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ARTIFICIAL NEURAL NETWORK FOR NEURAL ACTION POTENTIAL DETECTION

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ABSTRACT

Neural action potentials are electrical signals generated by neurons and are crucial for understanding the functioning of the nervous system. The project aims to develop a system that utilizes artificial neural networks (ANNs) for the detection of neural action potentials.

The project focuses on designing filters using ANNs in MATLAB to accurately detect and classify neural action potentials. The filters are trained using labelled data, where the input represents the electrical signals and the output indicates whether an action potential is present or not. The neural network learns to recognize patterns in the signals and makes predictions based on the training data.

The MATLAB program implements preprocessing techniques to remove noise and artifacts from the collected data. Relevant features are extracted from the preprocessed data to capture the characteristics of action potentials. These features include amplitude, duration, shape, and frequency content of the electrical signals.

Overall, the project seeks to contribute to the development of accurate and efficient methods for neural action potential detection using artificial neural networks in MATLAB. The results obtained from this project can enhance our understanding of neural activity and have implications for various fields, including neuroscience, neurology, and brain-computer interfaces.

Keywords (Artificial. Design Neural network. Implementation Neural network .Neural Action. Potential detection)

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LIST OF SYMBOLS / ABBREVIATIONS

Symbol	Description	Units
IIR	Infinite Impulse Response	
FIR	Finite Impulse Response	
FFT	fast Fourier transform	
DSPs	digital signal processors	
PNS	the peripheral nervous system	
BCIs	Brain-Computer Interfaces	
VNS	Vagus Nerve Stimulation	
DBS	Deep Brain Stimulation	
EMI	Electromagnetic Interference	
RFI	Radio Frequency Interference	
ENG	Electroneurogram	
EMG	Electromyogram	
EEG	Electroencephalogram	
ECG	Electrocardiogram	
fMRI	functional magnetic resonance imaging	
FINE	Flat-interface nerve electrode	
Hz	hertz	

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Chapter One

Introduction

Chapter One

1.1 Introduction

The human nervous system, a complex network of interconnected neurons that work together to form our thoughts and transmit signals to cause movements, and bodily functions, these signals travel in the form of action potentials. Understanding the dynamics of action potentials not only unveils the secrets of neural communication but also opens doors to transformative applications in medical diagnosis and therapeutic interventions. These signals travel along the length of nerve cells, known as neurons, and are responsible for transmitting sensory information, controlling movement, and regulating bodily functions. The speed at which nerve signals travel can vary depending on the type of nerve and the conditions in the body. Generally, nerve signals can travel at speeds ranging from approximately 1 meter per second to over 100 meters per second. This variation in speed is due to factors such as the diameter of the nerve fiber, the presence of a protective myelin sheath around the nerve, and the temperature of the surrounding environment. Overall, the process of nerve signal transmission is a remarkable aspect of the human body's ability to perceive and respond to the world around us.

1.2 Problem statement

Recognition of neural activity in a noisy environment is a critical point for scientists. The bandpass filter is an essential and most straightforward method for neural spike classification; however, this approach still very sensitive to the magnitude variances among the neural spike to be beneficial in biomedical applications.

1.3 Objective

Creating an enhanced bandpass filter using an artificial neural network to improve the neural spike detection and sorting based on velocity selective recording method. The proposed filter rejects the noise background and improves the selectivity depend on fibre conduction velocity.

1.4 Biosignals

In the realm of biomedical signals and sensors, a biosignal is a representation of a physiological phenomenon [1], regardless of its specific nature. Since there is a nearly unlimited number of physiological mechanisms of interest, the number of possible biosignals is very large. In the broadest sense, the variety of biosignals extends from a visual inspection of the patient up to signals recorded from the human body using sensors, e.g., electrocardiography, The extensive diversity of biosignals is most evident in the various methods of classifications, As a first classification method, a biosignal's existence could be take as a basis of classification, in particular there are permanent biosignals and induced biosignals.

[2]

Permanent biosignals such as electrocardiographic signal exist without any artificial impact, trigger, or excitation from outside the body and are available at any time, the source of the biosignal is already inside the body.

Induced biosignals such as electric plethysmography are biosignals that are artificially triggered, excited, or induced. In contrast to permanent biosignals, induced biosignals exist roughly for the duration of the excitation. That is, as soon as the artificial impact is over, the induced biosignal decays with a certain time constant determined by the body properties.

The second classification method considers the dynamic nature of biosignals. Accordingly there are quasi-static biosignal and Dynamic biosignals [1].

Quasi-static biosignals carry information in their steady-state level, where changes over time are minimal and exhibit a gradual nature. E.g. the core body temperature.

Dynamic biosignals undergo significant changes in the time domain, conveying the physiological information of interest through dynamic processes. E.g the beat-to-beat changes of the heart rate.

The third classification method relies on the origin of the biosignals as a basis for their classification [3]. The most prominent biosignals:

1. Electric biosignals: These are generated by electrical activity in the body, such as the electrocardiogram (ECG), electroneurogram (ENG), electroencephalogram (EEG), and electromyogram (EMG).

2. Magnetic biosignals: These are generated by non-stationary currents in the body, such as the magnetocardiogram (MCG).
3. Mechanic biosignals: These are generated by body deformations or local body skin vibrations, such as the mechanorespirogram.
4. Optic biosignals: These are generated by light absorption and scattering related to propagation volume and medium, such as the optoplethysmogram.
5. Acoustic biosignals: These are generated by sound waves produced by the body, such as heart sounds, lung sounds, and snoring sounds.
6. Chemical biosignals: These are generated by chemical reactions in the body, such as cortisol levels.
7. Thermal biosignals: These are generated by changes in body temperature, such as body core temperature.

1.5 Action Potentials

Neuron cells have different ion concentrations at the intracellular and extracellular space due to the selective permeability to different ions. The difference in ion concentrations causes an electrochemical voltage difference across the membrane, called the membrane potential. Under normal physiological conditions, the interior of the cell is negative with respect to the extracellular space without a net electric current flowing through the membrane
[4].

The membrane potential shifts from resting state where the inside of the cell is negatively charged compared to outside, shifting to depolarization state where a stimulus such as change in voltage causes ion channels (often sodium channels) to open and sodium ions rush into the cell making it less negative, if this depolarization reaches a threshold level it triggers the next stage, which is rising phase where the voltage-gated sodium channels open rapidly allowing a large influx of sodium ions, the membrane potential rapidly becomes positive, leading to the peak of the action potential, next stage is re-polarization in which the voltage-gated sodium channels close and voltage-gated potassium channels open moving potassium ions out of the cell, restoring negative charge inside and the membrane potential returns to the resting state, another stage is undershoot or hyper-polarization which happens in some cells where the membrane potential briefly becomes more negative than the resting state.

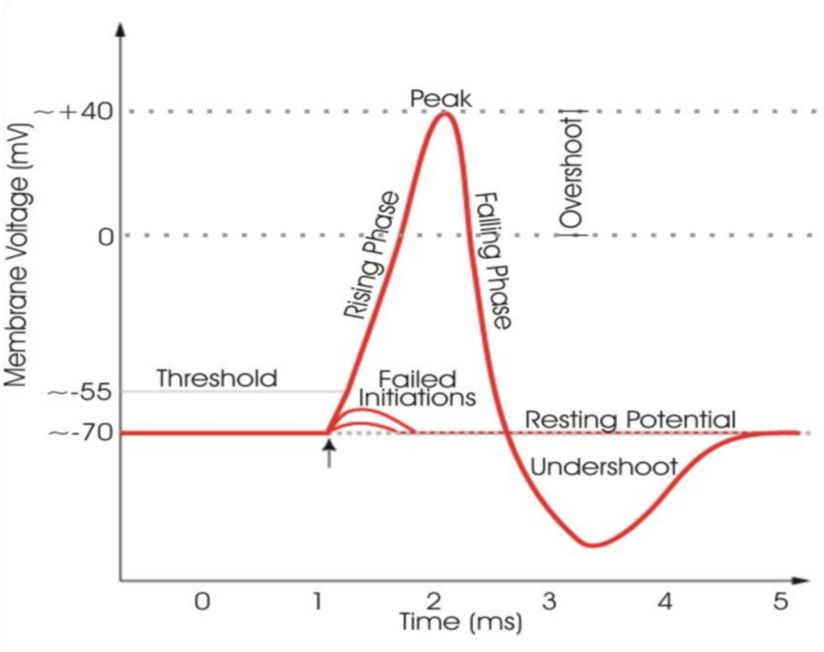


Figure 1.1 Action potential [5]

1.6 Neuron Structure

Neurons are the basic building blocks of the nervous system, and they play a crucial role in transmitting information throughout the body. The structure of a neuron can be divided into several key components [6]:

1. Cell Body (Soma): The cell body contains the nucleus and other organelles necessary for the neuron to function. It also integrates the incoming signals from other neurons.
2. Dendrites: These are the treelike extensions that project from the cell body. Dendrites receive signals from other neurons and transmit them toward the cell body.
3. Axon: The axon is a long, single extension that transmits electrical signals away from the cell body and toward other neurons, muscles, or glands.

4. Myelin Sheath: In some neurons, the axon is surrounded by a myelin sheath, which is made up of specialized cells called Schwann cells. The myelin sheath helps to insulate the axon and increases the speed of signal transmission.
5. Axon Terminals: At the end of the axon, there are small branches known as axon terminals. These terminals release neurotransmitters, which are chemical messengers that transmit signals to other neurons or to muscle cells.

The structure of neurons allows for the transmission of electrical and chemical signals across the nervous system, enabling functions such as sensation, movement, and cognition.

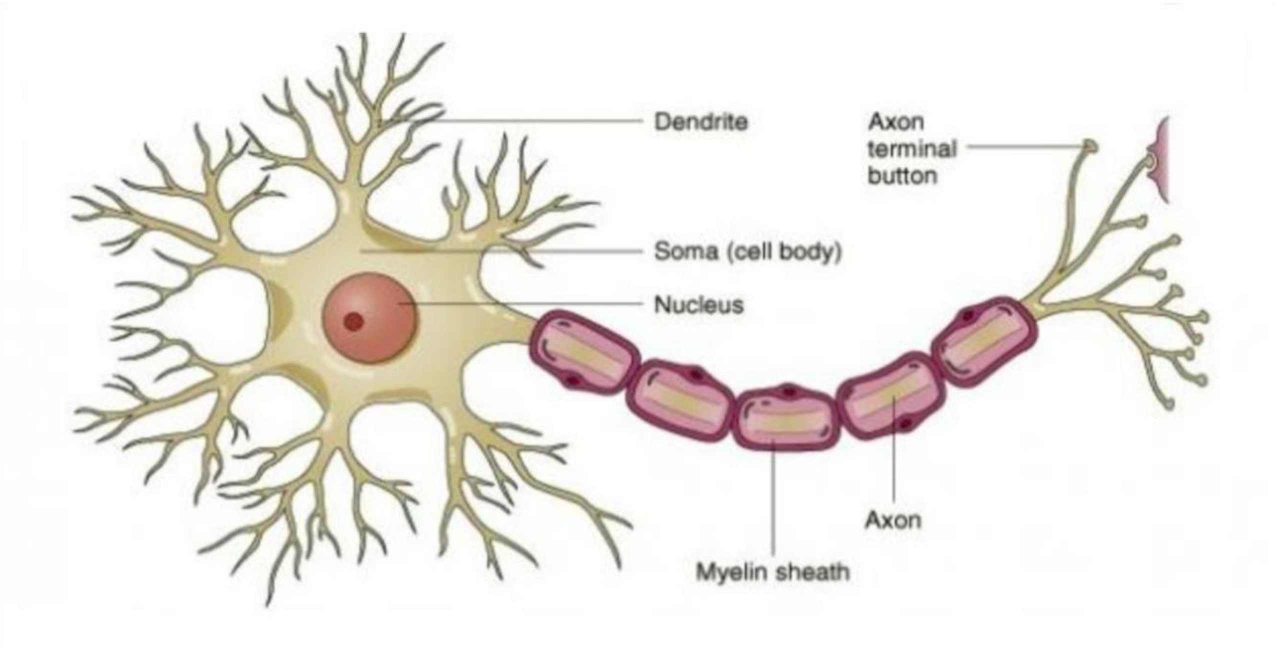


Figure1.2 NeuronStructure[6]

1.7 Recording neural signals

Electroneurography (ENG) is a technique used to record and analyze the electrical activity of nerves and muscles. It involves placing electrodes on the skin or directly on the nerve to measure the electrical signals generated by the nerve fibers. These signals can be used to diagnose nerve and muscle disorders, monitor nerve function during surgery, and study the physiology of the neuromuscular system.

There are many different Neuron signals that each have a wide range of different characteristics, such as having a different range of frequencies and amplitudes that underscore the varied nature of information processing within the nervous system [7], such as

- Electro-EncephaloGraphy (EEG) uses non-invasive surface electrodes placed on the scalp to record Summed post-synaptic potentials, this signal has a bandwidth of <100Hz with a very low spacial resolution of 3 cm, signal amplitude of 10-100 μV.
- Electro-CorticoGraphy (EcoGs): uses Moderately Invasive implanted (minute-penetrating) surface electrodes placed on the cortical surface, records synchronized postsynaptic potentials, has a bandwidth of 0.5-200Hz with a low spacial resolution of 0.5 cm, and a signal amplitude <100μV.
- Local Field Potentials (LPFs): uses Moderately Invasive Metal/silicon microelectrode placed in the brain, records Synchronized postsynaptic potentials, has a bandwidth of <200Hz with a moderate spacial resolution of 1 mm, and a signal amplitude of <5mV.
- Extracellular Action Potentials (EAPs): uses Invasive Metal/silicon microelectrode to sense action potentials in the brain, has a bandwidth of 0.17 kHz with a high spacial resolution of 0.2 mm, and a signal amplitude of <500μV.

1.8 Challenges of recording neural signals

Recording ElectroNeuroGrams (ENG) can be a complex process, and there are several important challenges associated with obtaining accurate and reliable recordings. Some of the most significant challenges include:

1. Signal Interference: The recording of ENG can be affected by various sources of interference, such as electrical noise from surrounding equipment, movement artifacts, and physiological signals from other nearby muscles. This interference can reduce the signal-to-noise ratio and make it challenging to obtain clear and accurate recordings.
2. Electrode Placement and Contact Impedance: Ensuring proper placement of electrodes and maintaining good contact impedance between the electrode and the skin is crucial for obtaining high-quality ENG recordings. Poor electrode

contact can lead to increased electrical noise and distorted signals, making it difficult to interpret the recorded data.

3. Signal Amplification and Filtering: Amplifying and filtering the raw ENG signals is essential to extract the relevant neural activity while reducing background noise. However, selecting the appropriate amplifier gain and filter settings can be challenging, as amplifying the signal too much can lead to saturation, while insufficient amplification may result in weak or indistinct signals.
4. Patient Factors: Patient-related factors, such as skin impedance variations, movement artifacts, and individual anatomical differences, can significantly impact the quality of ENG recordings. Patients with certain medical conditions or anatomical abnormalities may present additional challenges for acquiring accurate neural signals.
5. Data Interpretation: Once the ENG signals are recorded, accurately interpreting the data requires specialized expertise and may be challenging, particularly in the presence of complex waveforms, artifacts, or abnormalities.

1.9 Noise in the neural signal

Noise in neurophysiological measurements like EMGs, NCS, or EEGs refers to unwanted electrical signals that interfere with the desired neural signal. Types of noise that can affect these recordings include:

· Biological Noise: This comes from the physiological activity of the individual that is not the target of the measurement. In the case of EMG, this might be electrical activity from other muscles nearby that are not being studied, or heartbeats. For EEG, it could be eye movement or muscle activity.

· Technical Noise: This includes any kind of interference from the equipment itself or from outside sources. This kind of noise is typically electrical in nature and can come from:

- Thermal Noise: Resulting from the thermal motion of charges in conductors.
- Shot Noise: Due to the discrete nature of electric charge.

- Device Noise: Created by the recording apparatus, such as amplifiers or electrodes. It can include low-frequency drifts or highfrequency noise due to electronic circuitry.

· Environmental Noise: Interference picked up from other equipment or electronic devices in the environment can affect the signal. Common sources include:

- Electrical Networks: 50/60 Hz interference from the power supply can be a significant source of noise.
- Radio Frequency Interference (RFI): Comes from wireless devices and mobile phones.
- Electromagnetic Interference (EMI): Can emerge from a wide range of sources like computers, monitors, and medical equipment in the vicinity.

· Artifact: These are unintended signals that can be confused with or obscure the neural signal. In the case of EMG, movement artifacts can originate from the subject moving, whereas for EEG, electrode pops and skin potentials are common artifacts.

· Aliasing: This is a specific type of distortion that occurs when the signal is undersampled, and higher frequencies are incorrectly mapped into lower frequencies within the recorded signal.

1.10 Neural signaling applications

The use of neural signals in medical applications is a rapidly advancing field that combines neuroscience, bioengineering, and clinical practice to improve patient care. Here is a detailed explanation of some key medical applications of neural signals:

1. Neuroprosthetics:

- Prosthetic Limb Control: Utilizing neural signals allows patients with amputations to control prosthetic limbs with their thoughts. Brain-machine interfaces (BMIs) decode the neural signals associated with the intention of movement and translate them into commands for prosthetic devices.

