = 604.9$$

$$\therefore t_1 > t_{.005}$$

Therefore we reject the hypothesis:

$$\bar{X}_1 \neq \bar{X}_{avg}$$

We can not conclude that the mean of the hissing EMG is the same as the mean of biting EMG.

4.6.2 Comparison of Variances

We first compare the variances of the four episodes of biting EMG. These variances with their average are:

$$\bar{S}_1^2 = .0012$$

$$\bar{S}_2^2 = .0011$$

$$\bar{S}_3^2 = .0014$$

$$\bar{S}_4^2 = .0011$$

$$\bar{S}_{avg}^2 = .0012$$

We will use the F-distribution test [6]

we will compare \bar{s}_2^2 and, \bar{s}_3^2 , the ones which are the furthest apart.

Comparing the others will follow the same procedure.

We will assume that \bar{s}_2^2/\bar{s}_3^2 have an F-distribution.

from table 6 [6].

Degree of freedoms associated with $\bar{s}_2^2 : \nu_2 \rightarrow \infty$

$\bar{s}_3^2 : \nu_3 \rightarrow \infty$

$$F_{.1} = 2(1.00) = 2$$

$$\frac{\bar{s}_3^2}{\bar{s}_2^2} = \frac{.0014}{.0011} = 1.27$$

$$\frac{\bar{s}_3^2}{\bar{s}_2^2} < F_{.1} \quad F_{.1} = 2(F_{.05})$$

The probability that F will exceed $F_{.05}$ is .05, or 5 percent of the area under F distribution lies to the right of $F_{.05}$.

Since $F < F_{.1}$, we cannot reject the null Hypothesis:

$$H_0 = \overline{S_2^2} = \overline{S_3^2}.$$

Therefore we can conclude that it is possible that

$$\overline{S_2} = \overline{S_3}.$$

Next we will compare the variances of the biting EMG spectra to the variance of hissing EMG spectra.

Hypothesis :

$$\overline{S_1} = \overline{S_{avg}}$$

Where $\overline{S_1}$, is the variance of episode 1, $\overline{S_{avg}}$ is the average of the variances of episode 2 through 5.

From table $F_{,1} = 2;$

$$F = \frac{\overline{S_{avg}}}{\overline{S_1}}$$

$$F = \frac{.0012}{.000563}$$

$$F = 2.13$$

$$\therefore F > F_{,1}$$

Since the test failed, we can't conclude anything. It means that this particular test cannot tell that the variances are the same.

Statistical analysis tells us that it is possible for the four episodes to have the same mean and same variance. On the other hand from a physiological point of view, the biting episodes are generated by the same mechanism. In other words, the cat is given a stick to bite on it without stimulating the hypothalamus. Therefore, we can conclude by stating the four episodes of biting EMG have the same power spectrum, with the same mean and same variance.

We also compared the mean and variance of the hissing EMG spectra to the biting EMG spectra and the results of the tests did not allow us to conclude that they are the same. Hissing EMG is generated by stimulating the hypothalamus of the cat, whereas the biting EMG is generated by voluntary masticatory activity. This physiological characterization allows us to conclude that their power spectrum is different. For concluding this chapter, we state that the episodes of biting EMG have the same power spectrum with the same mean and same variance, and their power spectrum is different from the power spectrum of the hissing EMG.