- Cochlear Implants: These devices convert sound waves into electrical signals that can be relayed to the auditory nerve, providing a sense of sound to a person who is profoundly deaf or severely hard of hearing.
- Retinal Implants: Similar to cochlear implants, retinal implants capture visual signals and convert them into neural signals that can be sent to the brain, aiding those with certain types of blindness.

2. Diagnostics:

Neural signals are used in a variety of diagnostic applications, including:

» Epilepsy: Neural signals can be used to diagnose epilepsy by identifying abnormal electrical activity in the brain.This can be done using a variety of methods, such as electroencephalography (EEG), magnetoencephalography (MEG), and functional magnetic resonance imaging (fMRI).

» Sleep disorders: Neural signals can be used to diagnose sleep disorders by identifying abnormal sleep patterns.This can be done using a variety of methods, such as polysomnography (PSG), actigraphy, and sleep diaries.

» Brain tumors: Neural signals can be used to diagnose brain tumors by identifying abnormal growths in the brain.This can be done using a variety of methods, such as MRI, CT scan, and PET scan.

» Alzheimer's disease: Neural signals can be used to diagnose Alzheimer's disease by identifying abnormal changes in the brain.This can be done using a variety of methods, such as MRI, CT scan, and PET scan.

Neuralsignals are also being used in a variety of new diagnostic applications, such as:

» Mental health disorders: Neural signals can be used to diagnose mental health disorders by identifying abnormal patterns of brain activity.This can be done using a variety of methods, such as EEG, MEG, and fMRI.

» Neurodegenerative diseases: Neural signals can be used to diagnose neurodegenerative diseases by identifying abnormal changes in the brain.This can be done using a variety of methods, such as MRI, CT scan, and PET scan. » Neurological disorders: Neural signals can be used to diagnose neurological disorders by identifying abnormal patterns of brain activity.This can be done using a variety of methods, such as EEG, MEG, and fMRI.

Neuralsignals are a powerful tool for diagnosis, and they are being used in a growing number of applications.As research continues, neural signals are likely to play an even greater role in the diagnosis of a variety of diseases and disorders.

3. Neural Modulation Therapies:

- Deep Brain Stimulation (DBS): DBS involves implanting electrodes within certain areas of the brain to produce electrical impulses that regulate abnormal impulses. It’s used to treat a variety of debilitating neurological symptoms, most commonly the debilitating symptoms of Parkinson's disease, dystonia, and chronic pain.
- Vagus Nerve Stimulation (VNS): This technique is used mainly for treatmentresistant depression and intractable epilepsy

4. Brain-Computer Interfaces (BCIs):

BCIs can provide communication and control capabilities to individuals with severe motor disabilities resulting from ALS, cerebral palsy, stroke, or spinal cord injury. Sensors placed on the scalp (or in some cases, implanted) record brain signals, which are then decoded by a computer to perform certain tasks.

5. Clinical Research:

Neural signals are crucial in clinical research for understanding brain functions and the pathophysiology of various neurological disorders. This research can lead to the development of new diagnostic tools and treatments.

6. Rehabilitation:

Neurofeedback is a type of biofeedback that uses real-time displays of brain activity—most commonly EEG—to teach self-regulation of brain function. It is used in the treatment of ADHD, depression, anxiety, epilepsy, and PTSD.

7. Pain Management:

Transcutaneous Electrical Nerve Stimulation (TENS) uses low-voltage electrical current for pain relief, which is believed to work by blocking the transmission of pain signals along nerves and/or stimulating the production of endorphins, the body's natural painkillers.

Chapter Two

Literature Review

Chapter Two

2.1 Electrical Neural Interfaces

Electrical neural interfaces provide a connection between an individual's nervous system to an electronic circuit. These interfaces facilitate the bidirectional exchange of information between neurons or other components of the nervous system and external electronic systems.

Continuous technological progress in this field has provided more powerful tools for studying, restoring, and enhancing neural functions. However, the intricate nature of the nervous system poses significant challenges in crafting, developing, and integrating these functional devices at the system level.

2.1.1 Neural Interfaces Components

A) tissue interface: the part that directly interacts with neural tissues, such as neurons and other cells. It serves as the physical interface between the electronic components of the device and the biological structures within the nervous system. The tissue interface is responsible of both the detection of signals and stimulation between the electronic circuitry and the neural cells. Depending on the type of neural interface and its intended application, the tissue interface can take various forms, such as electrodes, microelectrode arrays, optical fibers and chemical sensors.

B) sensing interface: the component responsible for detecting and capturing neural signals. It acts as a bridge between the tissue interface (which interacts with the neural tissues) and the processing unit (which interprets and manages the recorded signals). The sensing interface plays a crucial role in ensuring the accurate and reliable capture of neural activity, including a neural signal acquisition module for signal amplification and digitization, and/or a neural stimulation module to elicit the activities of a neuron.

C) neural signal processing unit: the component responsible for analyzing, interpreting, and spike sorting which typically consists of a sequence of steps, including band-pass filtering the data, detection of threshold-crossing events, feature extraction of the spike shapes, and clustering of the waveforms, Figure 2.1 illustrates the Neural interface components.

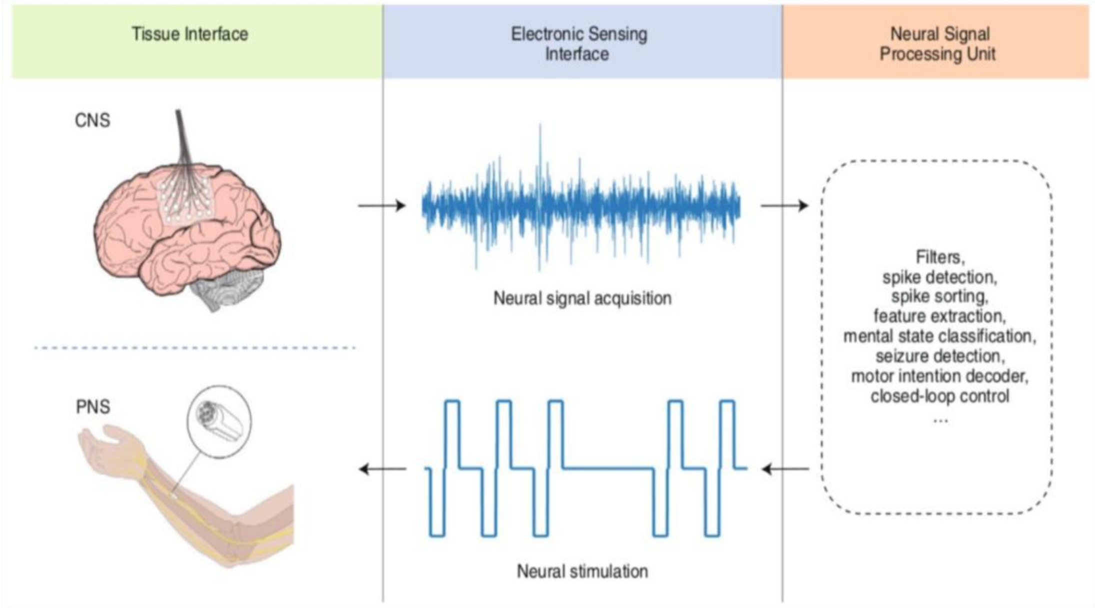


Figure 2.1 Neural Interface Components [13]

2.1.2 Interface Electrode types

There are several types of electrodes commonly used in ENG recordings [8 , 9], most common are:

1. Surface Electrodes: Surface electrodes are the most commonly used type in ENG measurements. These electrodes are placed on the surface of the skin, directly above the nerve being measured. They detect the electrical signals produced by the nerves and transmit them to the recording equipment. As shown in figure 2.2, Surface electrodes can be either disc electrodes or adhesive electrodes. Disc electrodes are small metal or silver chloride plates with a conductive gel or paste applied to the skin interface. Adhesive electrodes, on the other hand, have a conductive adhesive gel already applied to the electrode surface, allowing for easy attachment and removal. Surface electrodes are suitable for measurements that require good signal quality and are relatively easy to use.

   The use of conductive gel improves the quality of the recorded signals, and creates a better connection between the electrode and the skin, leading to cleaner and more reliable signal acquisition and helps to prevent any discomfort or irritation that may arise from direct contact between the electrode and the skin

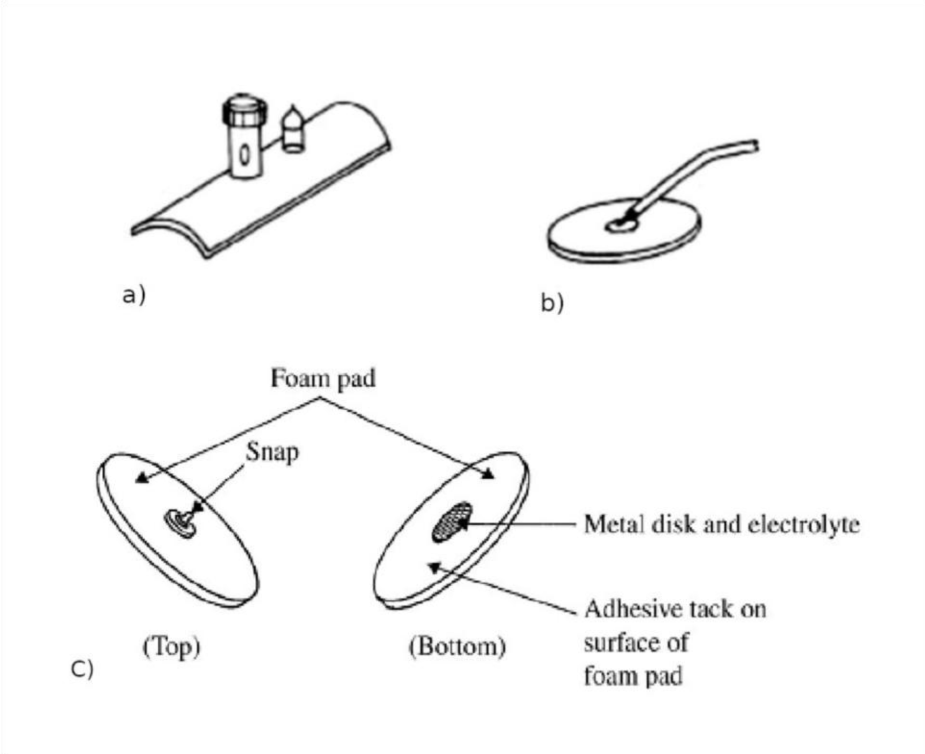


Figure 2.2 Surface ENG electrode

2. Needle Electrodes: also known as intramuscular electrodes, are used to measure the electrical activity within the muscle tissue. They consist of a thin, insulated needle with a metal or platinum recording electrode at the tip. The needle electrode is inserted directly into the muscle, allowing for precise measurements of muscle activity. Needle electrodes are commonly used in electromyography (EMG) studies, which assess the health and function of the muscles and the nerve supply to those muscles. Needle electrodes can provide more detailed information about nerve and muscle activity compared to surface electrodes.
3. Subdermal Needle Electrodes: are similar to needle electrodes but are inserted just beneath the skin instead of into the muscle tissue. They are used to measure the electrical activity of sensory nerves in the skin.
   Subdermal needle electrodes are typically used in nerve conduction studies (NCS) to assess the function and integrity of sensory nerves.

4. Cuff Electrodes: it is a type of neural interface device that consists of a tube or cuff placed around a nerve to record or stimulate neural activity. The cuff electrode typically has active sites attached to the inside of the cuff wall, which

make contact with the outer layer of the nerve (epineurium). The cuff electrode is designed to selectively interact with the nerve it encircles, allowing for the recording of extracellular potentials or the delivery of electrical stimulation to the nerve fibers. The design of the cuff electrode, including the number and size of active sites, influences its selectivity and effectiveness in interfacing with specific nerve fibers within the nerve trunk [11].

5. Ring Electrodes: also known as concentric electrodes, are used to measure the electrical activity of individual nerve fibers. They consist of a small metal ring with a small diameter, which is placed around a single nerve fiber. The ring electrode detects the electrical signals generated by the nerve fiber and provides detailed information about the activity of that specific fiber. Ring electrodes are commonly used in single-fiber electromyography (SFEMG) studies to assess nerve function in conditions such as myasthenia gravis.

It is important to note that the choice of electrode type depends on the specific ENG measurement being performed and the goals of the study. Different electrode types have advantages and disadvantages in terms of signal quality, invasiveness, and ease of use. Additionally, electrode placement and proper skin preparation are crucial for obtaining accurate and reliable measurements.

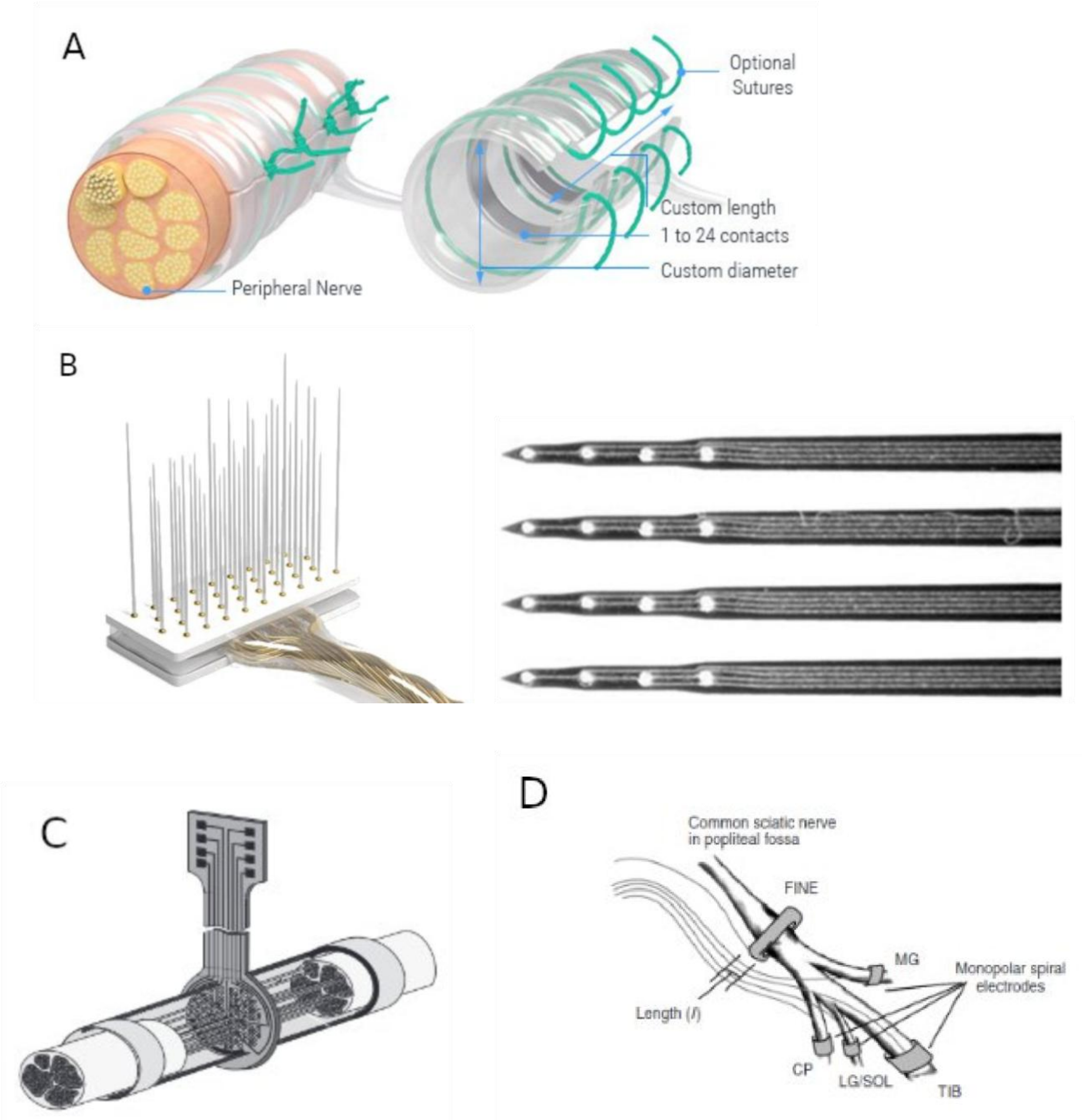


Figure 2.3Different types of electrodes for PNS interface [12]

A) Cuff-Electrode B) Microelectrode needle array

C) Regenerative electrode.