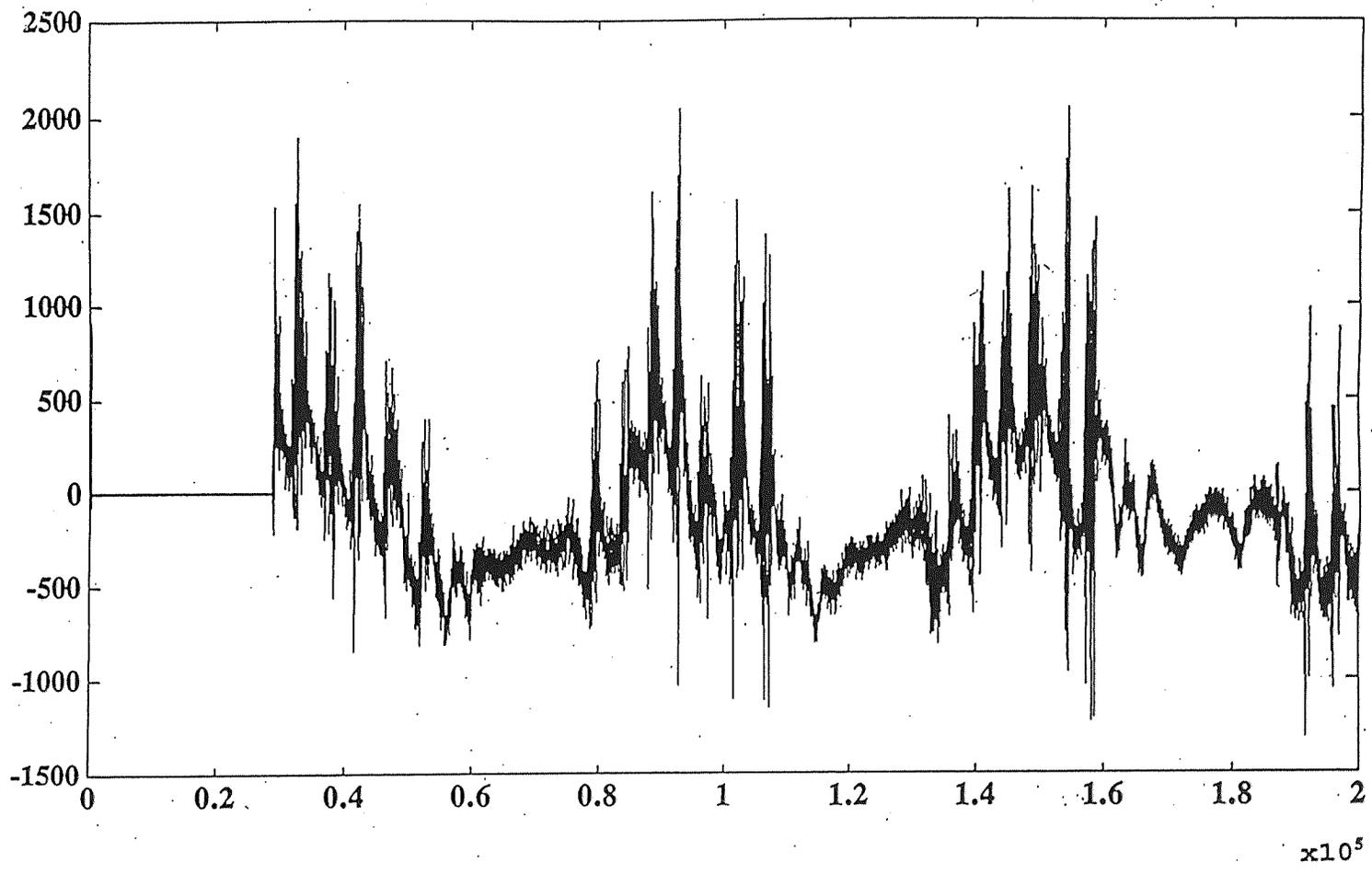


Figure 4.1.1. Plot of biting EMG file

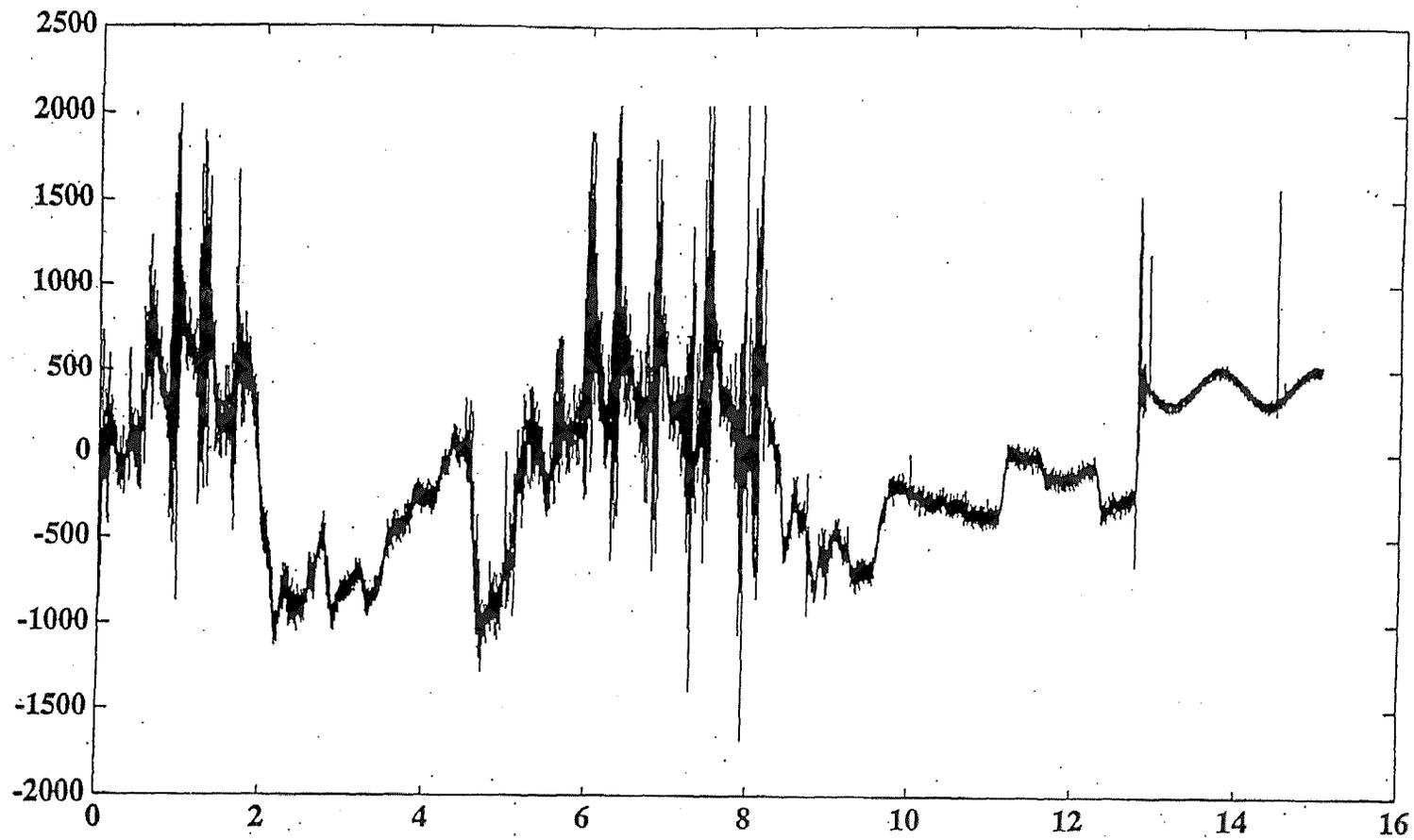


Figure 4.1.2. Plot of biting EMG file (continued)