D) Flat-interface nerve electrode (FINE)

The choice of electrodes significantly influences the precision and quality of the recorded signals, making it a critical aspect of neurophysiological investigations. In the realm of ENG, the various types of electrodes each have distinct characteristics and applications. Electrodes are usually characterized [3] by parameters like:

- Input impedance
- resistance towards electromagnetic interference (EMI)
- sensitivity towards artifacts
- signal to noise power ratio (SNR)
- electrode size
- spatial resolution

The nerve cuff electrode still has an unrivalled position as a tool for recording ENG signals from peripheral nerves One particular advantage of the cuff electrode is that the electrode is generally immune to noise sources that are lateral to the nerve and cuff electrode since they produce electrical fields that are shielded by the nerve cuff and shorted by the circumferential recording site of the electrode. However, noise sources producing electrical fields that are perpendicular produce a gradient through the nerve cuff, which is amplified by the bipolar recording configuration. [10, 13]

2.1.3 Neural Interfaces Categories

Based on technical milestones in the development of the sensing interface, neural interfaces can be roughly divided into four distinct generations [14]:

1. First Generation: simple Electrodes, The earliest neural interfaces involved basic electrodes for recording neural signals. these were primarily operated invitro such as the use of the patch clamp technique on neuron samples, or the use of surface electrodes in EEG or EMG.
2. Second Generation: Microelectrode Arrays or multi-channel neural interfaces which enabled in-vivo experiments, but the types of experiments that could be conducted were limited by the cable used to connect the in-vivo electrodes and the workstation for data acquisition, signal processing and control. These devices alleviated the work of sample preparation in the patch-clamp technique and allowed direct wired communication to living subjects.
3. Third Generation: Implantable Devices that marked a significant advancement, allowing for long-term monitoring and interaction with the nervous system. These implantable interfaces were designed to be compact, cable-free devices and allowed for wireless communication of control signals and data. this generation introduced

on-chip neural signal processing and feature extraction, the ability to process signals and extract discriminative features.

4. Fourth Generation: Integrated neural interfaces which involves interfaces that enable bidirectional communication between the brain and external devices. BMIs hold promise for applications in prosthetics, neurorehabilitation, and neuroprosthetics.

2.1.4 Neural Interface Signal Processing

The next step after sensing and amplifying neuron signals, is processing the signal, by first de-noising using bandpass filter, followed by threshold-crossing and conversion from analogue to digital via ADC and then lastly the signals are processed and analysed for spikes feature extraction [13] .

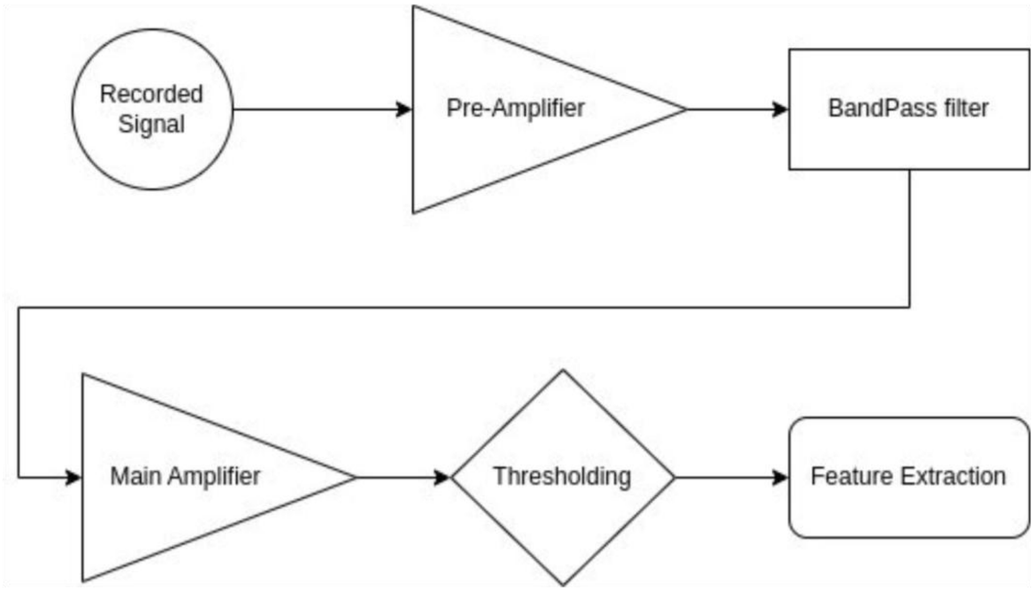


Figure 2.4 Neural Interface Processing system [13]

2.2 Filters Taxonomy

Filters are essential components in various signal processing and communication systems. They are used in a wide range of applications, including channel equalization, noise reduction, audio and video processing, biomedical signal processing, and financial data analysis.

Filters serve several primary functions, including attenuating a specific frequency band (low-pass, high-pass, and band-pass filters) from a signal, decomposing a signal into sub-bands (filter-banks, graphic equalizers, sub-band coders, frequency multiplexers), modifying the frequency spectrum of a signal (telephone channel equalization, audio graphic equalizers), and modelling the input-output relationship of systems (telecommunication channels, human vocal tract, music synthesizers).

Filters can be classified based on different criteria, such as:

· Linear filters versus nonlinear filters.
· Time-invariant filters versus time-varying filters.
· Adaptive filters versus non-adaptive filters.
· Recursive versus non-recursive filters.
· Direct-form, cascade-form, parallel-form, and lattice structures.

Each classification has its own characteristics and advantages, and the choice of filter type depends on the specific application and requirements.
There are many different types of filters, each with its own specific purpose. Figure 2.5 shows some of the most common types of filters used in neural signal processing include:

a) Low-pass filters remove high-frequency noise from a signal. This type of filter is often used to remove electrical noise from neural signals.
b) High-pass filters remove low-frequency noise from a signal. This type of filter is often used to remove muscle activity from neural signals.
c) Band-pass filters remove frequencies outside of a specified range. This type of filter is often used to isolate specific frequency bands of interest.
d) Band-stop filters remove frequencies within a specified range.This type of filter is often used to remove interference from a signal.

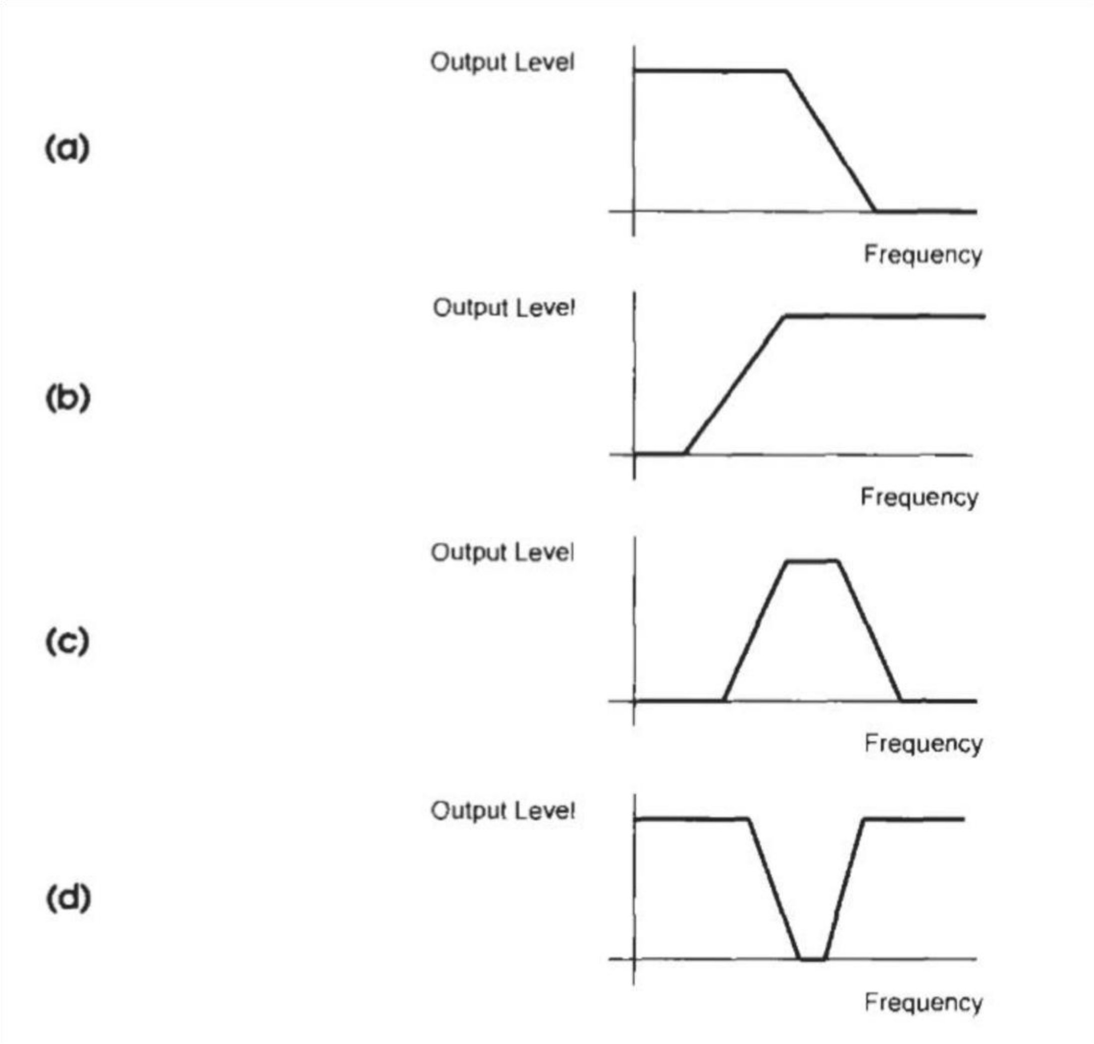


Figure 2.5 Common Filter Types:
a) Low-pass filter, b) High-pass filter, c) Band-pass filter,
d) Band-stop filter

The function of a filter is determined by its frequency response. The frequency response of a filter is a plot of the filter's output amplitude as a function of frequency. The frequency response of a filter can be used to determine the types of noise that the filter will remove from a signal.

The noise that is eliminated by a filter is called the filter's rejection band.The rejection band of a filter is the range of frequencies that the filter will not pass.The width of the rejection band is determined by the filter's bandwidth.The bandwidth of a filter is the range of frequencies that the filter will pass.

The effectiveness of a filter in removing noise from a signal is determined by its order. The order of a filter is the number of mathematical operations that are performed on the signal to produce the filtered output. The higher the order of a filter, the more noise it will remove from a signal. However, higher-order filters are also more computationally expensive.

Filters are an essential tool for neural signal processing. They are used to remove noise and other artifacts from neural signals, making them easier to interpret. There are many different types of filters, each with its own specific purpose. The choice of filter for a particular application will depend on the types of noise that need to be removed from the signal.

The Analogue and Digital are explained with detail in the subsections bellow:

2.2.1 Analogue Filters:

Analogue filters are electronic circuits that process continuous-time signals. These filters use passive components (such as resistors, capacitors, and inductors) and active components (such as operational amplifiers) to modify or extract specific frequency components of a signal. Analog filters have been widely used in various applications, including audio amplification, radio communication, and analog signal processing.

There are several types of analog filters, including low-pass filters, high-pass filters, band-pass filters, and band-stop filters. These filters are characterized by their frequency response, which describes how they attenuate or pass different frequency components of a signal.

Analog filters have some advantages over digital filters, such as their ability to handle continuous-time signals without the need for sampling and their potential for higher precision and accuracy. However, analog filters are limited by factors such as component tolerances, temperature drift, and sensitivity to noise.

2.2.2 Digital Filters:

Digital filters are a type of signal processing filters that operate on discrete-time signals [15], such as those obtained from digital systems or sampled analog signals. These filters use mathematical algorithms to modify or extract specific components of a signal. Digital filters have several advantages over analog filters, including flexibility, accuracy, and ease of implementation.

The advantages of digital filters compared to analog filters are as follows:

1. Flexibility: Digital filters offer greater flexibility in designing and modifyingfilter characteristics. The filter coefficients can be easily adjusted to achieve the desired frequency response and filter performance. This flexibility allows for precise control and manipulation of signals.
2. Precision: Digital filters operate on discrete samples, allowing for highaccuracy and resolution compared to analog filters. They can achieve precise control over the filter response, leading to better signal processing and filtering performance.
3. Reproducibility: Digital filters can be implemented using software orhardware, allowing for easy replication and reproducibility of filter designs. The same filter design can be applied to different signals or systems without physical modifications. This reproducibility is especially useful in applications that require consistent and reliable filtering performance.
4. Stability: Digital filters can be designed to be stable and robust, ensuringconsistent performance over time. Stability analysis and control techniques can be applied to digital filters to guarantee their stability. In contrast, analog filters may be susceptible to component variations and environmental factors that can affect their stability.
5. Versatility: Digital filters can be easily implemented and integrated withother digital signal processing algorithms and systems. They can be combined with various techniques such as windowing, oversampling, and adaptive filtering to enhance performance. This versatility makes digital filters suitable for a wide range of applications.
6. Signal Processing Techniques: Digital filters provide access to a wide rangeof advanced signal processing techniques, such as fast Fourier transform (FFT), multirate signal processing, and adaptive filtering. These techniques can enhance the performance and capabilities of digital filters in various applications.

7. Cost and Size: Digital filters can be implemented using software algorithmson general-purpose processors or dedicated digital signal processors (DSPs). This eliminates the need for costly and bulky analog components, leading to cost savings and smaller system sizes.

8. Filter Design Tools: Digital filter design tools and software libraries arewidely available, making it easier to design and implement digital filters. These tools provide a graphical interface for designing filters and offer various optimization techniques to achieve desired filter characteristics efficiently.

Types of digital filters

There are two main types of digital filters: Finite Impulse Response (FIR) filters and Infinite Impulse Response (IIR) filters.

FIR Filters:

FIR filters are characterized by a finite impulse response, meaning that the filter's output depends only on the current and previous input samples. FIR filters are implemented using convolution, where the filter coefficients are convolved with the input signal. They have a linear phase response, which means that all frequency components of the signal are delayed by the same amount.

FIR filters have several desirable properties, such as stability, linear phase response, and the ability to have a sharp cutoff in the frequency domain. They are commonly used in applications that require precise control over the frequency response, such as audio and video processing, image filtering, and communication systems, Figure 2.6 .

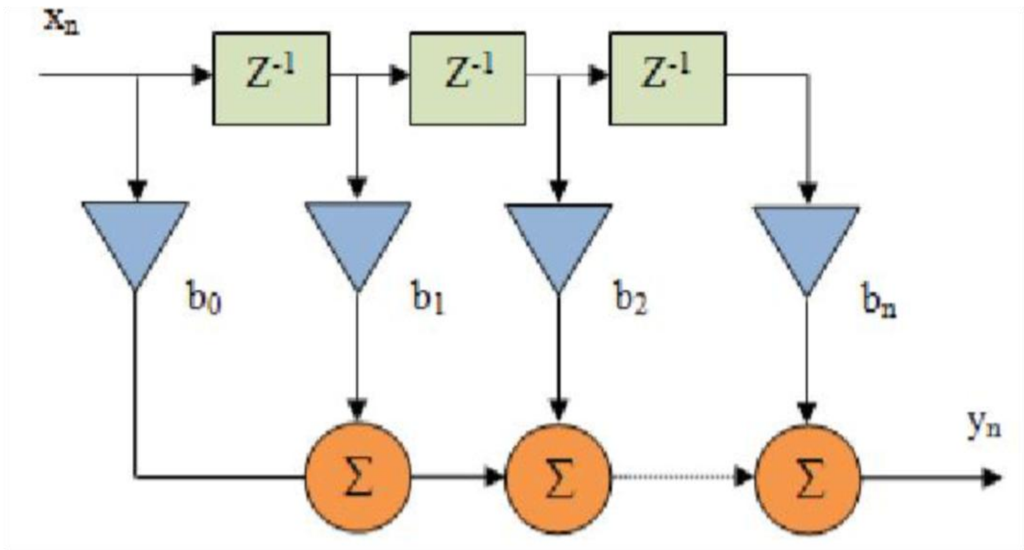


Figure 2.6 FIRfilterblockdiagram

IIR Filters:

IIR filters are characterized by an infinite impulse response, meaning that the filter's output depends on the current and previous input samples as well as the previous output samples. IIR filters are implemented using recursive equations, where the output is a linear combination of the input and previous output samples.

IIR filters have a feedback loop, which allows them to achieve a desired frequency response with fewer coefficients compared to FIR filters. They are commonly used in applications that require compact filter designs, such as audio equalization, biomedical signal processing, and control systems Figure 2.7 .