$\times 10^4$

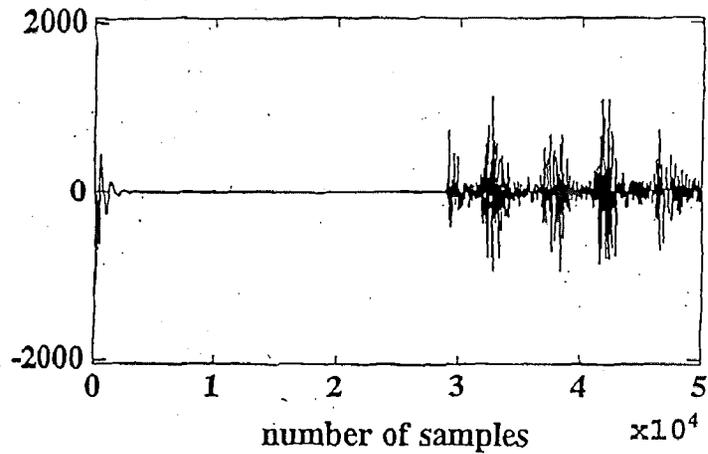


Figure 4.2.1. Biting EMG, band-pass filtered; 10-1K Hz. First 50 K samples

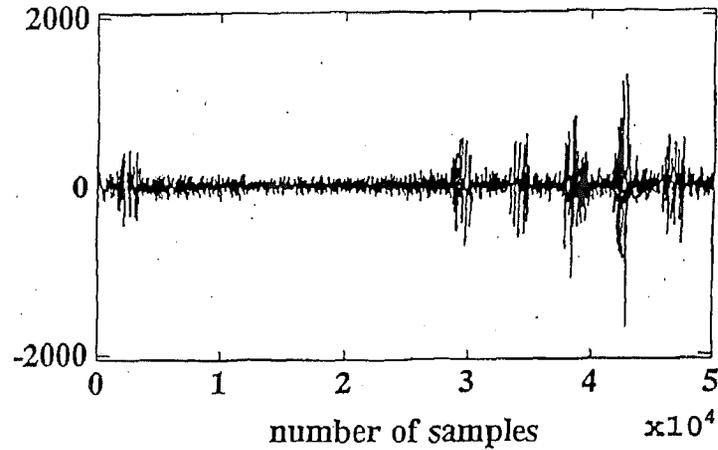


Figure 4.2.2. Second 50 K samples

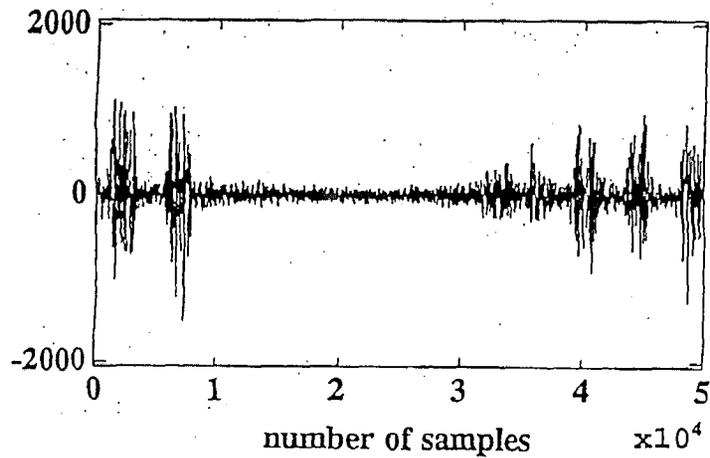


Figure 4.2.3. Third 50 K samples

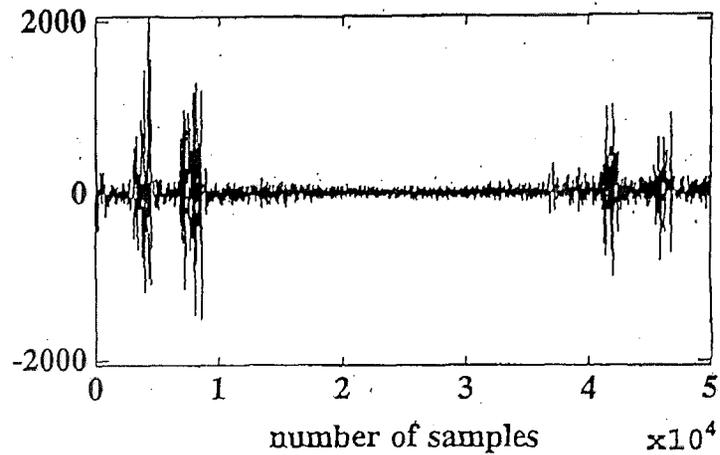


Figure 4.2.4. Fourth 50 K samples

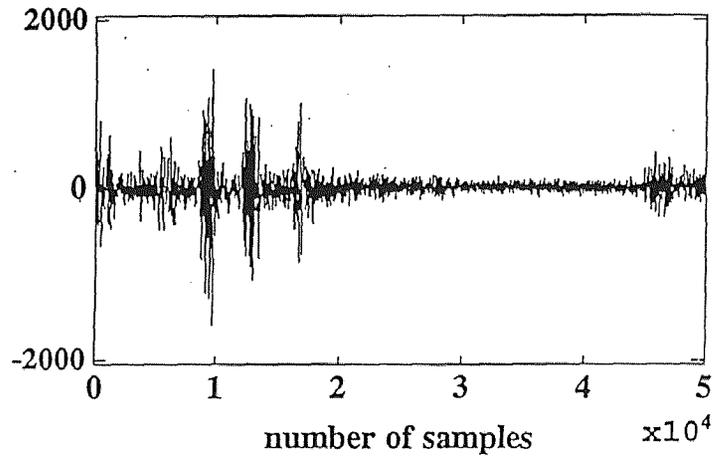


Figure 4.2.5. Fifth 50 K samples

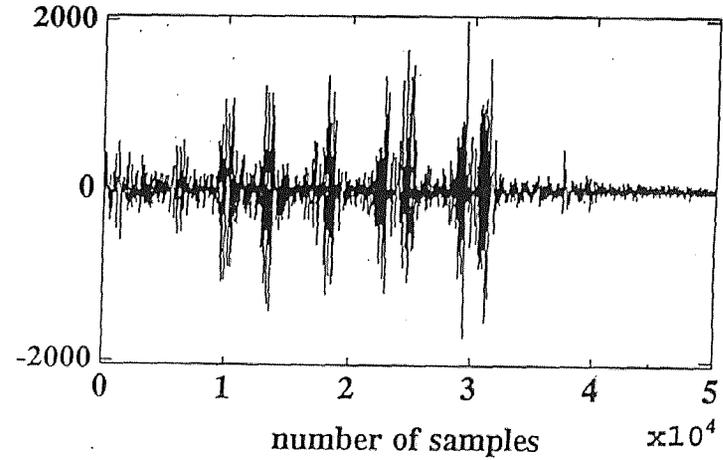


Figure 4.2.6. Sixth 50 K samples

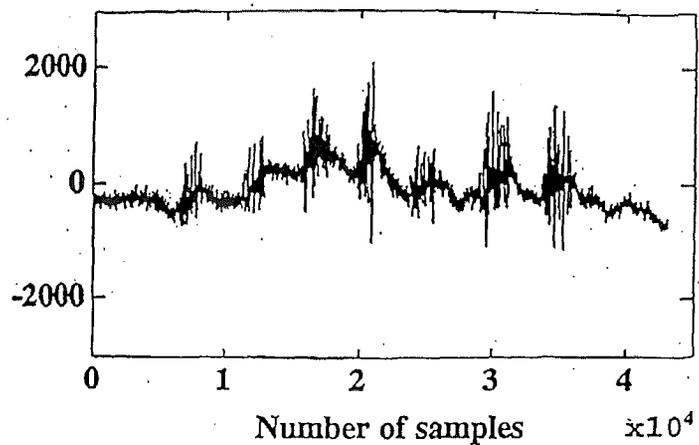


Figure 4.3.1. Biting EMG, Episode 2

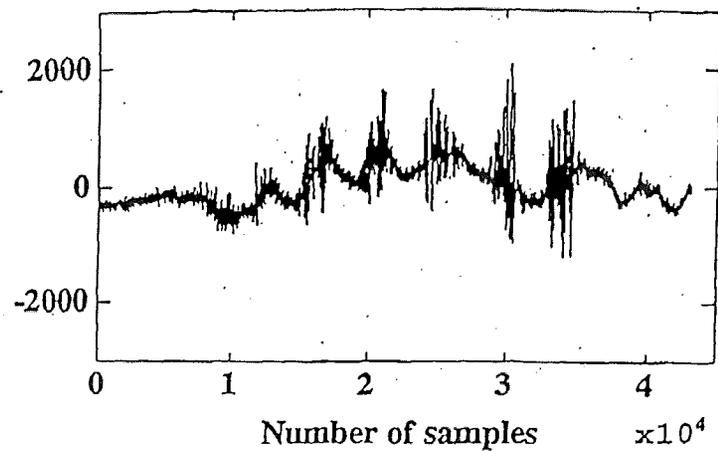


Figure 4.3.2. Biting EMG, Episode 3

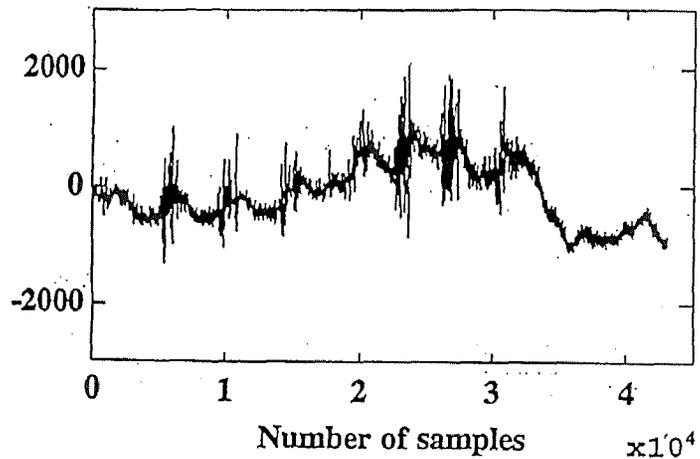


Figure 4.3.3. Biting EMG, Episode 4

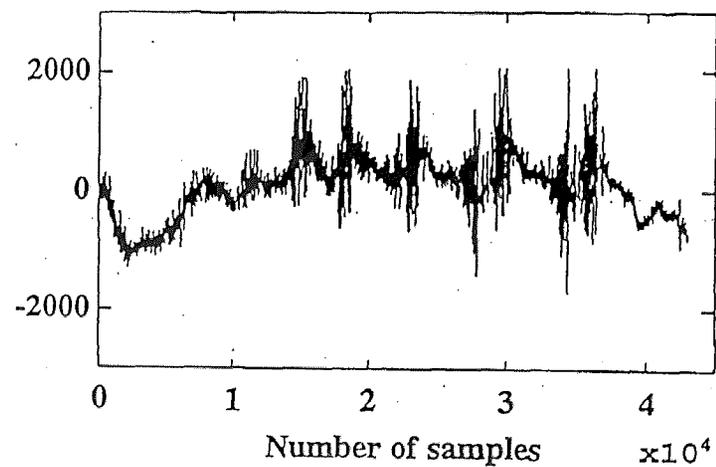


Figure 4.3.4. Biting EMG, Episode 5

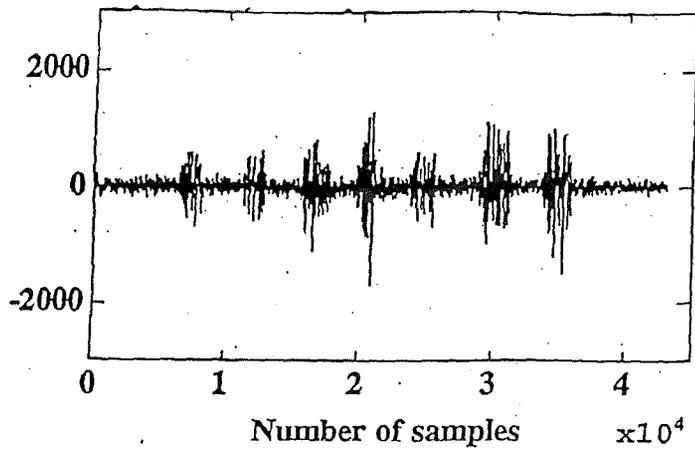


Figure 4.4.1. Episode 2, band-pass filtered; 10-1,000 Hz.

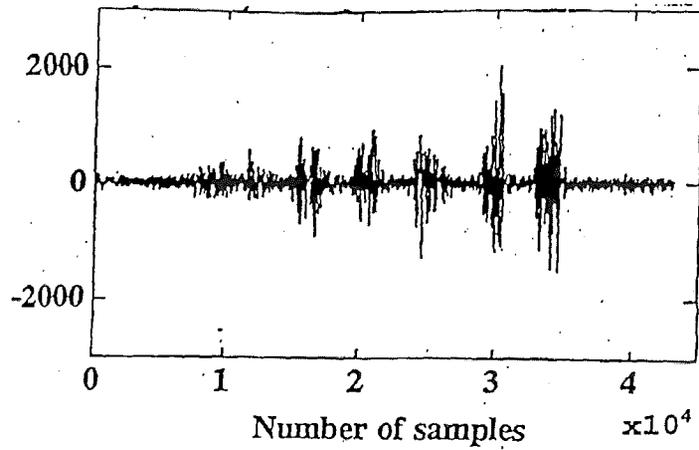


Figure 4.4.2. Episode 3, band-pass filtered; 10-1,000 Hz.

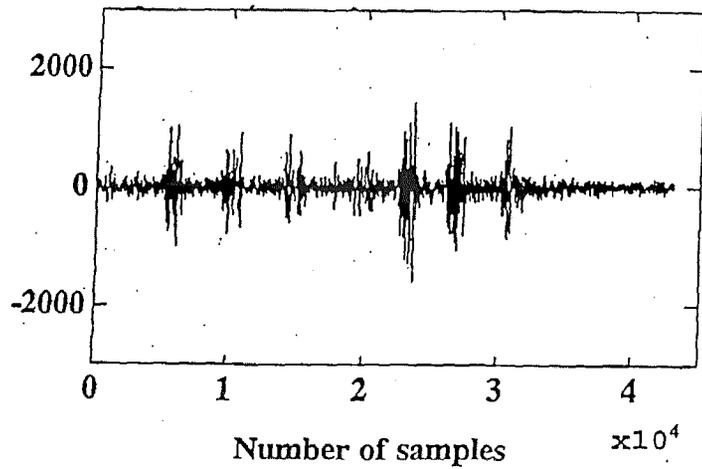


Figure 4.4.3. Episode 4, band-pass filtered; 10-1,000 Hz.

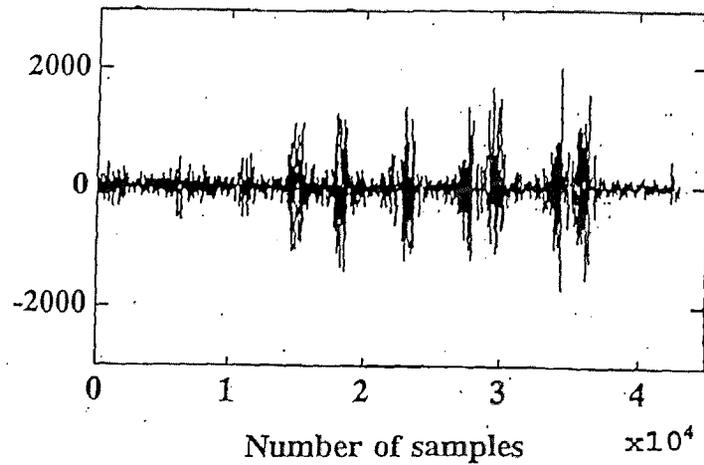


Figure 4.4.4. Episode 5, band-pass filtered; 10-1,000 Hz.