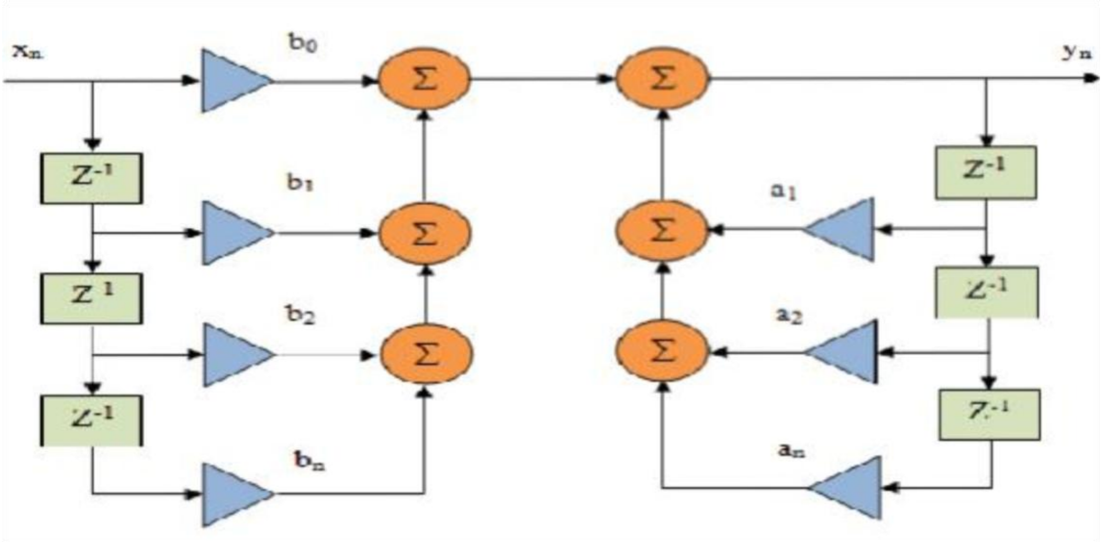


Figure 2.7 IIR filter block diagram

In the context of ElectroNeuroGram (ENG), an IIR filter can be used to process and analyze the signals obtained from neural activity recordings. ENG refers to the measurement and analysis of electrical signals generated by the nervous system, particularly the brain and peripheral nerves. These signals can provide valuable information about neural activity and can be used in various applications such as studying brain function, diagnosing neurological disorders, and controlling prosthetic devices [16].

The IIR filter can be applied to the recorded ENG signals to remove noise, unwanted frequencies, or artifacts, and enhance the desired neural signals. This filtering process helps to improve the accuracy and reliability of the recorded data, making it easier to extract meaningful information from the signals. The specific design parameters of the IIR filter, such as filter order, cutoff frequency, and filter type, can be adjusted based on the characteristics of the ENG signals and the desired filtering goals [17].

Differences between IIR and FIR filters:

1. Frequency Response:
   - IIR filters can achieve sharper roll-off and steeper transition bands compared to FIR filters for the same filter order.

   - FIR filters have linear phase response, which means they introduce minimal phase distortion in the filtered signal. IIR filters, on the other hand, have a non-linear phase response, which can introduce phase distortions.

2. Filter Order and Complexity:

   - IIR filters generally require fewer coefficients (lower order) compared to FIR filters to achieve a similar frequency response.
   - FIR filters have a fixed order determined by the number of coefficients, while IIR filters can have an arbitrary order due to the feedback mechanism.
3. Stability:
   - FIR filters are inherently stable because they do not have any feedback. They are less prone to oscillations and can handle a wider range of input signals without instability issues.

- IIR filters can be unstable if the poles of the transfer function are located outside the unit circle in the Z-plane. Careful design and analysis are required to ensure stability.

4. Implementation:
  - FIR filters are typically implemented using a simple linear convolution operation, making them computationally efficient.
  - IIR filters require recursive calculations due to the feedback mechanism, which can be computationally more complex and may require more processing resources.

5. Transient Response:
  - FIR filters have a finite impulse response, which means they settle to zero after a finite number of samples. This results in a zero transient response.
  - IIR filters, on the other hand, have an infinite impulse response, which can result in a non-zero transient response that takes longer to settle.

2.2.3 Frequency response characteristics

Filter response characteristics refer to the behaviour of filters that process signals, typically in the context of electronic engineering or signal processing. Here are several key characteristics of filters:

1. Frequency Response: This describes how a filter attenuates or amplifiessignals of different frequencies. It's usually displayed graphically in a Bode plot, showing the gain or loss in dB as a function of frequency.

2. Passband: The range of frequencies that a filter allows to pass through withminimal attenuation. For a low-pass filter, this would be from 0 Hz up to a certain cutoff frequency. For a high-pass filter, it would start from a cutoff frequency and extend to higher frequencies.
3. Stopband: Frequencies outside the passband that the filter significantlyattenuates. Ideally, a filter would completely reject these frequencies, but in practical designs, there is often some leakage.

4. Cutoff Frequency: The frequency at which the filter starts to significantlyattenuate the signal. For example, a -3 dB point is commonly used as the cutoff frequency.

5. Roll-off Rate: This is the rate at which the filter attenuates frequenciesoutside the passband. It is usually measured in decibels per octave or decibels per decade (10x frequency increase).

6. Phase Response: The change in phase of the signal as it passes through thefilter. This characteristic is important in applications where the timing of the signal is critical.

7. Ripple: The variation in the filter's attenuation in the passband or stopband.In some filters, such as Chebyshev filters, some ripple is allowed in exchange for sharper roll-off characteristics.

8. Group Delay: It is the derivative of the phase response and represents thetime delay of the signal as it passes through the filter. Uniform group delay is often desirable to avoid signal distortion.
9. Impulse Response: It depicts how the filter responds to a very short inputsignal (an impulse). This can provide insights into the temporal characteristics of a filter and its stability.

10. Pole-Zero Plot: This graphical representation shows the locations of polesand zeros of the filter's transfer function in the complex frequency plane, providing insight into the filter's behavior and stability.

Each filter type (Butterworth, Chebyshev, Bessel, Elliptic, etc.) has a different set of these characteristics that make them suitable for different applications.

1- The Butterworth filter is a type of signal processing filter designed to have a frequency response as flat as possible in the passband. It is characterized by a maximally flat magnitude response in the passband.

2- The Chebyshev filters are designed to have a frequency response that ripples in the passband. They offer steeper roll-off compared to Butterworth filters, at the expense of passband ripple. Chebyshev filters come in two variants – Type I and Type II.

3- The Elliptic filter is also known as Cauer filter, the elliptic filter offers the sharpest transition between the passband and the stopband among the four types. It achieves this by allowing ripples in both the passband and stopband.

4- The Bessel filter is known for its maximally flat group delay characteristics in the passband, making it suitable for applications where pulse distortion needs to be minimized.

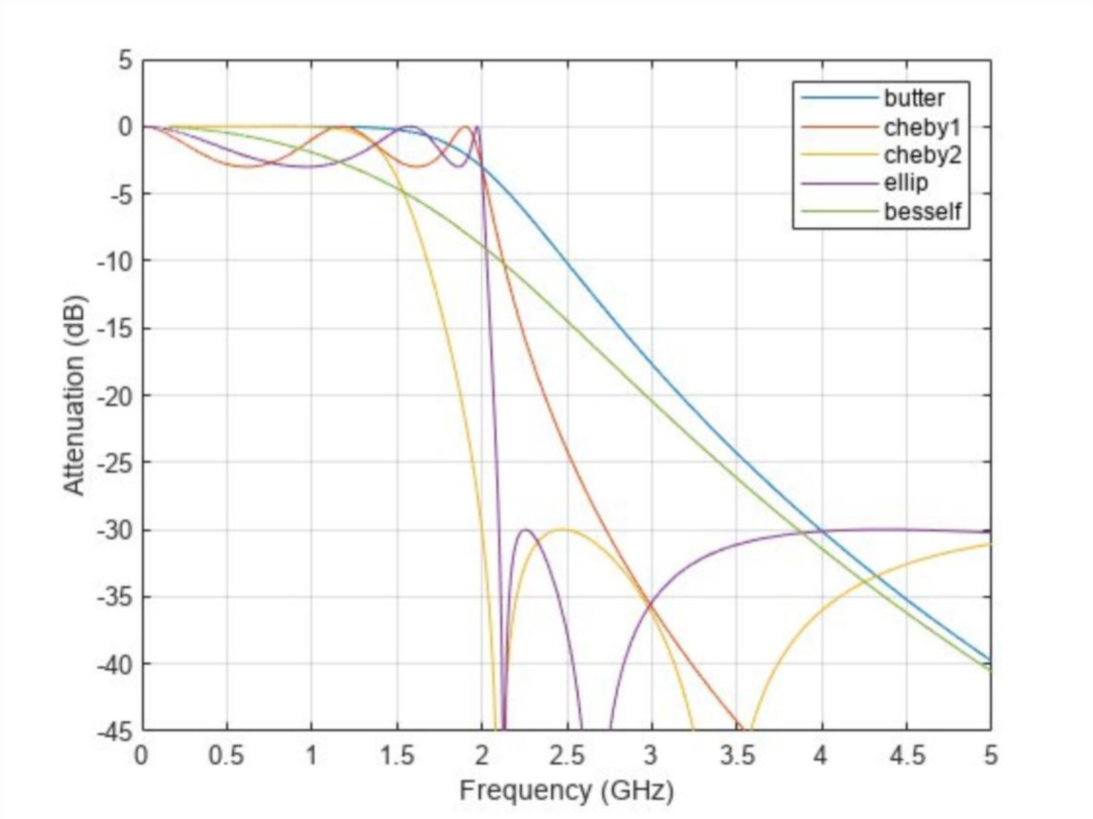


Figure 2.8 Comparative plots of filter response characteristics

Chapter Three

Designing AP Detection System Using Bandpass Filters

Chapter Three

Methodology

In this chapter we are going to outline the step-by-step process we'll use to handle neuron action potential signals. This involves practical approaches like filtering, processing, and analysis. We'll be using MATLAB to create a system for processing and detecting our action potential signals.

3.1 Our Recorded Signals

Here we show our recorded signals, in figures 3.1, 3.2, 3.3 and 3.4

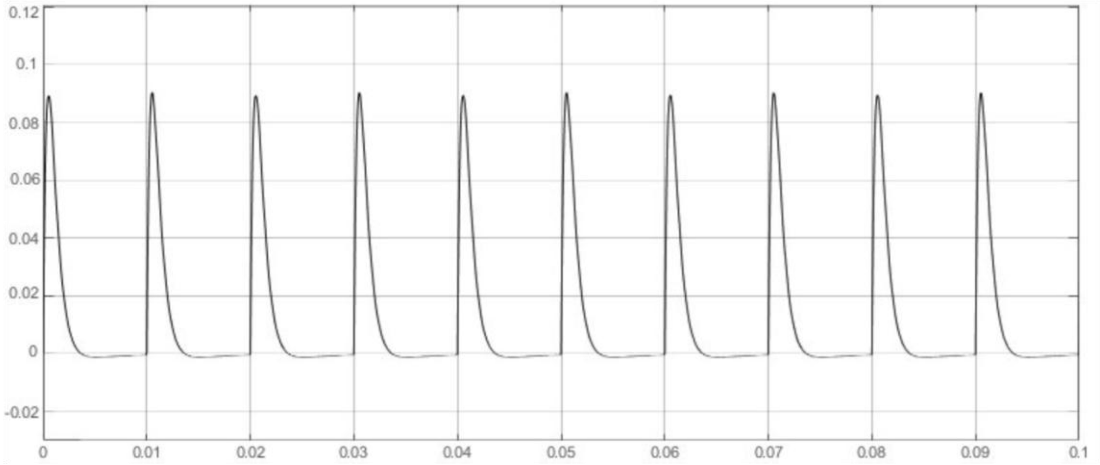


Figure 3.1 Target PNS Motor Neural signal

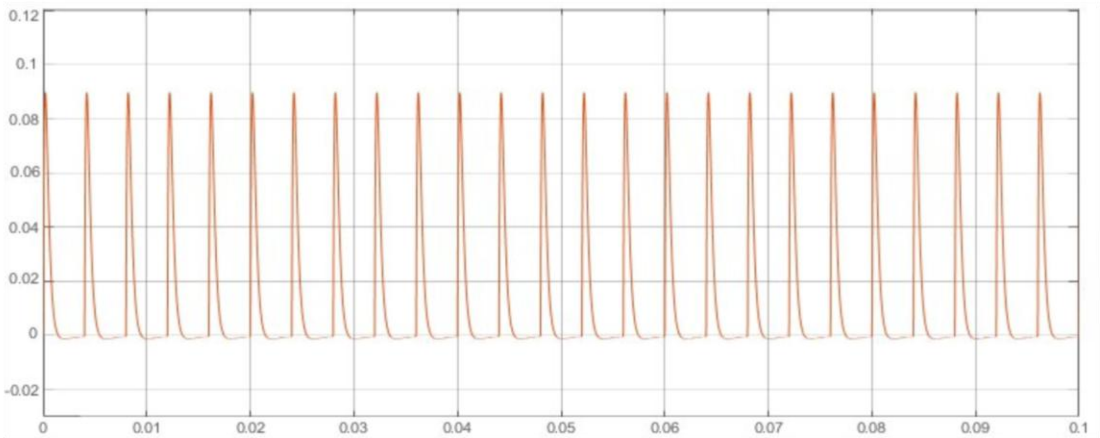


Figure 3.2 2nd Neural Signal

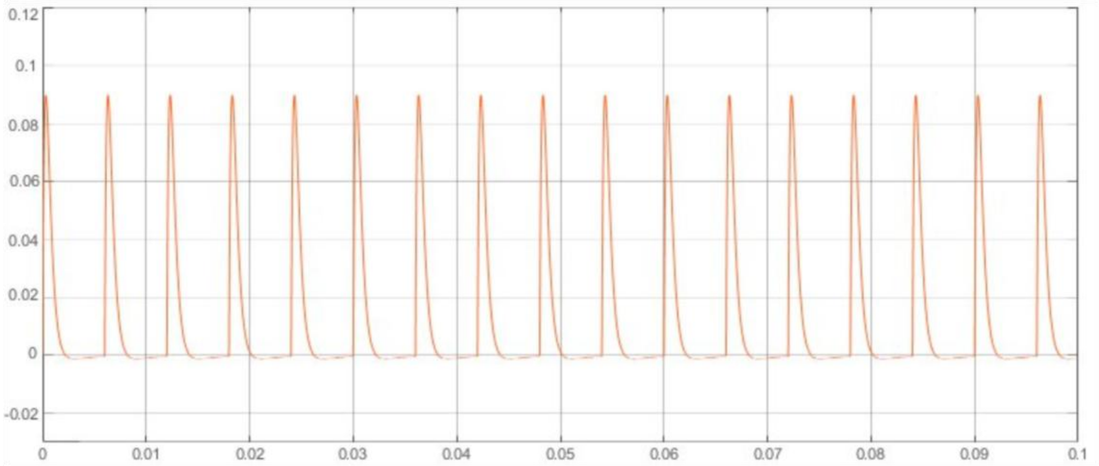


Figure 3.3 3rd Neural Signal

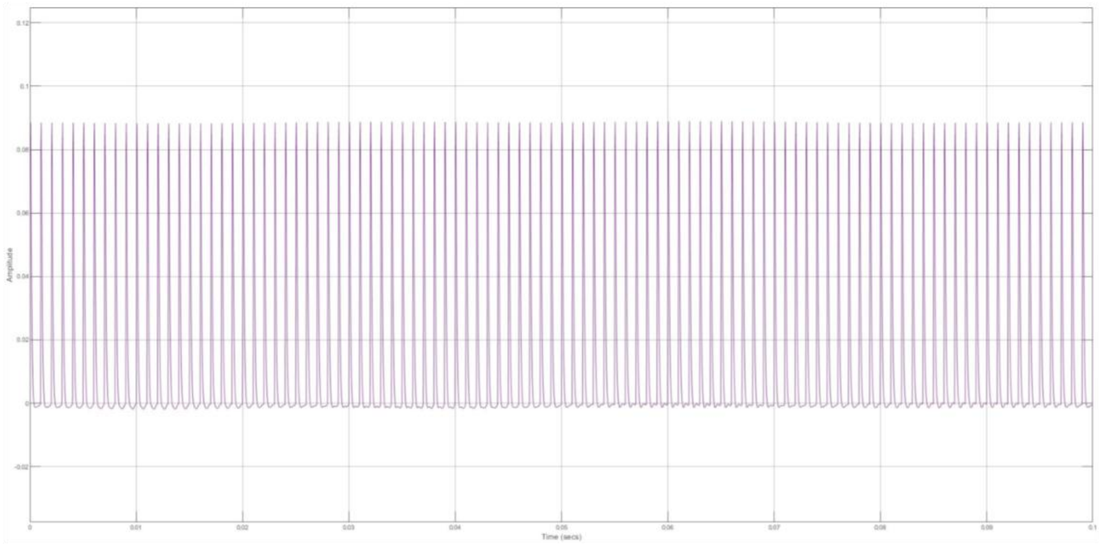


Figure 3.4 4th Neural Signal Analysing the frequency spectrum of our signals, figures 3.5, 3.6, 3.7 and 3.8:

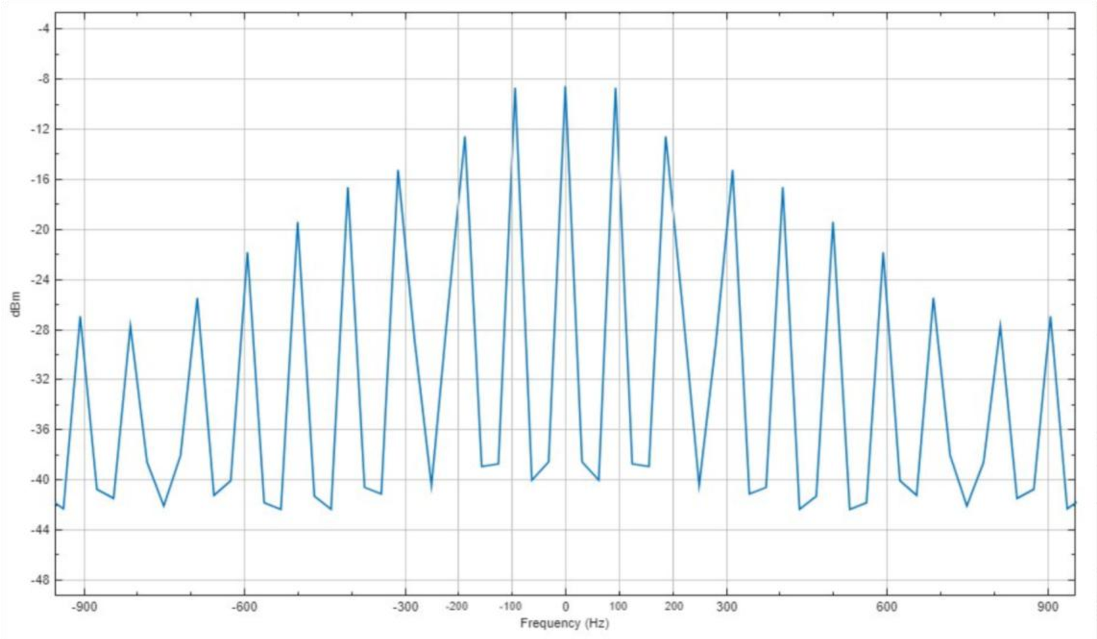


Figure 3.5 Target PNS Motor Neural signal Frequency Spectrum

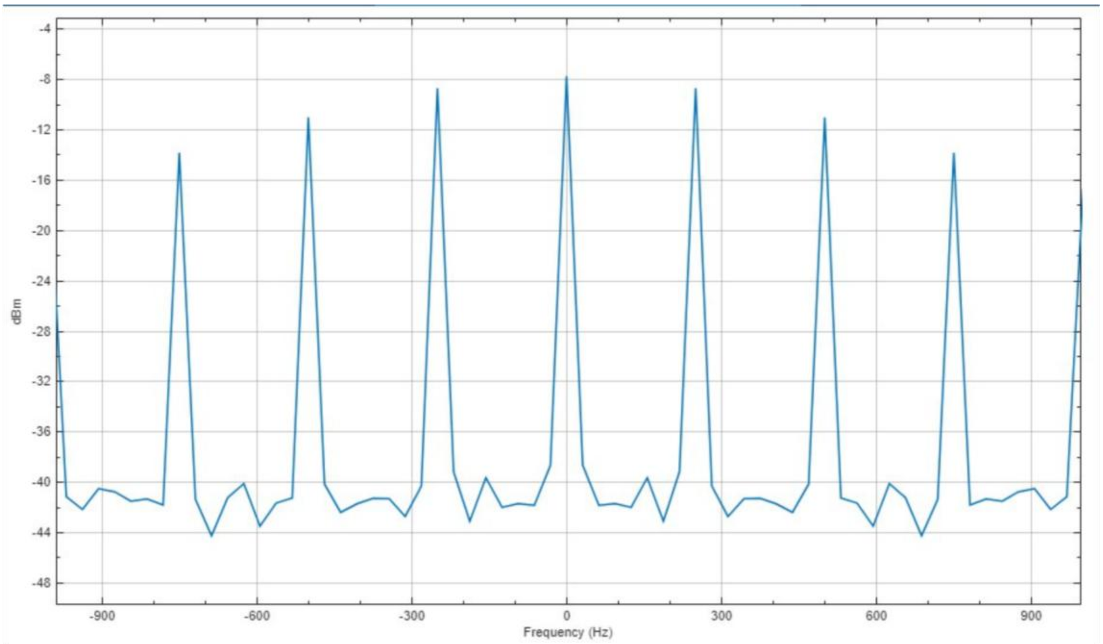


Figure 3.6 2nd Neural signal Frequency Spectrum

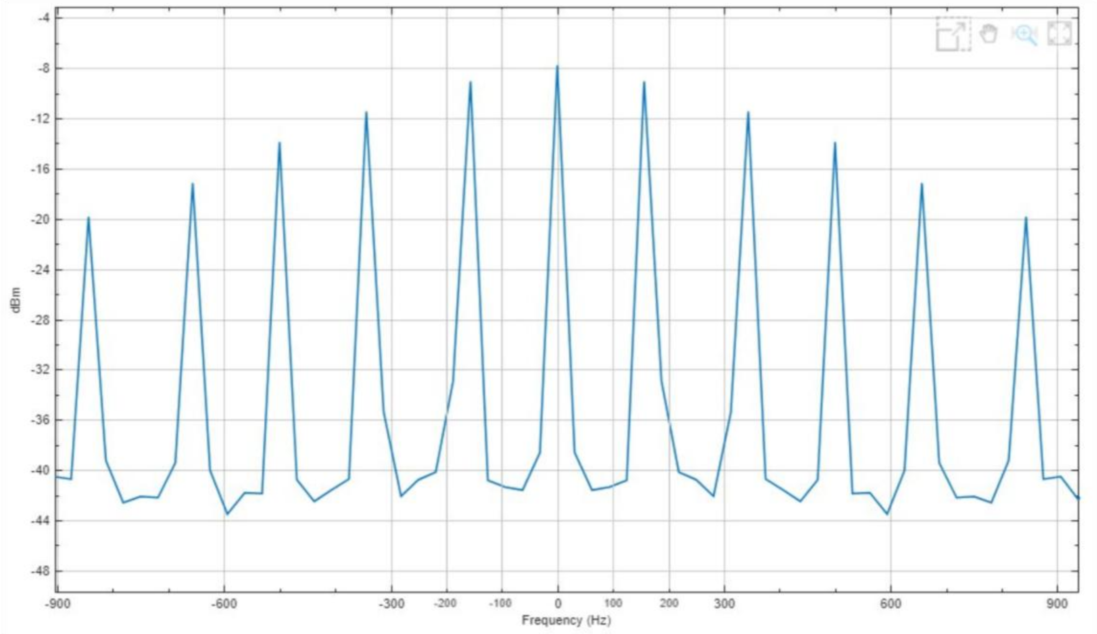


Figure 3.7 3rd Neural signal Frequency Spectrum

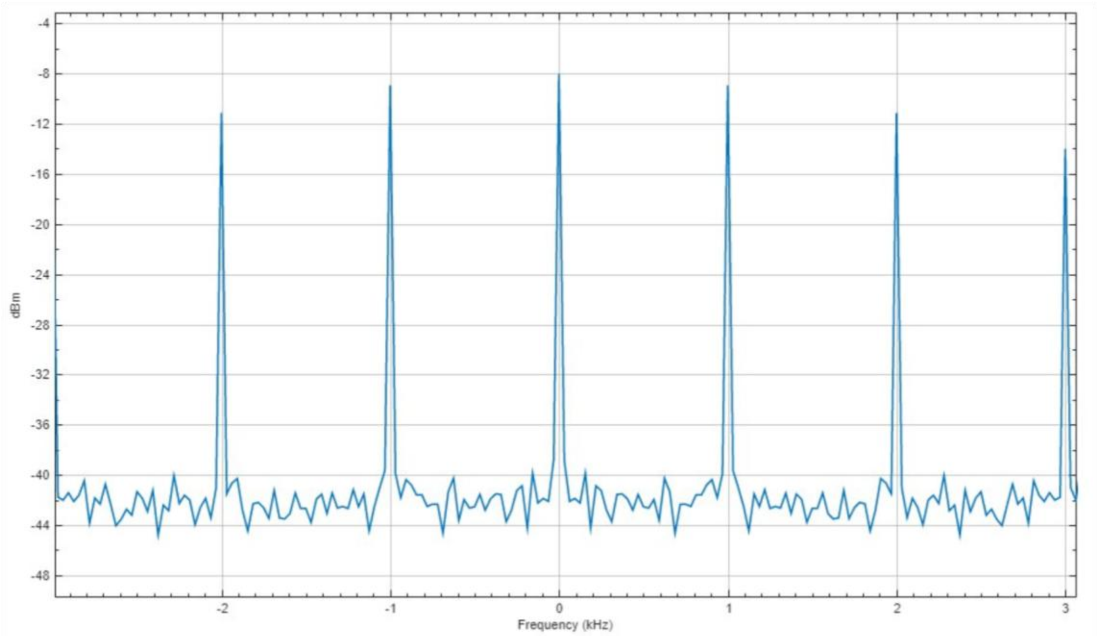


Figure 3.8 4th Neural signal Frequency Spectrum

3.2 Analysis of our signals

Analysis of the frequency spectrums shows that: our target signal has a peak at 100 Hz and decreasing harmonics at 200 Hz and
300 Hz,

while the 2nd Neuron Action Potential signal has a peak around 250 Hz, the 3rd signal has a peak at 150 Hz and 4th signal has a peak at 1 kHz and 2 kHz.

Therefore we will use a bandpass filter with a centre frequency at 100 Hz, and bandwidth of 20 Hz, and we will use a steep cut-off.

3.3 Designing system

Our proposed detection system will use a Bandpass filter that extracts only our desired features, followed by an amplifier and a threshold:

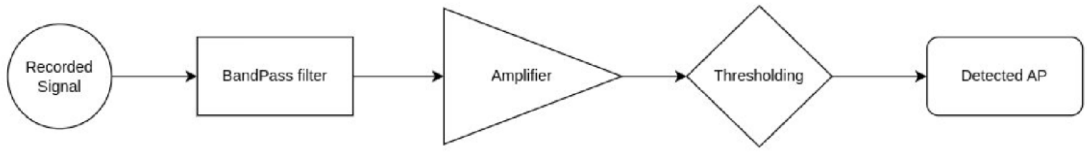


Figure 3.9 Proposed Action Potential detection system

3.4 Selecting Bandpass filter type

Matlab offers a wide selection of both FIR and IIR filters, for our purposes we will use an IIR filter because the require far less coefficients, meaning lower filter order and processing cost.

The IIR filters available:

1. Butterworth.
2. Chebyshev Type I.
3. Chebyshev Type II.
4. Elliptic.
5. Least Pth-norm.
6. Constrained Least Pth-norm.

To select which filter we are going iterate through each filter and compare the order requirement, magnitude response and output gain. we will be using Matlab filter design and analysis tool to create and compare different filters.

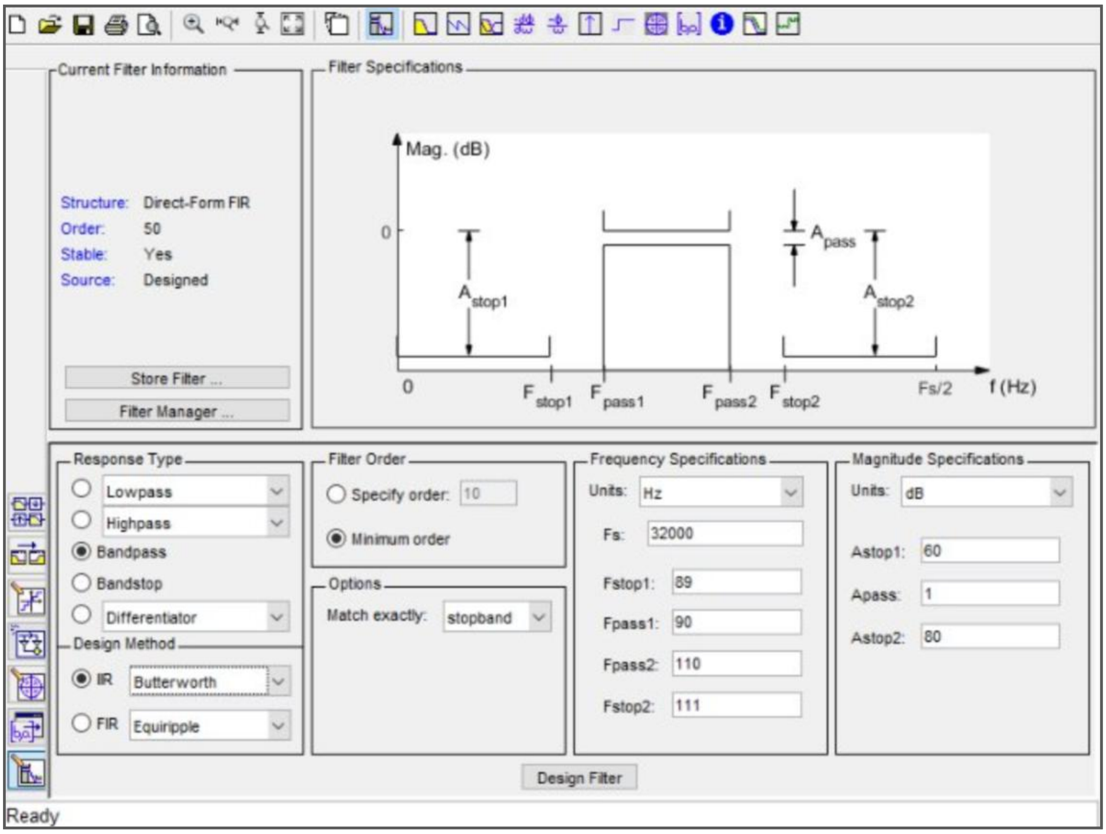


Figure 3.10 Matlab filter design tool

1. Butterworth Filter:

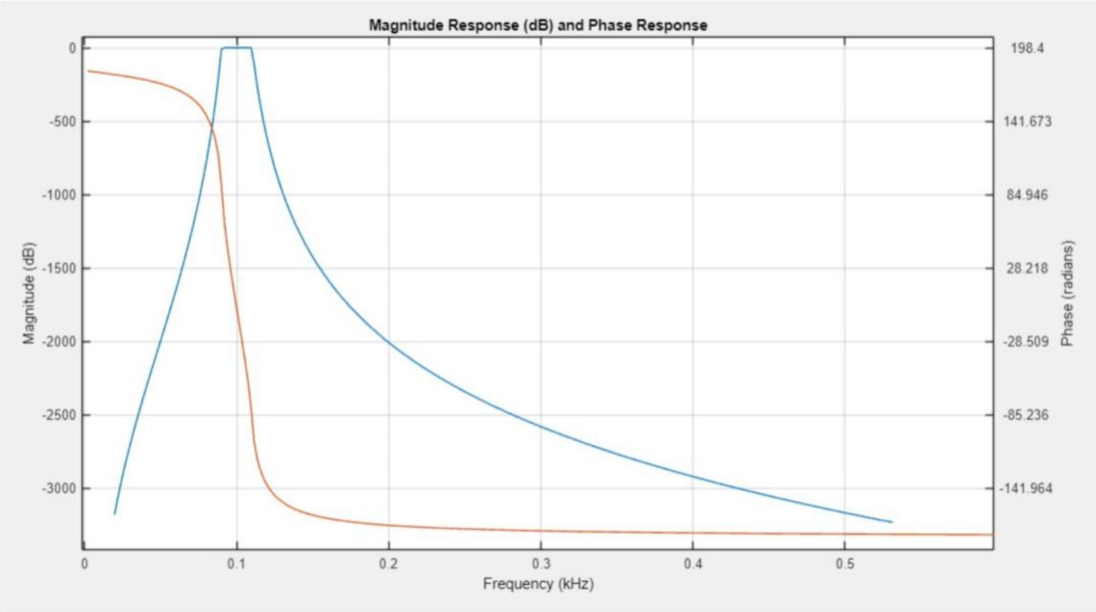


Figure 3.11 Butterworth filter Magnitude and phase response plot
(blue is magnitude response, and yellow is phase response)

Structure:	Direct-Form II, Second-Order Sections
Order:	230
Sections	115
Stable:	Yes
Source:	Designed

Figure 3.12 Butterworth filter Order and Section count

The Butterworth filter is the first option in IIR filters, even with matlab automatically deciding the least order we still require an order of 230 to achieve our specified range and cut-off slope.

2. Chebyshev Type I Filter:

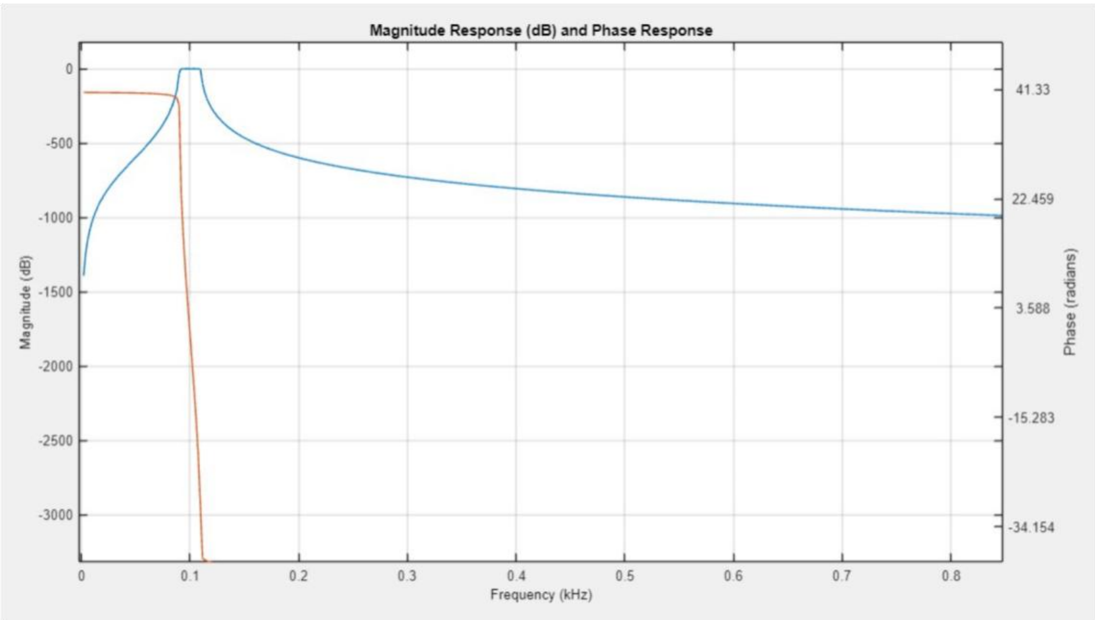


Figure 3.13 Chebyshev Type I filter Magnitude and phase response plot

Structure:	Direct-Form II, Second-Order Sections
Order:	52
Sections	26
Stable:	Yes
Source:	Designed

Figure 3.14 Chebyshev Type I filter Order and Section count

Next is the Chebyshev Type I Filter. which requires an order of 52, which is significantly lower than Butterworth, the result is a less steep drop (more gradual) than butterworth.

3. Chebyshev Type II Filter:

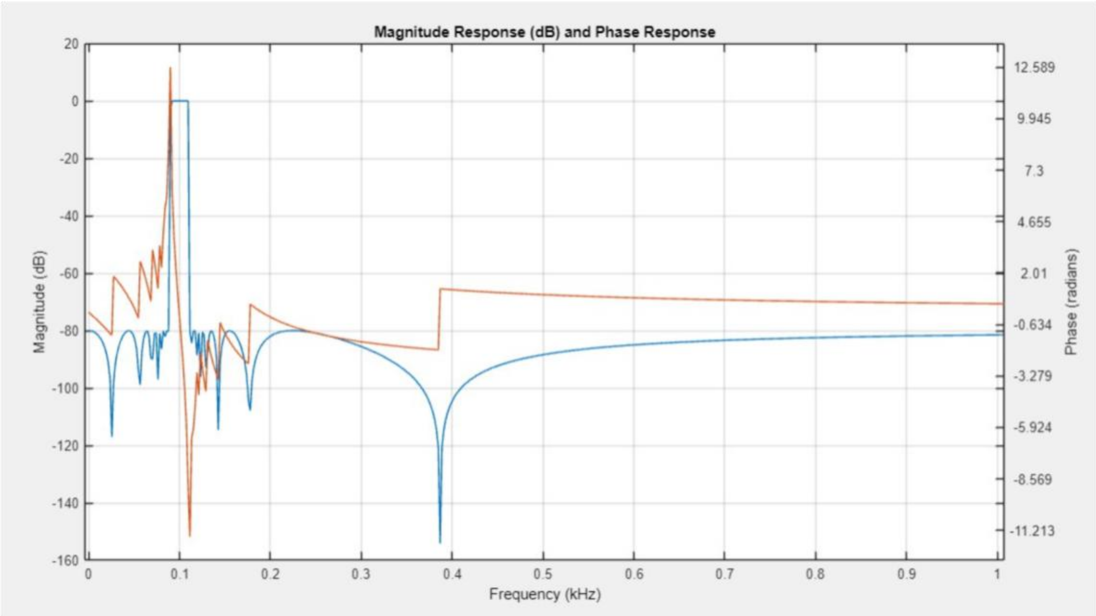


Figure 3.15 Chebyshev Type II filter Magnitude and phase response plot

Structure:	Direct-Form II, Second-Order Sections
Order:	52
Sections:	26
Stable:	Yes
Source:	Designed

Figure 3.16 Chebyshev Type II filter Order and Section count

Then the Chebyshev Type II filter which also required an order of 52. which results in a very steep drop off but has ripple in pass band.

4. Elliptic Filter:

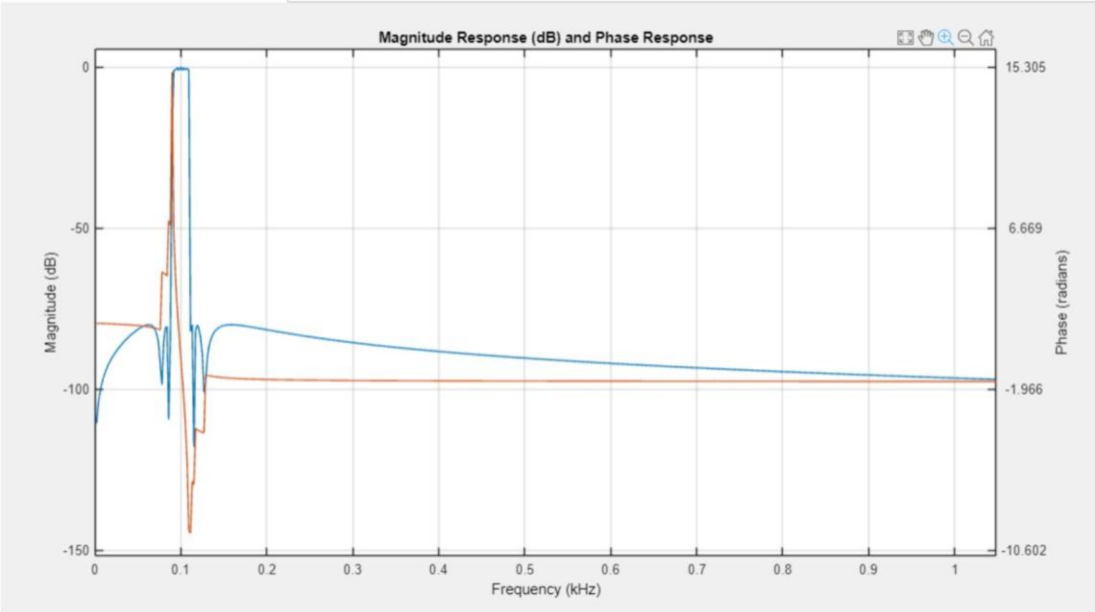


Figure 3.17 Elliptic filter Magnitude and phase response plot

Structure:	Direct-Form II, Second-Order Sections
Order:	22
Sections	11
Stable:	Yes
Source:	Designed

Figure 3.18 Elliptic filter Order and Section count

Afterwards we have the Elliptic filter required an order of 22. which also has a steep response but has less ripple in cutt off region and minuscule pass band ripple.

5. Least Pth-norm Filter:

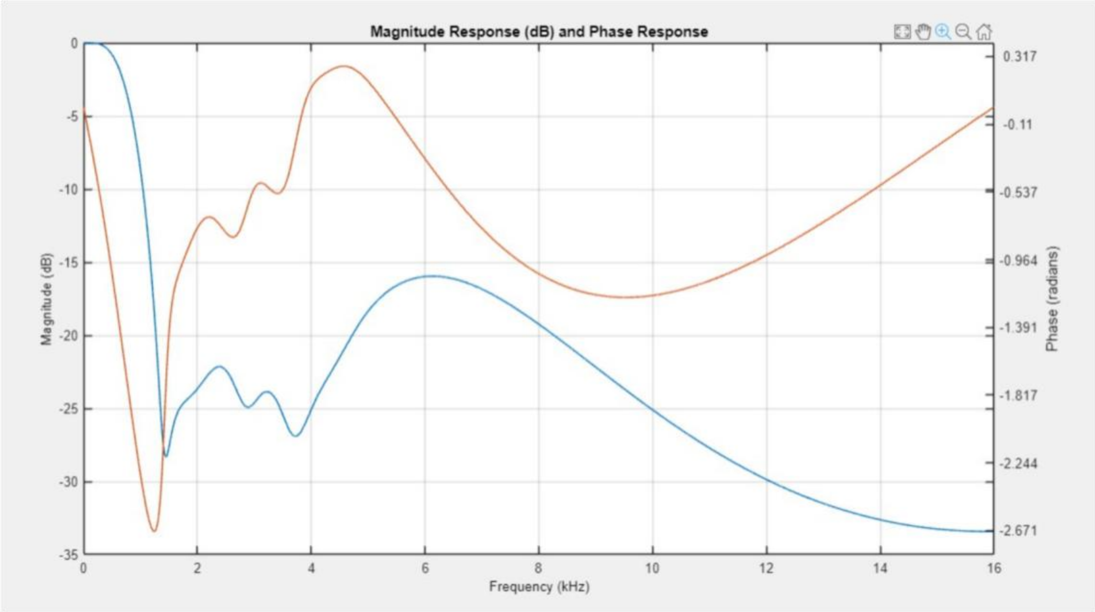


Figure 3.19 Least Pth-norm filter Magnitude and phase response plot

Structure:	Direct-Form II, Second-Order Sections
Order:	38
Sections	19
Stable:	Yes
Source:	Designed

Figure 3.20 Least Pth-norm filter Order and Section count

The Least Pth-norm filter required an order of 38. The response starts from 0 hz dropping gradually until 1.5 kHz, this does not achieve our desired passband therefore the filter is not adequate for our use.

6. Constr. Least Pth-norm Filter:

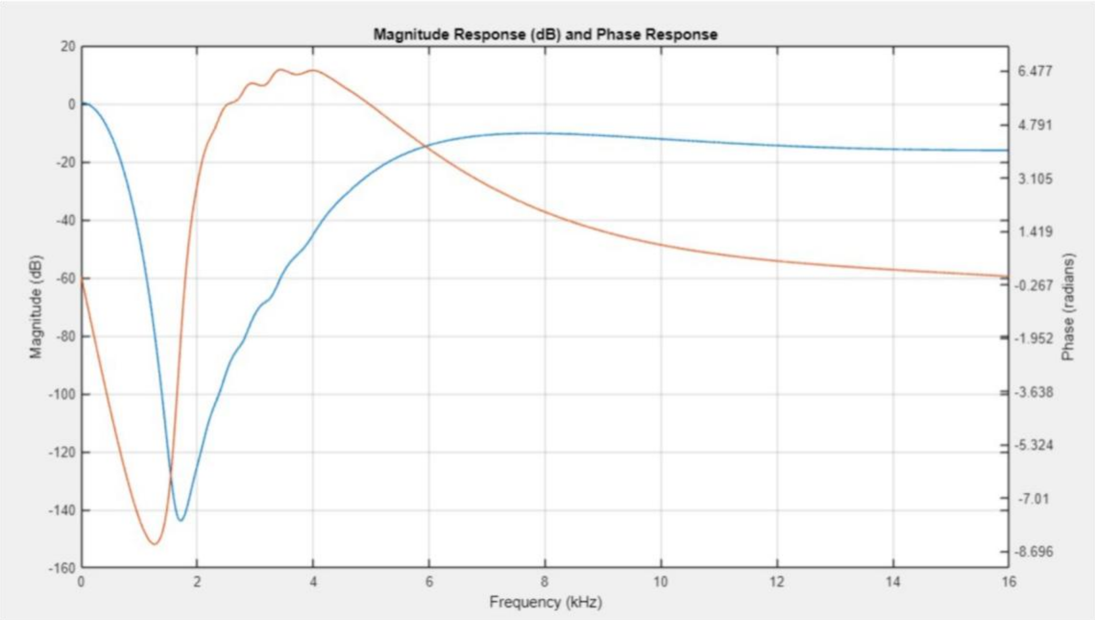


Figure 3.21 Constr. Least Pth-norm filter Magnitude and phase response plot

Structure:	Direct-Form II, Second-Order Sections
Order:	44
Sections	22
Stable:	Yes
Source:	Designed

Figure 3.22 Constr. Least Pth-norm filter Order and Section count

The Constr. Least Pth-norm filter required an order of 44 and resulted in a response similar to Least Pth-norm, this does not achieve our desired passband requirements, therefore the filter is not adequate for our use.

Now we compare each filter's signal for each of our signals Using the formula:

$$Gain\ (dB) = 20\log_{10}\left(\frac{Signal_{Out}}{Signal_{In}}\right)$$

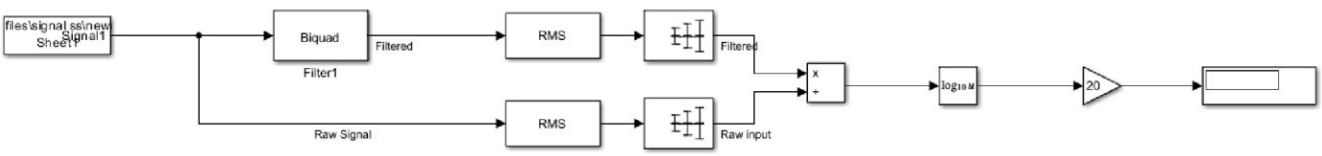


Figure 3.23 Filter gain calculation simulink system

Filter	Order	Target Signal (100 Hz) Gain (db)	2nd signal Gain (db)	3rd signal Gain (db)	4th signal Gain (db)
butterworth	230	-3.738	-39.44	-39.04	-39.53
chebyshev-type-1	52	-2.348	-38.34	-38.08	-38.36
chebyshev-type-2	52	-1.639	-37.13	-36.92	-37.14
elliptic	22	-1.788	-37.57	-37.57	-37.79
least-pth	38	-2.368	-2.241	-2.286	-2.919
constr-least-pth	44	-2.105	2.212	-2.062	-2.537

Table 3.1 Filter Order to Gain comparison

We conclude that Elliptic filter has the highest selectivity while requiring the least order. We will use the Elliptic filter for our Action Potential detection system.

3.5 Designing Detection System

Applying our very narrow filter we get the 100hz component, which for our target signal is:

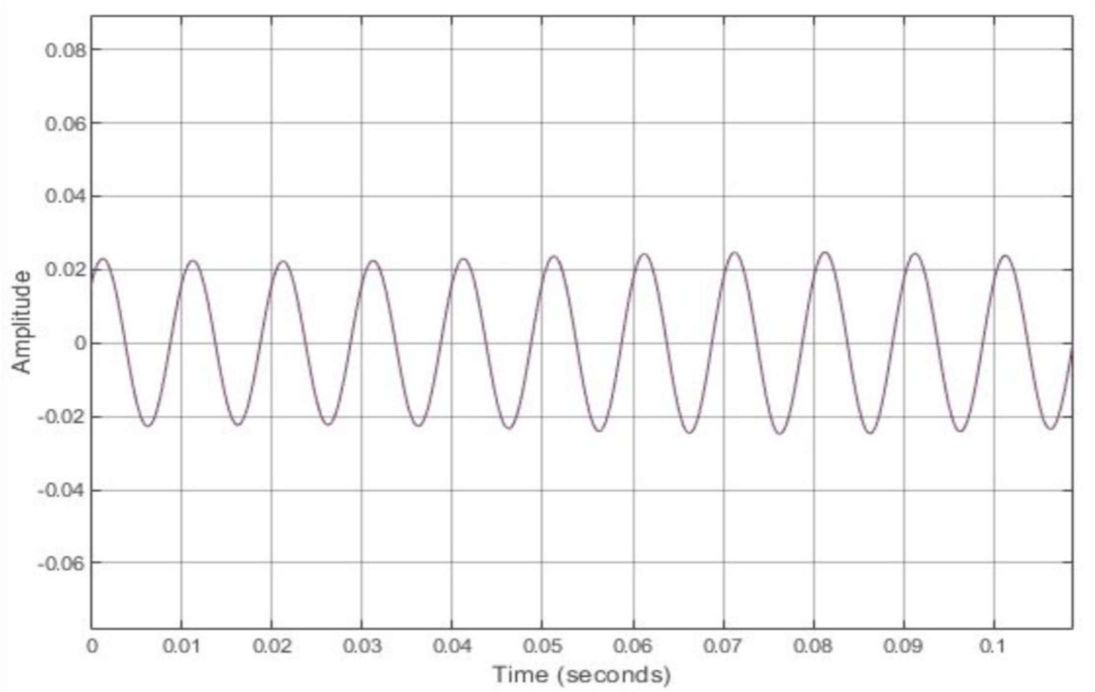


Figure 3.24 Result of applying filter to target AP signal

As for our other signals, the output is nearly zero:

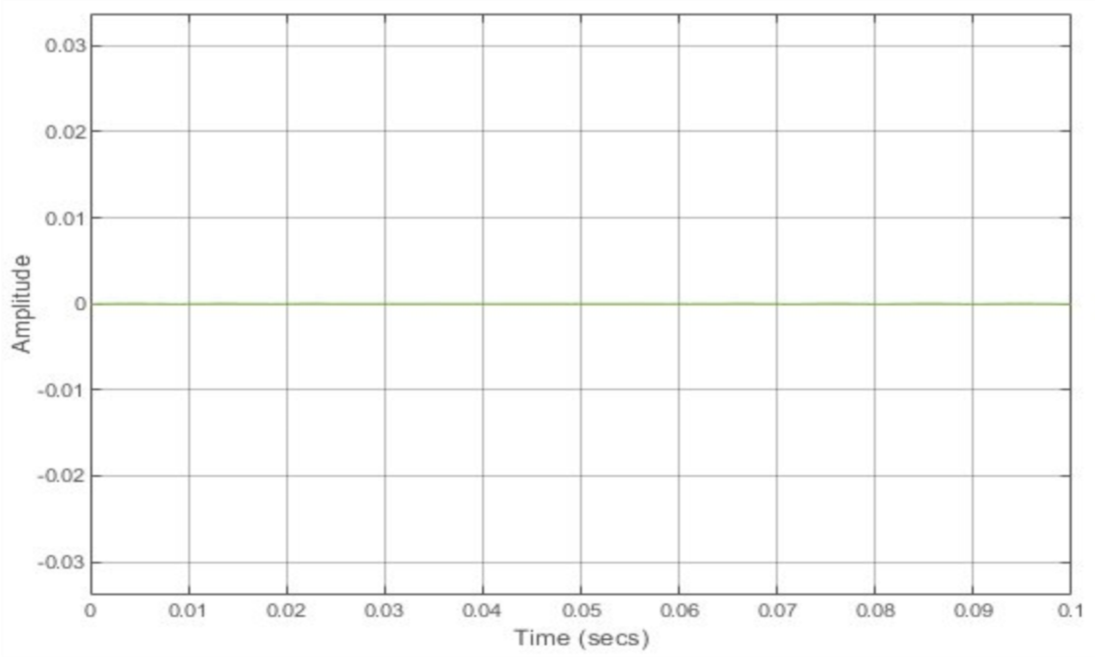


Figure 3.25 Result of applying filter to 2nd, 3rd and 4th signals

after wards we use a threshold to detect the signals (when amplitude is higher than threshold value we register a peak) as such:

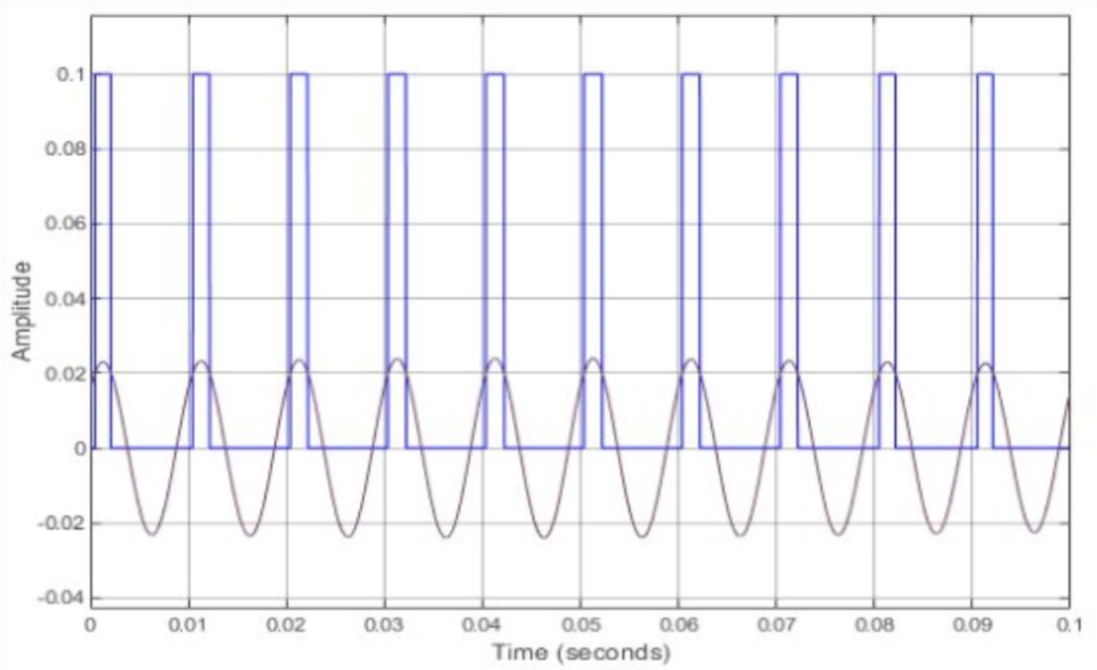


Figure 3.26 Applying threshold (Blue signal is output)

Then we apply an edge detector to only register the rising point of threshold, as such:

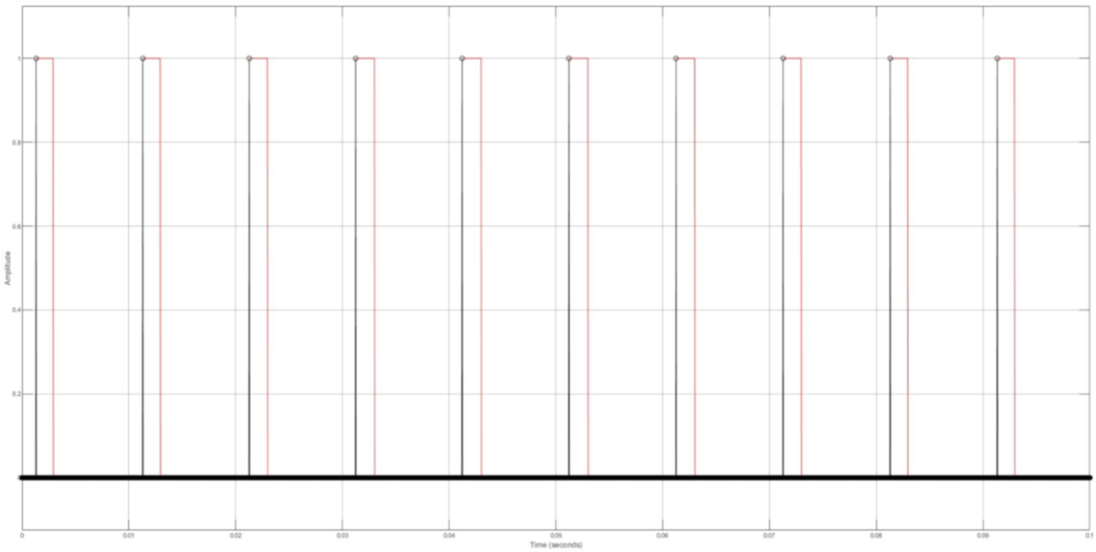


Figure 3.27 Applying edge detector (black signal is output)

The final result is unit impulses corresponding to our detected action potentials, as such:

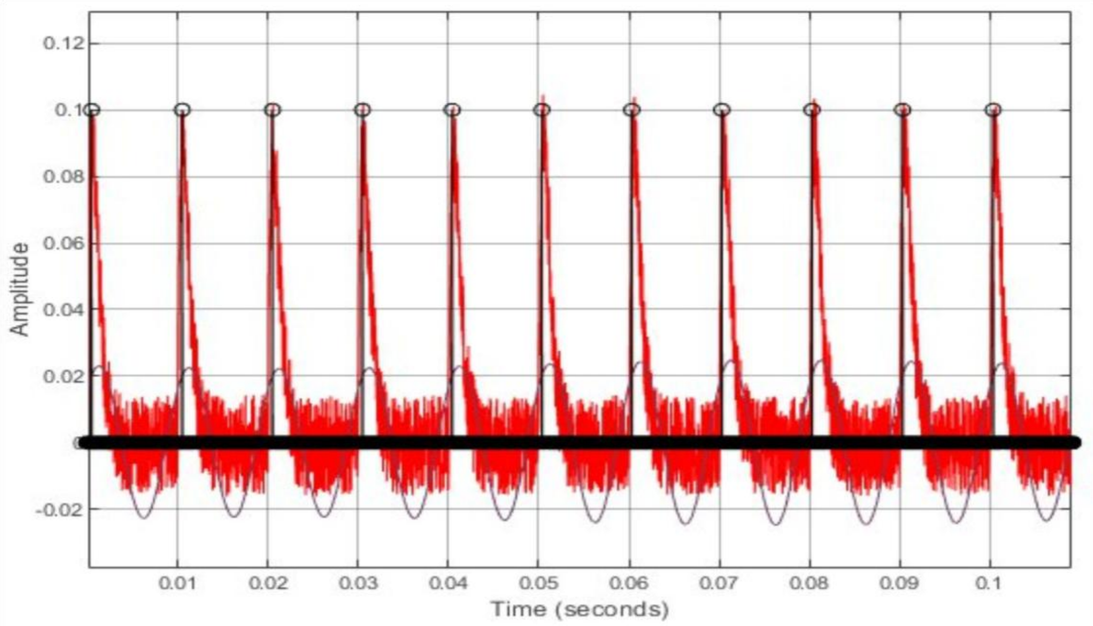


Figure 3.28 Final output of our signal compared to input (system output is black signal, red signal is input)

The system developed for detecting 100 Hz action potentials demonstrates exceptional specificity and accuracy, exclusively responding to stimuli within the 100 Hz frequency range. the system consistently detects action potentials at this frequency with high precision, showcasing its reliability and suitability for targeted neural signal analysis. This focused response capability ensures that only relevant signals are identified, minimizing false positives and enhancing the system's effectiveness in real-world applications requiring selective action potential detection.

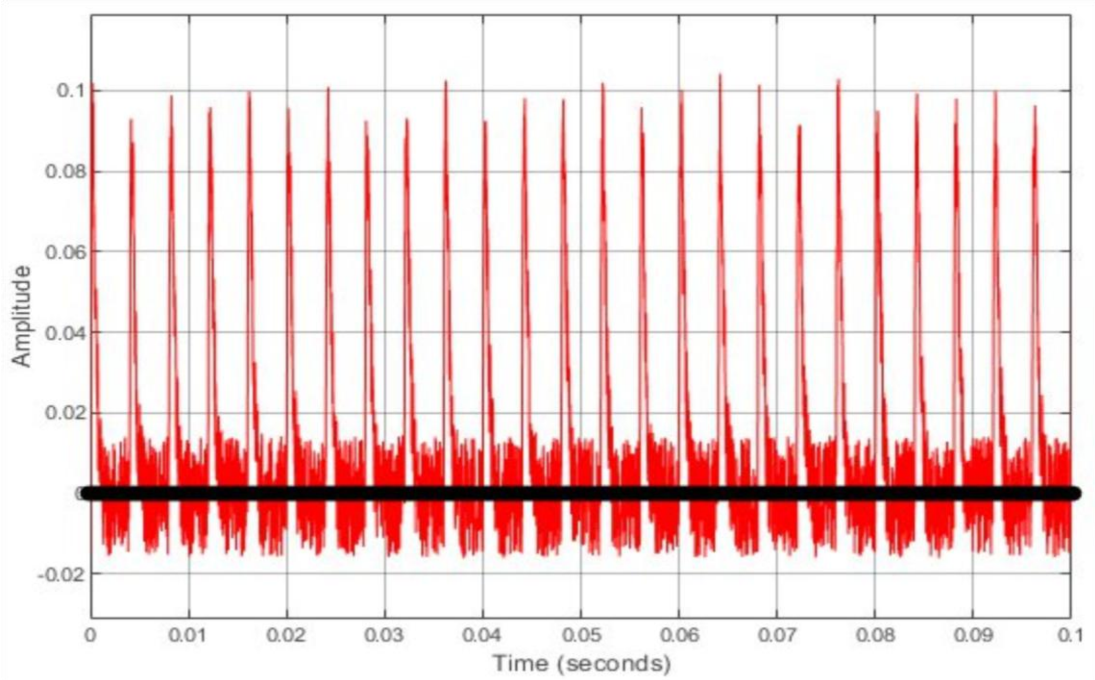


Figure 3.29 System output for 250 Hz signal (2nd signal)

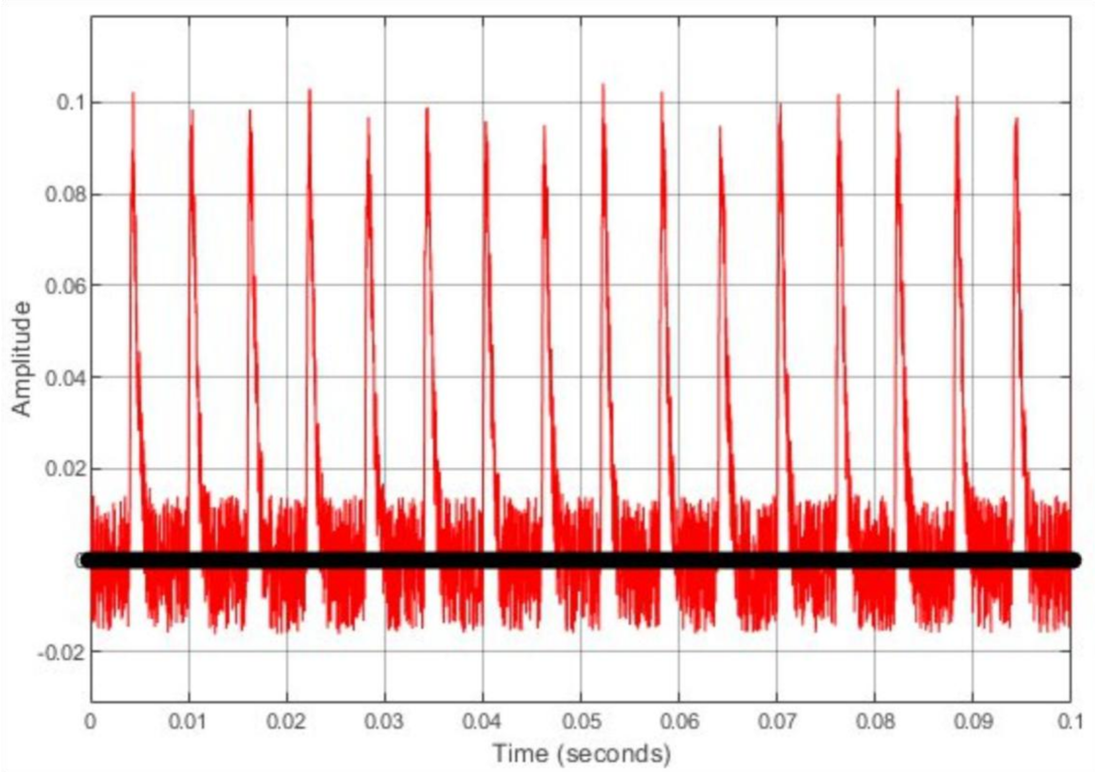


Figure 3.30 System output for 150 Hz signal (3rd signal)

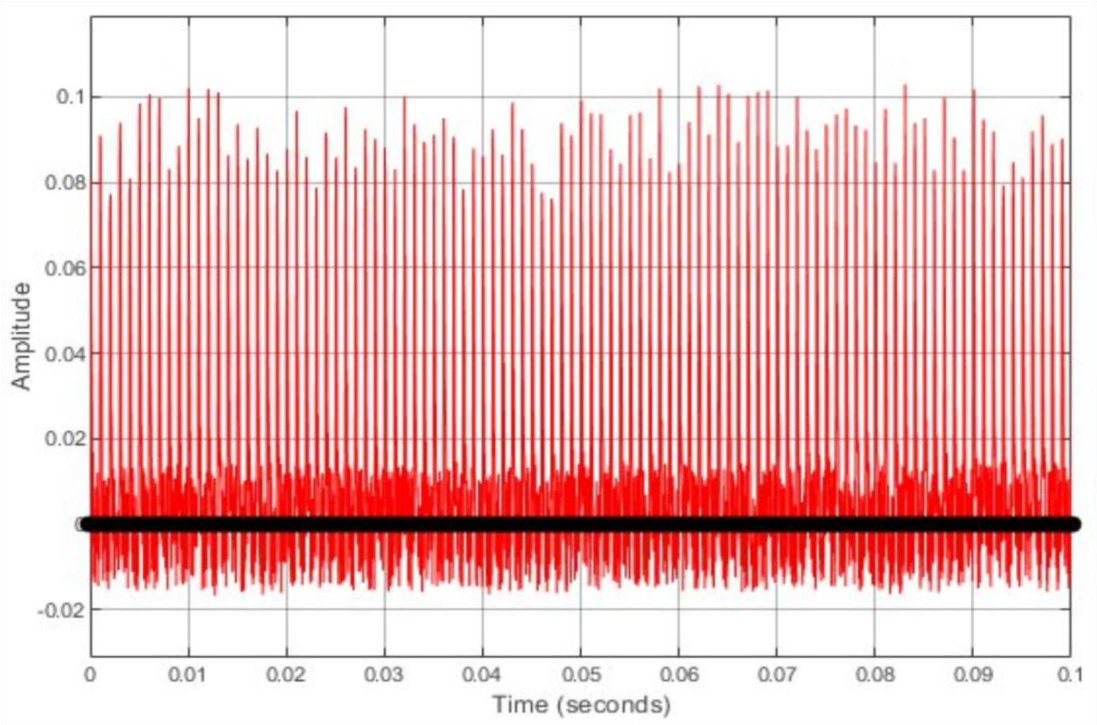


Figure 3.31 System output for 1 kHz signal (4th signal)

3.6 Final system

Ourfinalsystemsystem:

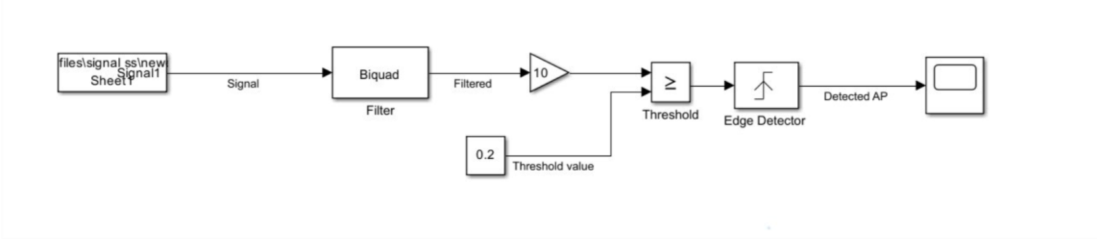


Figure 3.32 Action potential detection system

We have created a system capable of detecting action potentials and is insusceptible to noise and other signals, this system requires an IIR Elliptic bandpass filter with an order of 22 and a thresholder (comparator op-amp),

Chapter Four

Artificial Neural Networks

Chapter Four

Artificial Neural Networks (ANNs) are computational models inspired by the structure and function of the human brain. They consist of interconnected nodes, called neurons, that work together to process and learn from complex data. Each neuron receives input, performs a computation, and then passes its output to the next layer of neurons. ANNs are widely used in machine learning and deep learning tasks due to their ability to recognize patterns and make decisions based on data. They can be used for tasks such as image and speech recognition, natural language processing, and autonomous driving.