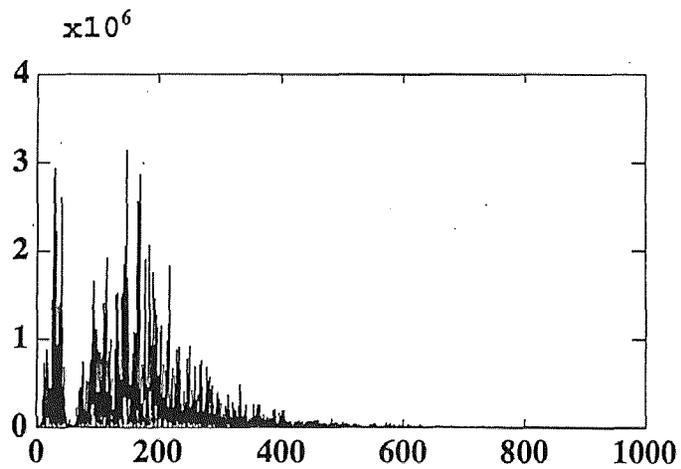


Figure 4.5.1. Spectrum of biting EMG; Episode 2

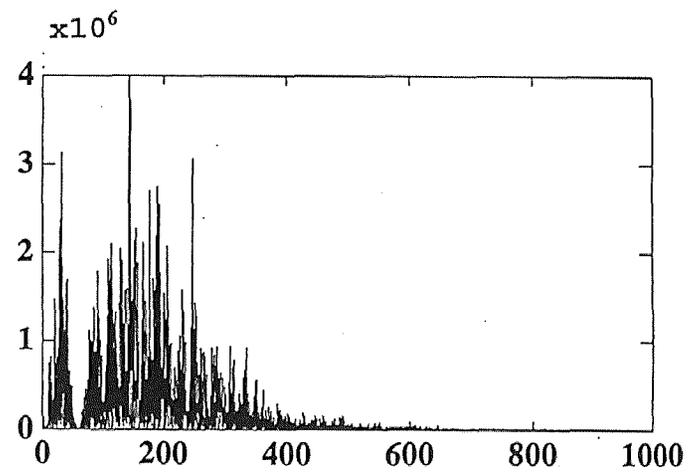


Figure 4.5.2. Spectrum of biting EMG; Episode 3

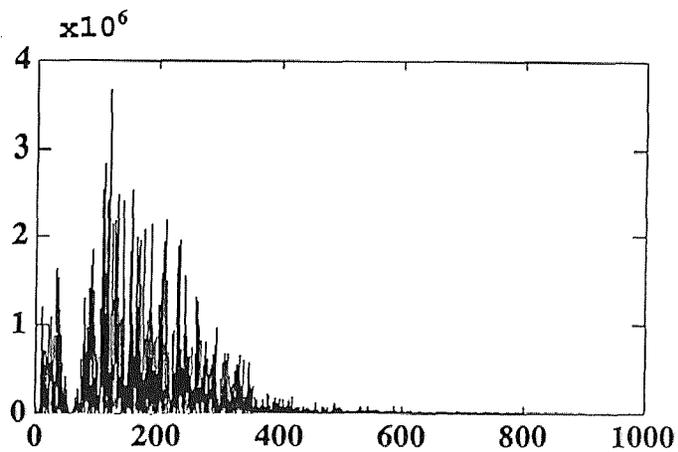


Figure 4.5.3. Spectrum of biting EMG; Episode 4

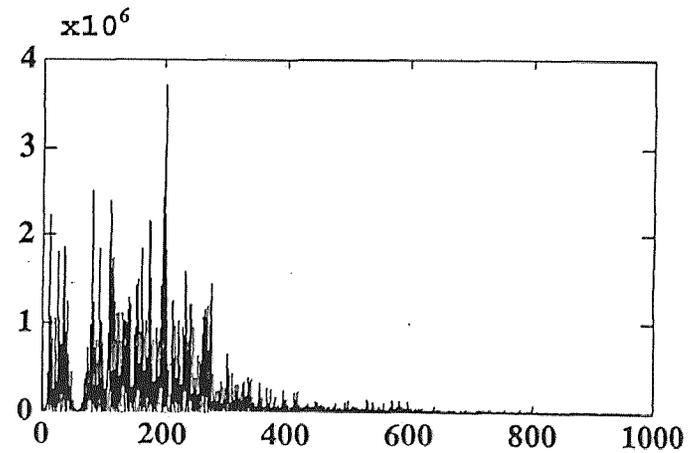


Figure 4.5.4. Spectrum of biting EMG; Episode 5

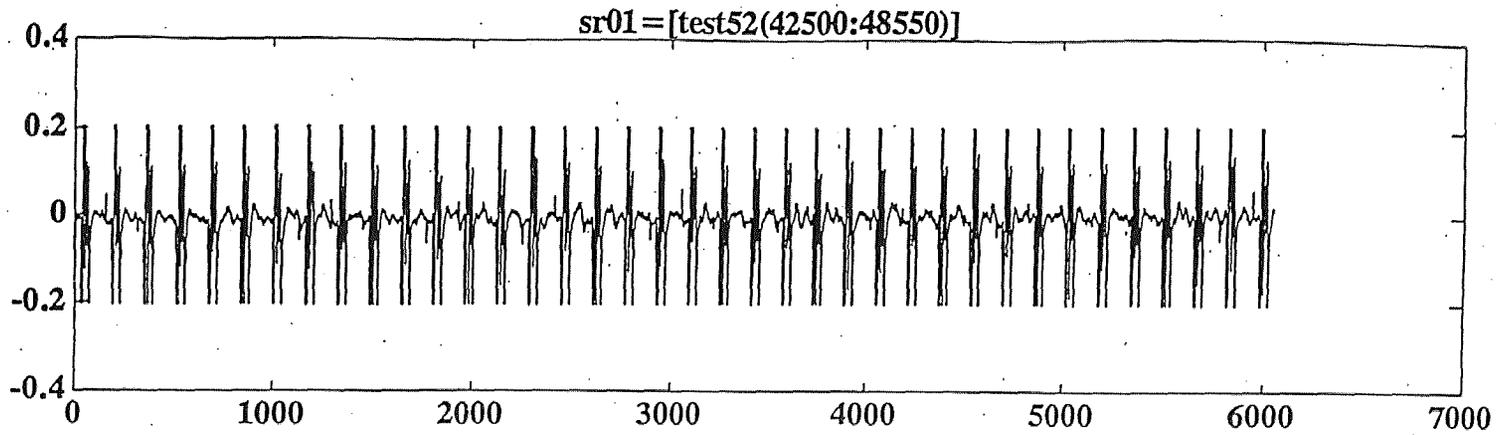


Figure 4.7.2. Plot of the desired response d_j

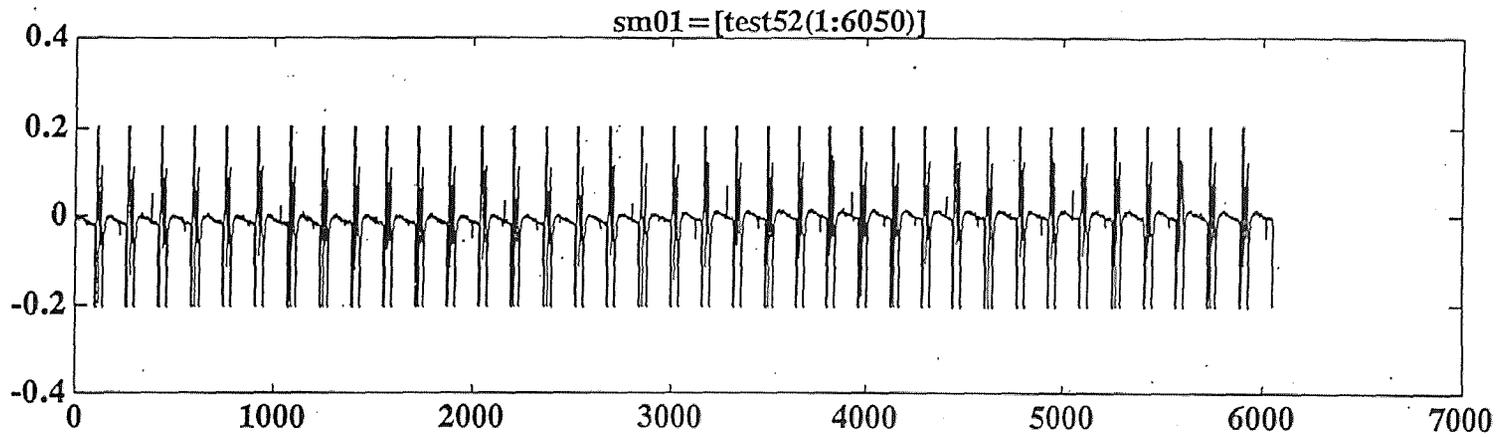


Figure 4.7.3. Plot of the reference signal x_j

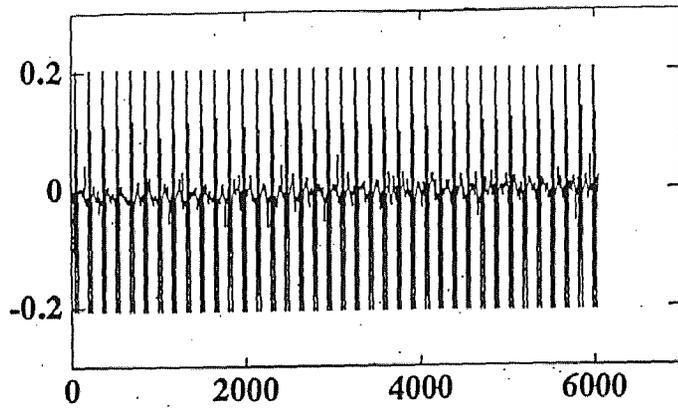


Figure 4.7.4. Stimulus+hissing EMG

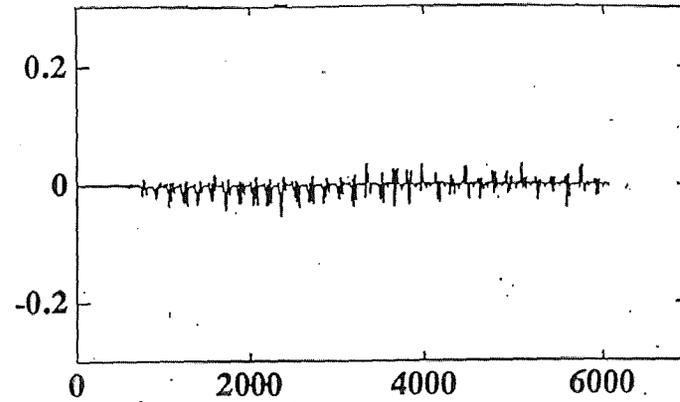


Figure 4.7.5. LMS output; hissing EMG,
 $L=18$, $\alpha=.01$, $\mu=.15$

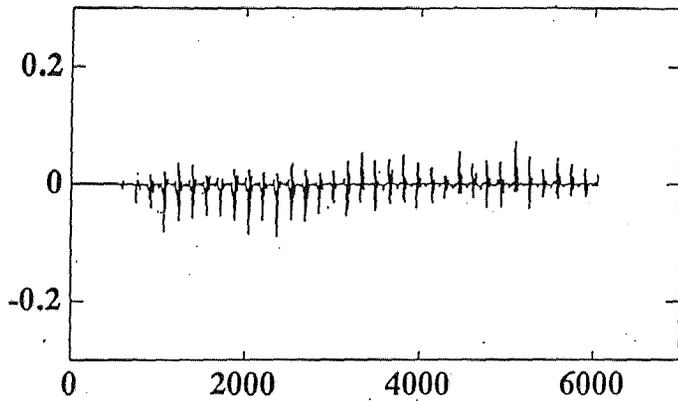


Figure 4.7.6. LMS output; hissing EMG,
 $L=4$, $\alpha=.01$, $\mu=.15$

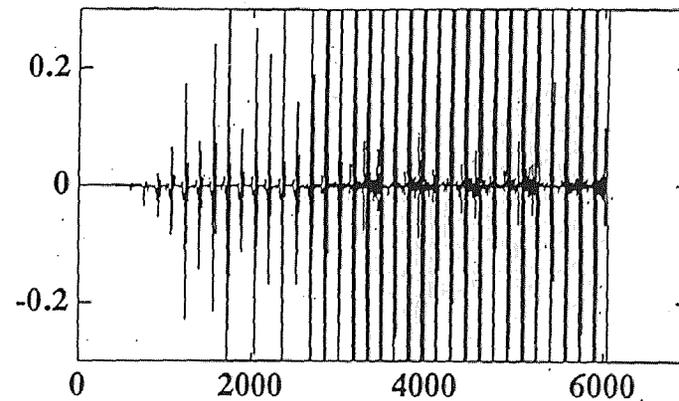


Figure 4.7.7. LMS output; hissing EMG,
 $L=4$, $\alpha=.01$, $\mu=.2$

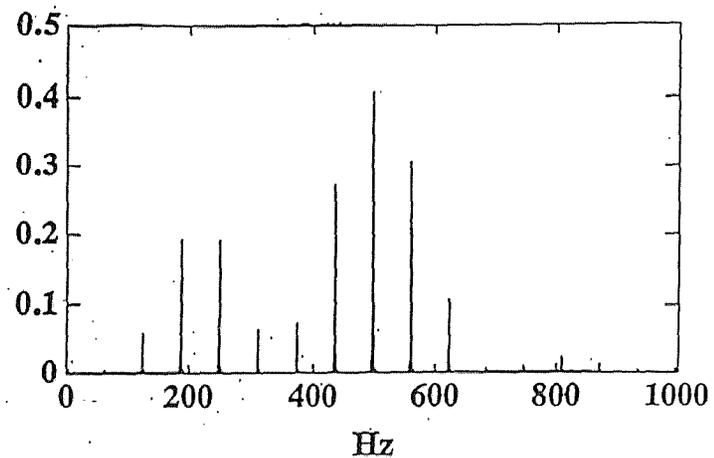


Figure 4.7.8. Stimulus spectrum, $N=2^{16}$

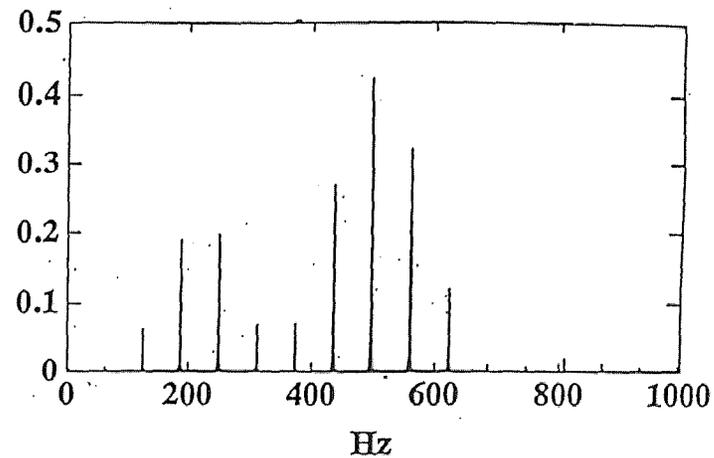


Figure 4.7.9. Stimulus+response spectrum, $N=2^{16}$

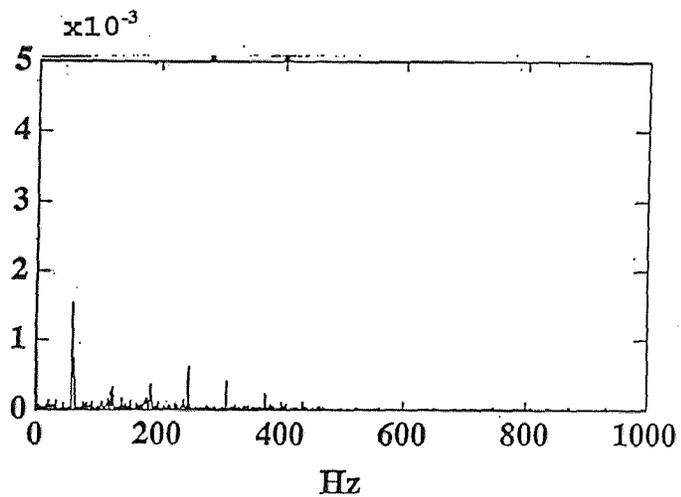


Figure 4.7.10. Hissing spectrum, $N=2^{16}$

CHAPTER 5

CONCLUSION

The physiological goal of the experiment was to modulate the masseter jaw muscle by stimulating the hypothalamus of the cat. This goal was achieved by watching the cat grinding its teeth immediately following stimulation.

The analysis goal was to extract the signal produced by this "teeth grinding" (hissing EMG), where this hissing EMG was embedded in a stimulus artifact. This goal was achieved by adaptively filtering the signal collected from the masseter jaw muscle during stimulation. We used successfully the LMS algorithm to cancel the stimulus and leave the hissing EMG as the output. There are ways of measuring the performance of an LMS algorithm but they will not be covered in this work because of the shortage of time. We analyzed biting EMG collected in episodes of data, which was produced by having the cat chew on a stick. We then applied spectrum analysis to both types of EMG signals to investigate their power in the frequency domain. Finally we applied statistical analysis and the results are:

A - biting EMG

We used the student T-test, F-test and the χ^2 -test, and because the tests did not fail we found that all power spectrum episodes have the same mean and same variance.

We then supported our analysis with the fact that physiologically, these episodes were produced in the same natural way, that is, biting on a stick.

It is known that the skeletal muscle is controlled by the somatic nervous system [1] (see figure 5.1).

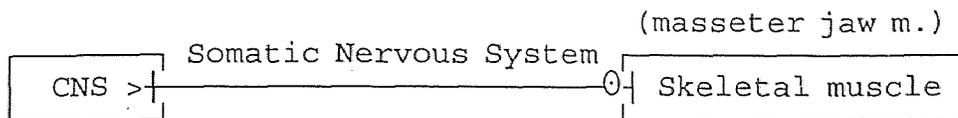


Figure 5.1 Efferent division of the peripheral nervous system. Overall plan of the Somatic system.

The path is a direct connection between the Central Nervous System (CNS) and the muscle by a non ganglionic nerve, where some of these nerves could be one meter long.

Therefore with the physiological support we concluded the power spectrum is the same for each episode.

The question arises that if they are the same, then why do their plots look different? The answer is that the episodes were recorded successively and each episode had its own random noise added to it, due to the electronics used, the movement of the cat etc. With this in mind one should expect differences.

Since the biting EMG power spectrum was the same in four successive episodes of data, we conclude that the biting EMG must have followed the same nerve path to generate masticatory activity.

B - Hissing EMG

The same statistical tests were used to compare the hissing EMG power spectrum to the average power spectrum of the biting EMG. The tests failed to conclude that they are equal. Since one phenomenon is produced by having the cat chew on a stick, the other by stimulating its hypothalamus, we find that the physiology again supports our statistics. Therefore we concluded that they are different.

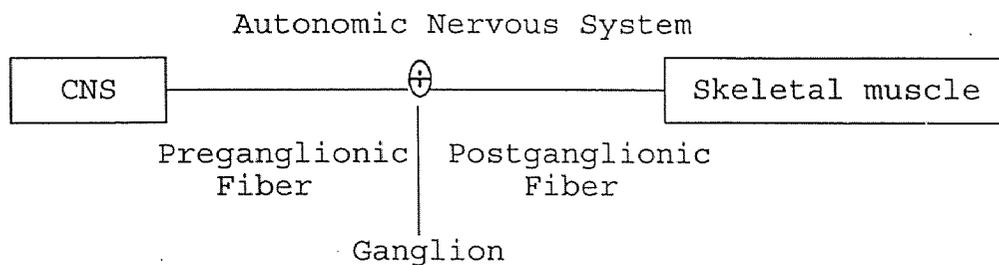


Figure 5.2 Efferent division of the peripheral nervous system. CNS-Skeletal muscle plan of the autonomic nervous system.

It is known that the sympathetic division of the autonomic nervous system, constricts skeletal muscle and dilates certain others [1]. Since hypothalamic stimulation manifested jaw muscle activity, that is, the cat does not realize its jaw muscle movement or does not desire to grind its teeth, then it must be the sympathetic nervous system that either constricts or dilates the masseter jaw muscle . Using *figure 5.2* and analysis findings, we conclude that the hissing EMG follows a different nerve path than the biting EMG. This path contains preganglionic fibers, ganglion and postganglionic fibers.

Assumptions made during analysis

To proceed with the LMS algorithm, we assumed the system is linear. From the output collected at the masseter jaw muscle, we considered the part that contained stim only our input signal (reference signal) to the LMS algorithm and canceled from the part that contained stim plus hissing EMG (desired response). We then assumed that this input signal has zero mean and is wide sense stationary and we said that this was necessary to give a good estimate to the input signal power ($r(0)$). We also for convenience set $w(0) = 0$ as an initial condition. Note that it could be set to some other value.

We should point out that, when we use computers to collect data, we are actually using an estimate of the signals, because signals during the experiment are continuous and they are sampled and digitized to be processed by the digital

computer. In other words they become discrete signals. It is not the sampling process that makes the signals an estimate but the use of electronics, because they add random noise.

Future work improvement

Suggestions to improve the experiment:

- The 60 Hz notch filter should not be used. This component can be canceled adaptively.
- The gain should be less than or equal to 200 to avoid data clipping.
- The sampling frequency should be less than 10,000 samples/sec, probably 3,000 samples/sec. This would obey the sampling theorem because the highest frequency was 1,500 Hz in the stimulus plus hissing EMG files. And this will make the files smaller when unpacked and easier to handle.
- A third channel should be added to collect stim only. This will make adaptive filtering easier to use.

Suggestions for future work

We should apply modern spectrum analysis to EMG studies to investigate from a different prospective. For example, the issue of eigenvalue spread and correlation matrix of sequences of EMG should be examined.

We should also monitor other signals such as the EEG and the EKG simultaneously with the EMG. With these signals in hand we could investigate the changing pattern of EMG by analyzing

simultaneously with the EEG and the EKG.

The finding of this work:" the stimulated EMG follows a different path than the natural EMG", should be researched more to map these nerves. This would help solve the problem of craniomandibular disorder (CMD) which involves pain in the masticatory jaw muscles and results in damaging the temporomandibular joint (TMJ). By mapping the nerves that make up the path of the stimulated EMG, we could give medication to TMJ patients to inhibit these nerves from conducting this type of EMG.

APPENDIX

- 1- *Data Conversion*
- 2- *Program #1: Band-pass Filter Design*
- 3- *Program #2: Spectral Analysis*
- 4- *Program #3: Filter Splitter*
- 5- *Program #4: Adaptive Stim-Canceler*
- 6- *Program #5: Zero Crossing*
- 7- *Digital Filter Design*

1. Data Conversion

TEST1.DAT : 400,384 bytes (binary)
 # of samples 200,192

Table 3.3.1 Test1.dat file unpacking

| FILE | ASCII size in bytes | Starting sample - Ending sample |
|------------|------------------------|------------------------------------|
| TEST10.PRN | 190,726 | 1 K - 50 K |
| TEST11.PRN | 281,356 | 50 K - 100 K |
| TEST12.PRN | 278,640 | 100 K - 150 K |
| TEST13.PRN | 294,144 | 150 K - 200.192K |

TEST2.DAT : 700,416 bytes (binary)
 # of samples 350,208

Table 3.3.2 Test2.dat file unpacking

| FILE | ASCII size in bytes | Starting sample - Ending sample |
|------------|------------------------|------------------------------------|
| TEST20.PRN | 192,860 | 1 K - 50 K |
| TEST21.PRN | 284,034 | 50 K - 100 K |
| TEST22.PRN | 281,304 | 100 K - 150 K |
| TEST23.PRN | 277,163 | 150 K - 200 K |
| TEST24.PRN | 275,188 | 200 K - 250 K |
| TEST25.PRN | 267,741 | 250 K - 300 K |
| TEST26.PRN | 269,841 | 300 K - 350.208K |

TEST3.DAT : 360,448 bytes (binary)
of samples 180,224

Table 3.3.3 Test3.dat file unpacking

| FILE | ASCII size in bytes | Starting sample - Ending sample |
|------------|------------------------|------------------------------------|
| TEST30.PRN | 190,151 | 1 K - 50 K |
| TEST31.PRN | 277,754 | 50 K - 100 K |
| TEST32.PRN | 272,311 | 100 K - 150 K |
| TEST33.PRN | 152,247 | 150 K - 180.224K |

TEST4.DAT : 360,448 bytes (binary)
of samples 180,224

Table 3.3.4 Test4.dat file unpacking

| FILE | ASCII size in bytes | Starting sample - Ending sample |
|------------|------------------------|------------------------------------|
| TEST40.PRN | 188,482 | 1 K - 50 K |
| TEST41.PRN | 292,623 | 50 K - 100 K |
| TEST42.PRN | 273,935 | 100 K - 150 K |
| TEST43.PRN | 143,979 | 150 K - 180.224K |

TEST5.DAT : 460,800 bytes (binary)
 # of samples 230,400

Table 3.3.5 Test5.dat file unpacking

| FILE | ASCII size in bytes | Starting sample - Ending sample |
|------------|------------------------|------------------------------------|
| TEST50.PRN | 194,025 | 1 K - 50 K |
| TEST51.PRN | 275,378 | 50 K - 100 K |
| TEST52.PRN | 271,544 | 100 K - 150 K |
| TEST53.PRN | 261,270 | 150 K - 200 K |
| TEST54.PRN | 175,335 | 200 K - 230.400K |

TEST6.DAT : 420,864 bytes (binary)
 # of samples 210,432

Table 3.3.6 Test6.dat file unpacking

| FILE | ASCII size in bytes | Starting sample - Ending sample |
|------------|------------------------|------------------------------------|
| TEST60.PRN | 204,285 | 1 K - 50 K |
| TEST61.PRN | 260,241 | 50 K - 100 K |
| TEST62.PRN | 270,892 | 100 K - 150 K |
| TEST63.PRN | 257,894 | 150 K - 200 K |
| TEST64.PRN | 66,594 | 200 K - 210.432K |

TEST7.DAT : 440,320 bytes (binary)
of samples 220,160

Table 3.3.7 Test7.dat file unpacking

| FILE | ASCII size in bytes | Starting sample - Ending sample |
|------------|------------------------|------------------------------------|
| TEST70.PRN | 201,638 | 1 K - 50 K |
| TEST71.PRN | 258,824 | 50 K - 100 K |
| TEST72.PRN | 262,523 | 100 K - 150 K |
| TEST73.PRN | 260,268 | 150 K - 200 K |
| TEST74.PRN | 107144 | 200 K - 220.160K |

TEST8.DAT : 800,768 bytes (binary)
of samples 400,384

Table 3.3.8 Test8.dat file unpacking

| FILE | ASCII size in bytes | Starting sample - Ending sample |
|------------|------------------------|------------------------------------|
| TEST80.PRN | 200,354 | 1 K - 50 K |
| TEST81.PRN | 273,315 | 50 K - 100 K |
| TEST82.PRN | 251,195 | 100 K - 150 K |
| TEST83.PRN | 276,395 | 150 K - 200 K |
| TEST84.PRN | 247,500 | 200 K - 250 K |
| TEST85.PRN | 257,171 | 250 K - 300 K |
| TEST86.PRN | 273,706 | 300 K - 350 K |
| TEST87.PRN | 301,834 | 350 K - 400.384K |

This section completes data collection, unpacking and storage, the BINARY files are stored in the tape and floppies, the ASCII files are stored on PC and floppies.

At this point, we need to transfer the files (ASCII format) from a PC to the Sun-workstations at the mechanical computer lab. We have three communications software (maybe more) available at NJIT, but there is no single PC connected to the Sun-workstation at the mechanical department, this was a problem because the ASCII files are stored on floppies. The only way to do it is to transfer the files to Hertz (VAX system), then from there to the Sun-workstation. We used FTP (file transfer) which is the fastest one. We also contributed a lot of work unpacking and transferring the same files to Dr. Dun at Rutgers University using EMail. This last communications software is not as fast as FTP. But still the process was very time consuming because in the beginning we started with only 1 MB of disk space in each account : MESUNW, HERTZ.

Then the files in ASCII format are transferred from HERTZ to MESUNW, FTP program adds at the end the file two lines, one blank and one containing a control-z character. This causes a problem trying to load the files into MATLAB, the reason is that MATLAB could not read those lines added by FTP, then the files are edited to delete these characters using VI editor (in UNIX environment).

The program STREAMER.EXE adds also a one to the beginning of each file, which indicates that data has been collected from channel one of DASH16 board. This had to be deleted also because it is not part of the data.

```
% Program #1
%
% Program to design band-pass filter
%
% b and a are coefficients of the filter
% Lower cutoff frequency = 10 Hz
% Upper cutoff frequency = 1,000 Hz
% f_s is the sampling frequency =10,000 Hz
%
% f_s = 10000;
%
% order of filter is 2 x n = 10
%   n = 5;
%   W_n = 2 * [10,1000]/f_s;
%   [b,a] = butter(n,W_n)
%
% test50 = x_0, test51 = x_1, test52 = x_2, test53 = x_3,
% test54 = x_4, test55 = x_5
%
%   y_0 = filter(b, a, x_0);
%   y_1 = filter(b, a, x_1);
%   y_2 = filter(b, a, x_2);
%   y_3 = filter(b, a, x_3);
%   y_4 = filter(b, a, x_4);
%   y_5 = filter(b, a, x_5);
```

```

%% Program #2
%%
%% This program calculates FFTs and power spectrum of each episode
%% and plot results and their statistical parameters.
%%  $X_2, X_3, X_4, X_5$  are episode's data samples
%%  $F_s$  is sampling frequency
%%  $f$  is frequency
%%  $X_{2d}, X_{3d}, X_{4d}, X_{5d}$  is detrended data
%%  $N$  is FFT size
%%  $Y_2, Y_3, Y_4, Y_5$  are FFT of  $X_{2d}, X_{3d}, X_{4d}, X_{5d}$ 
%%  $Py_2, Py_3, Py_4, Py_5$  are power spectrums of episodes
%%
    N = 2^16;
    f_s = 10000;

%%
%% This will array the frequency, and use the symmetry
%%
    f = f_s*(0:N/2-1)N;

%%
%% Calculation of FFT's
%%
    Y_2 = fft(X_{2d}, N);
    Y_3 = fft(X_{3d}, N);
    Y_4 = fft(X_{4d}, N);
    Y_5 = fft(X_{5d}, N);

%%
%% Calculation of power spectrums
%%
    Py_2 = Y_2 * conj(Y_2)/N_j;
    Py_3 = Y_3 * conj(Y_3)/N_j;
    Py_4 = Y_4 * conj(Y_4)/N_j;
    Py_5 = Y_5 * conj(Y_5)/N_j;

%%
%% Program to plot spectra. Subplot will divide the screen up to %
four parts
%%
    subplot(221), plot(f, Py_2(1:N/2))
    title(' Episode 2 - Spectrum')
    xlabel('H_z')
    subplot(222), plot(f, Py_3(1:N/2))
    title(' Episode 3 - Spectrum')
    xlabel('H_z')
    subplot(223), plot(f, Py_4(1:N/2))
    title(' Episode 4 - Spectrum')
    xlabel('H_z')
    subplot(224), plot(f, Py_5(1:N/2))
    title(' Episode 5 - Spectrum')
    xlabel('H_z')

```

```

%%
% Program to normalize spectra, calculation of maximum point
%
    m2 = max(PY2);
    m3 = max(PY3);
    m4 = max(PY4);
    m5 = max(PY5);
%
% Divide spectrum by maximum point
%
    PY2n = [PY2]/m2;
    PY3n = [PY3]/m3;
    PY4n = [PY4]/m4;
    PY5n = [PY5]/m5;
%
% Calculation of means and their averages
%
    mu2 = mean([PY2n]);
    mu3 = mean([PY3n]);
    mu4 = mean([PY4n]);
    mu5 = mean([PY5n]);
    mean(mu2, mu3, mu4, mu5)
%
% Calculation of variances and their means
%
    s2^2 = cov(PY2n);
    s3^2 = cov(PY3n);
    s4^2 = cov(PY4n);
    s5^2 = cov(PY5n);
    mean(s2^2, s3^2, s4^2, s5^2);
%
% Calculation of standard deviations and their means
%
    s2 = std(PY2n);
    s3 = std(PY3n);
    s4 = std(PY4n);
    s5 = std(PY5n);
    mean(s2, s3, s4, s5);
%
% Calculation of input power of signal s(k)=sm01(k)
% The signal s(k) is supposed to be stationary with
% zero mean - P(omega) = r(0) = Σxi
%
    s(k) = sm01(k);
    P = 0;
    For i=1:6050;
        P=P+sum(s(i)^2);
    end

```

```
c
c   Program #3
c
c   Program to open a data file, read samples of designated
c   intervals, and store them in files
c   Initialization
c   INTEGER i
c   DIMENSION x(50010)

C   ROUTINE*****
OPEN (1, FILE = 'test52.prn', STATUS = 'OLD')

11  FORMAT(F10.4)
DO 10 i=1,50000
READ(1,11)x(i)
10  CONTINUE

OPEN (2, FILE = 'sm01.prn', STATUS = 'NEW')
DO 20 i=1,6050
WRITE(2,11)x(i)
20  CONTINUE

OPEN (3, FILE = 'DUMP1.prn', STATUS = 'NEW')
DO 30 i=6049,42499
write(3,11)x(i)
30  CONTINUE

OPEN (4, FILE = 'sr01.prn', STATUS = 'NEW')
DO 40 i=42500,48550
WRITE(4,11)x(i)
40  CONTINUE

OPEN (5, FILE = 'DUMP2.prn', STATUS = 'NEW')
DO 50 i=48551,50000
write(5,11)x(i)
50  CONTINUE

END
```

```

C
C   Program #4      ADAPTIVE STIM CANCELER
C
C   X(0:N-1)= data vector (output replaces input)
C   N         = number of data samples and of adaptive iterations
C   D(0:N-1)= desired response vector
C   B(0:L)    = adaptive coefficient vector
C   L         = order of adaptive system
C   mu        = REAL convergence parameter mu (0.0 < MU < 1.0)
C   sig       = input signal power estimate
C   AL        = exponential forgetting factor alpha (0 < AL < 1)
C   px(0:L)   = vector that retains past inputs for block mode
C   IERROR    = 0 no error detected
C               1 filter order L < 0
C               2 convergence parameter MU < 0 or MU > 1
C               3 input signal power estimate sig < 0
C               4 forgetting factor AL < 0 or AL > 1
C               5 response yk exceeds 1.E10
C   SR01      : data containing desired response D(1:6050)
C   SM01      : data containing data vector X(1:6050)
C   RESP      : output of adaptive filter
C
C   DIMENSION X(0:6049),D(0:6049),B(0:4),px(0:4)
C   real mu
C   data B/5*0./,px/5*0./
C
C   data L/4/,N/6050/,mu/.1/,sig/46.355/,Al/.01/
C   OPEN(UNIT=1,FILE='SR01.PRN',STATUS='OLD')
C   OPEN(UNIT=2,FILE='SM01.PRN',STATUS='OLD')
C   OPEN(UNIT=3,FILE='RESP.PRN',STATUS='NEW')
C
C   DO 10 i=0,6049
C       READ (1,*) D(i)
C       READ (2,*) X(i)
10  CONTINUE
C
C   CALL SPNLMS (X,N,D,B,L,mu,sig,AL,px,IERROR)
C   if (IERROR.NE.0) Then
C       PRINT *, ' spnlms error =',ierror
C       STOP
C   ENDIF
C   do 20 i=0,6049
C       WRITE (3,*) X(i)
20  CONTINUE
C
C   END

```

```

SUBROUTINE spnlms (X,N,D,B,L,mu,sig,AL,px,IERROR)
DIMENSION X(0:6049),D(0:6049),B(0:L),px(0:L)
REAL mu

IERROR = 0
WRITE(*,*) 'mu=',mu
IF(L.LT.0) IERROR=1
IF(mu.LE.0..OR.mu.GE.1.) IERROR = 2
IF(sig.LE.0) IERROR = 3
IF(AL.LT.0..OR.AL.GE.1.) IERROR = 4
IF(IERROR.NE.0) RETURN
IERROR = 5
DO 5 K=0,6049
    px(0) = X(K)
    X(K) = 0
DO 1 LL=0,L
    X(K)=X(K)+B(LL)*px(LL)
1 CONTINUE
IF(abs(X(K)).GT.1.E10) RETURN
E=D(K)-X(K)
sig=AL*(px(0)**2)+(1-AL)*sig
TMP=2*mu/((L+1)*sig)
DO 2 LL=0,L
    B(LL)=B(LL)+TMP*E*px(LL)
2 CONTINUE

DO 3 LL=L,1,-1
    px(LL)=px(LL-1)
3 CONTINUE

5 CONTINUE
IERROR=0
RETURN

END

```



```

/* parse and read command line arguments */
while ((c=getopt(argc,argv,"i:")) !=EOF) {

    switch(c) {

/* specify input file */
    case 'i':
        if ((infile=fopen(optarg,"r")) == NULL){
            ierr =1;
            printf("ERROR - main - cannot open %s\n",
                optarg);
            exit(1);
        }
        printf("input data file:\t\t%s\n\n\n",optarg);
        i_flg = 1;
        break;
    default:
        ierr=1;
        break;
    }
}

/* check that all necessary options have been specified */
if(!i_flg)
    ierr = 1;

/* if error then print the help string */
if (ierr) {
    printf("Usage:\tzcross \\ \n");
    printf("\t\t -i input_data_file \\ \n");
    exit(1);
}
nread=2;
num=count=0;
while (nread>0) {

    nread = fread(x,sizeof(int),1000,infile);

/* for(i=0;i<nread;i++)
   printf(" x[%d]=%d\n",i,x[i]);*/

    a=x[0];
    for(i=1;i<nread;i++) {

        if (a*x[i] < 0)
        {
            printf("there is a zero crossing before sample
                %d\n\n",i+count);
        }
    }
}

```

```

        num++;
        dely=(float) (x[i]-a);
        xzero=(float) (i+count-1) - (float) (a/dely);
        printf(" the new zero crossing is at sample
               %f\n\n",xzero;
    }
    if (x[i] == 0)
    {
        printf("there is a zero crossing at sample
               %d\n\n",i+count);
        num++;
    }
    a=x[i];
}
count=count+nread;
}

printf("the total # of zero crossings is
        %d\n\n\n",num);
fclose(infile);

    printf("\n*****\n")'
    printf("          END OF PROGRAM          \n")'
    printf("\n*****\n")'
} /* finished main program          */

```

7. Digital Filter Design

Specification: tenth order butterworth band-pass filter with lower cutoff frequency of 10 Hz and upper cutoff frequency of 1,000 Hz.

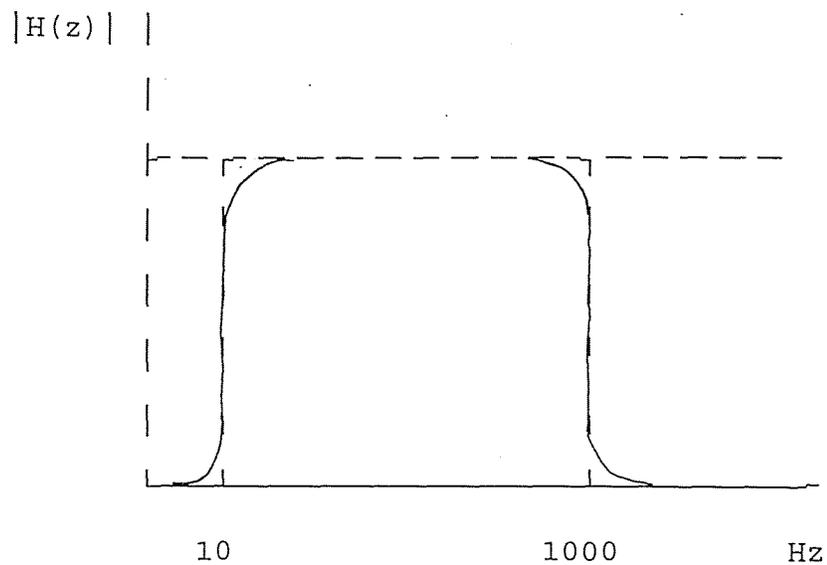


Figure 6.1 Magnitude of transfer function

Assuming that the system is linear, the tenth order digital filter is characterized by the difference equation:

$$y(n) = b(1)x(n) + b(2)x(n-1) + \dots + b(10)x(n-9) - a(2)y(n-1) - a(3)y(n-2) - \dots - a(10)y(n-9) \quad (4-1)$$

where $x(n)$ is our input sequence

and, $y(n)$ is our output sequence

Taking the z transform of equation (4-1), we obtain:

$$Y(z) = \frac{b(1) + b(2)z^{-1} + \dots + b(10)z^{-9}}{1 + a(2)z^{-1} + \dots + a(9)z^{-9}} X(z)$$

$$Y(z) = H(z) X(z)$$

where $H(z)$ is the transfer function of the system.

The direct form II structure realization of the filter is:

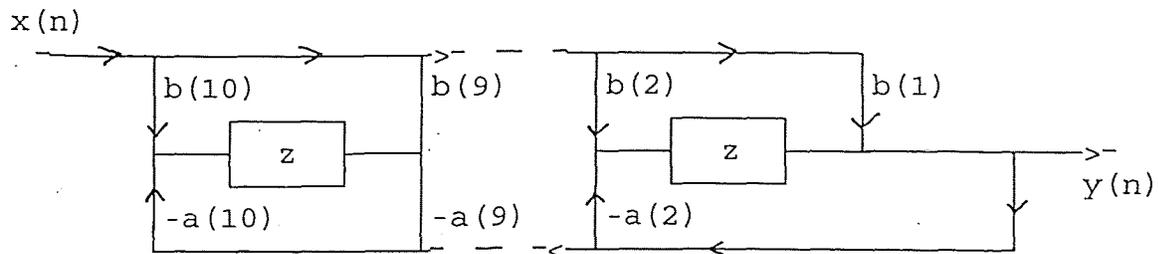


Figure 6.2 Direct form II realization

[See program #1 for filter design]

The coefficients of the filter are:

| | |
|----------------|------------------|
| b(1) = .0012 | a(1) = 1 |
| b(2) = 0 | a(2) = - 7.9792 |
| b(3) = -.0061 | a(3) = 28.7224 |
| b(4) = 0 | a(4) = -61.4932 |
| b(5) = .0123 | a(5) = 86.7979 |
| b(6) = 0 | a(6) = -84.4580 |
| b(7) = -.0123 | a(7) = 57.3972 |
| b(8) = 0 | a(8) = -26.9050 |
| b(9) = .0061 | a(9) = 8.3253 |
| b(10) = 0 | a(10) = - 1.5355 |
| b(11) = -.0012 | a(11) = .1282 |

The zeroes of the transfer function are:

$$b_1 = -1.0069$$

$$b_2 = b_3^* = -1.0021 + 0.0065i$$

$$b_4 = b_5^* = -0.09944 + 0.0040i$$

$$b_6 = 1.0030$$

$$b_7 = b_8^* = 1.0009 + 0.0029i$$

$$b_9 = b_{10}^* = 0.9975 + 0.0018i$$

The poles of the transfer function are:

$$P_1 = P_2^* = 0.6872 + 0.4746i$$

$$P_3 = P_4^* = 0.9980 + 0.0061i$$

$$P_5 = P_6^* = 0.9946 + 0.0035i$$

$$P_7 = 0.9942$$

$$P_8 = P_9^* = 0.5543 + 0.2361i$$

$$P_{10} = 0.5168$$

The filter is stable and minimum phase.

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