One of the earliest and most influential models of ANNs is the Perceptron, proposed by Frank Rosenblatt in 1957. Since then, there have been many advancements in neural network architectures, such as Convolutional Neural Networks (CNNs) for image processing and Recurrent Neural Networks (RNNs) for sequential data [18].

4.1 ANN Structure

Artificial Neural Networks are composed of a network of interconnected artificial neurons, an artificial neuron typically consists of three main components: inputs, weights, and an activation function. Inputs represent the information received by the neuron, which can be numerical values or binary values. Each input is associated with a weight, which determines the significance of that input in the computation. The activation function determines the output of the neuron based on the weighted sum of the inputs.

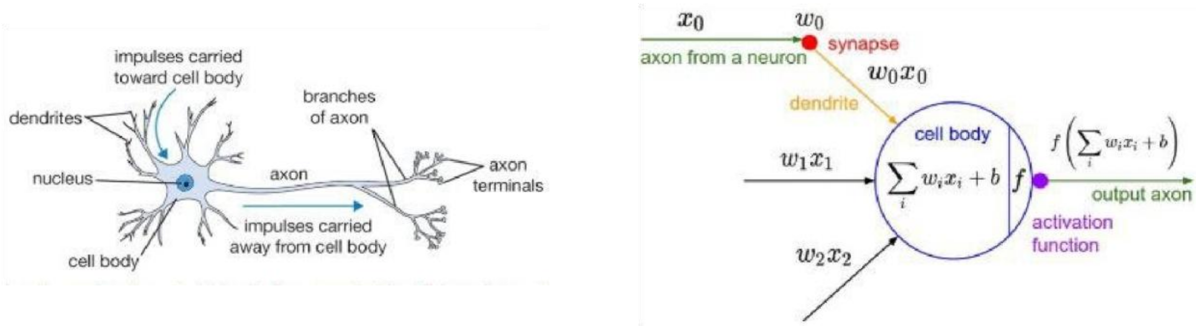


Figure 4.1 Artificial Neuron

4.1.1 Artificial Neuron

Neurons in a neural network are organized into layers, with each layer exhibiting the same behavior. Typically, all the neurons in a layer have the same activation function. Within a layer, the neurons can be fully interconnected or not connected at all. Neurons in one layer can also be connected to neurons in another layer. This organization of neurons into layers and the connectivity pattern within and between layers is referred to as the network architecture.

· Input Layer: The neurons in the input layer receive external input signals and simply pass them on to the neurons in another layer without performing any computation.

· Output Layer: The neurons in the output layer receive signals from neurons in either the input layer or the hidden layer.

· Hidden Layer: The layer of neurons that is situated between the input layer and the output layer is known as the hidden layer.

4.1.2 Artificial Neuron Activation Functions

Activation functions in artificial neural networks play a crucial role in introducing non-linearity to the model, allowing it to learn complex patterns and relationships within the data. Here is a detailed explanation of activation functions commonly used in neural networks:

1. Sigmoid Activation Function:
   · The sigmoid function, also known as the logistic function, squashes the input values to a range between 0 and 1.
   · It was popular in the past for binary classification tasks due to its smooth gradient, allowing for stable updates during training.
   · However, the sigmoid function suffers from vanishing gradient problems, making it less suitable for deep neural networks.

2. Hyperbolic Tangent (Tanh) Activation Function:
   · The tanh function is another activation function that squashes input values to the range of -1 to 1.
   · Similar to the sigmoid function, tanh is symmetric around the origin and allows negative values as well.
   · Tanh can be helpful for certain types of networks but can still encounter the vanishing gradient issue.

3. Rectified Linear Unit (ReLU) Activation Function:
   · The ReLU function is a simple yet powerful activation function that sets all negative values to zero and passes positive values unchanged.

· ReLU has become the standard choice for many deep learning tasks due to its effectiveness in training deep neural networks.
· However, ReLU can suffer from the dying ReLU problem, where neurons may no longer activate and contribute to the network's learning.

4. Leaky ReLU and Parametric ReLU:
   · Leaky ReLU and Parametric ReLU are variations of the ReLU function that address the dying ReLU problem by allowing a small gradient for negative values.
   · They help maintain non-zero gradients during training, preventing neurons from becoming inactive.

5. Other activation functions:
   · Other activation functions such as ELU (Exponential Linear Unit), SELU (Scaled Exponential Linear Unit), and Swish have also been introduced to address different issues like vanishing gradients and training stability.

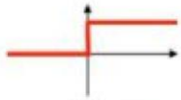
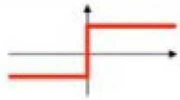
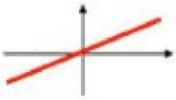
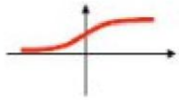
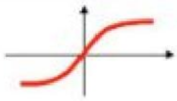
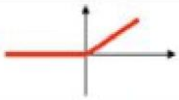
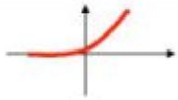
Activation function	Equation	Example	1D Graph
Unit step (Heaviside)	$\phi(z) = \begin{cases} 0, & z < 0, \\ 0.5, & z = 0, \\ 1, & z > 0, \end{cases}$	Perceptron variant	
Sign (Signum)	$\phi(z) = \begin{cases} -1, & z < 0, \\ 0, & z = 0, \\ 1, & z > 0, \end{cases}$	Perceptron variant	
Linear	$\phi(z) = z$	Adaline, linear regression	
Piece-wise linear	$\phi(z) = \begin{cases} 1, & z \geq \frac{1}{2}, \\ z + \frac{1}{2}, & -\frac{1}{2} < z < \frac{1}{2}, \\ 0, & z \leq -\frac{1}{2}, \end{cases}$	Support vector machine	
Logistic (sigmoid)	$\phi(z) = \frac{1}{1 + e^{-z}}$	Logistic regression, Multi-layer NN	
Hyperbolic tangent	$\phi(z) = \frac{e^{z} - e^{-z}}{e^{z} + e^{-z}}$	Multi-layer Neural Networks	
Rectifier, ReLU (Rectified Linear Unit)	$\phi(z) = max(0, z)$	Multi-layer Neural Networks	
Rectifier, softplus	$\phi(z) = \ln(1 + e^{z})$	Multi-layer Neural Networks	

Table 4.1 Artificial Neuron Activation Functions

4.2 ANN Classification by Layers

Neural Networks can be classified as single layer networks or multilayer networks. The number of layers in a network is determined by the number of layers with weighted interconnection links between them. The input layer is not counted as a layer because it does not perform any computation.

The network architecture refers to how the neurons are organized into layers and how they are connected within and between those layers

a) Single Layer Network:

· A single layer network consists of one layer of connection weights.

· It includes an input layer that receives signals from the environment and an output layer that produces responses.

· This type of network is often used for pattern classification tasks.

a) Multilayer Network:

- A multilayer network consists of one or more hidden layers situated between the input and output layers.
- These hidden layers allow for more complex computations and can help in solving a broader range of problems.
- Networks with non-linear activation functions in their layers can theoretically solve any problem, but training them can be challenging.

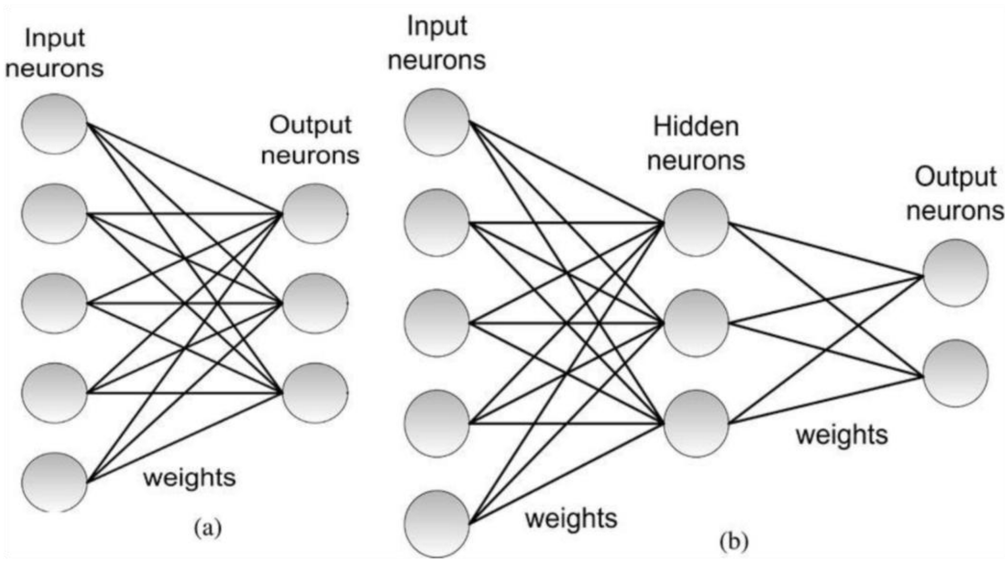


Figure 4.2 (a) Architecture of a single layer perceptron. The architecture consists of a layer on input neurons fully connected to a single layer of output neurons. (b) Extension to a multi-layer perceptron including more than one layer of trainable weights. In this example, the network includes 3 layers: input, hidden and output layer. Each connection between two neurons is given by a certain weight.

4.3 Types of Neural Network Training

Training a multilayer neural network can be difficult due to issues like vanishing gradients, overfitting, and hyperparameter tuning. It often involves using techniques like backpropagation and optimizers to adjust the model's weights and biases.

One important thing about artificial neural networks is that they can learn. Researchers are studying how both biological and artificial neural networks learn. Some basic questions about human learning are: How do we learn? What is the most effective way to learn? How much and how quickly can we learn? What are the obstacles to learning?

In simple terms, learning is when a neural network adjusts itself based on a stimulus and produces the desired response. It is an ongoing process where the network continuously responds to input and develops new classifications if the input is not recognized.

Training is the process where the network adjusts its parameters (synaptic weights) in response to input stimuli, so that the actual output matches the desired output. When the actual output matches the desired one, the network has completed the learning phase and has acquired knowledge.

There are different types of learning algorithms:

1. Supervised training: This requires pairing each input with a target output. During training, an input is given to the network, which produces an output. This output is compared to the target output. If they are different, the network generates an error signal. This signal is used to adjust the synaptic weights so that the actual output matches the target output. Supervised training relies on a supervisor or teacher to minimize errors. The specific calculations used to minimize errors depend on the algorithm and optimization techniques.

Supervised training is used in various applications such as pattern classification and multilayer neural networks.

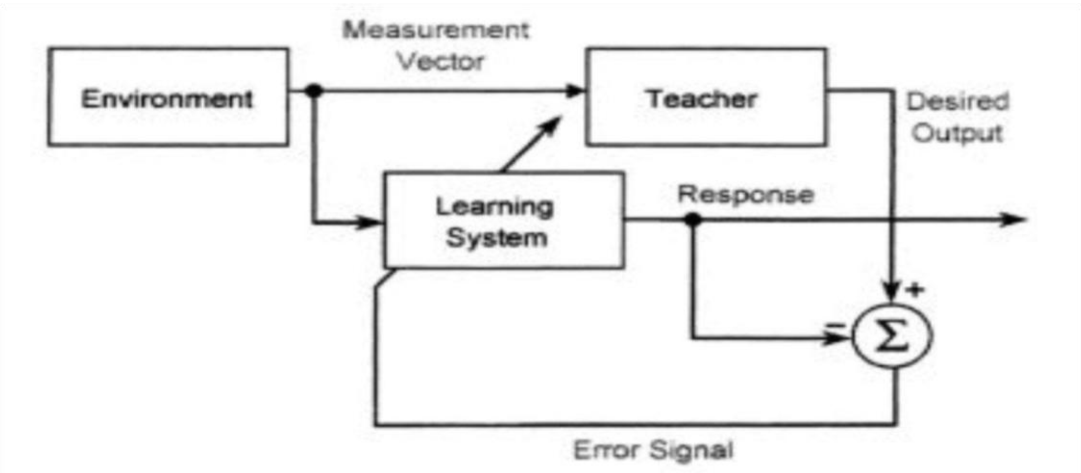


Figure 4.3 Block diagram of supervised-learning model

2. Unsupervised Training: Unsupervised training is used in self-organizing neural networks. Unlike supervised learning, unsupervised training does not require a teacher or specific training data. Instead, input vectors of similar types are grouped together without any guidance on how a typical member of each group looks or which group a member belongs to. During training, the neural network receives input patterns and organizes them into categories. When a new input pattern is applied, the neural network provides an output indicating the class to which the input pattern belongs. If a class cannot be found for the input pattern, a new class is created. Unsupervised training does not require a teacher, but certain guidelines or properties of the objects can be used for grouping, such as color or shape.
   Without any guidelines, the success of grouping may vary.

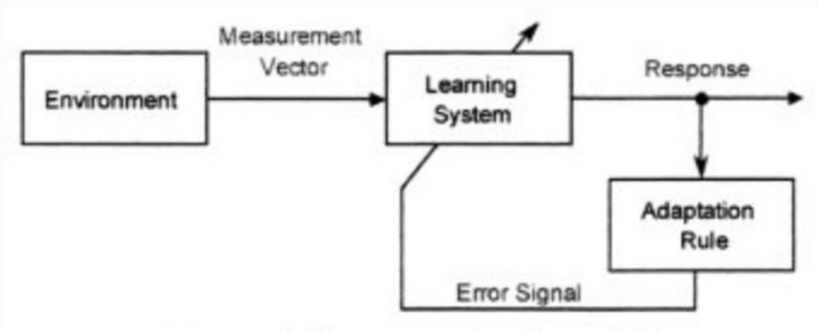


Figure 4.4 Unsupervised-training model

3. Reinforced Training: Reinforced training is similar to supervised training, but the teacher only provides a pass or fail indication instead of indicating how close the actual output is to the desired output. Therefore, the error signal generated during reinforced training is binary.

4.4 Non-Linear Time-Series ANNs

A non-linear input-output neural network is a type of artificial neural network that is designed to model and predict time series data. Time series data refers to a sequence of observations taken at regular intervals over time.

The main idea behind a non-linear input-output network is to use the historical values of the time series as inputs to the network, and train it to predict the future values of the time series as outputs. The network learns the underlying patterns and relationships in the data, and uses them to make predictions.

The main component of a non-linear time series ANN is the layer of time delays which allows the network to have a finite dynamic response to time series input data. As well as a network of interconnected neurons where the outputs of the neurons in one layer serve as inputs to the neurons in the next layer, and so on, until the final output layer produces the predicted values of the time series.

The weights of the connections between the neurons are adjusted during the training process using an optimization algorithm, such as gradient descent, to minimize the difference between the predicted values and the actual values of the time series. This process is known as training or learning, and it allows the network to capture the underlying patterns in the data.

Non-linear input-output networks have been successfully applied to a wide range of time series prediction tasks [19], including stock market prediction, weather forecasting, and economic forecasting. They are particularly effective in cases where the relationship between input and output is complex and non-linear.

4.5 Designing our ANN

We will be using Matlab Neural Network Time-Series tool to design our ANN, input sampling frequency is 32 kHz and each signal will be 0.1 S long therefore each signal will have 3200 samples. Therefore input neurons will be 3200 neuron, we will require a larger number of neurons in hidden layer, through trial and error we have found 4000 Neurons in hidden layer and 16 time delays to be the sweet spot.

4.5.1 Our Training Dataset

For our desired signal (100 Hz), the input will be the signal with noise, and target output is the peaks detected:

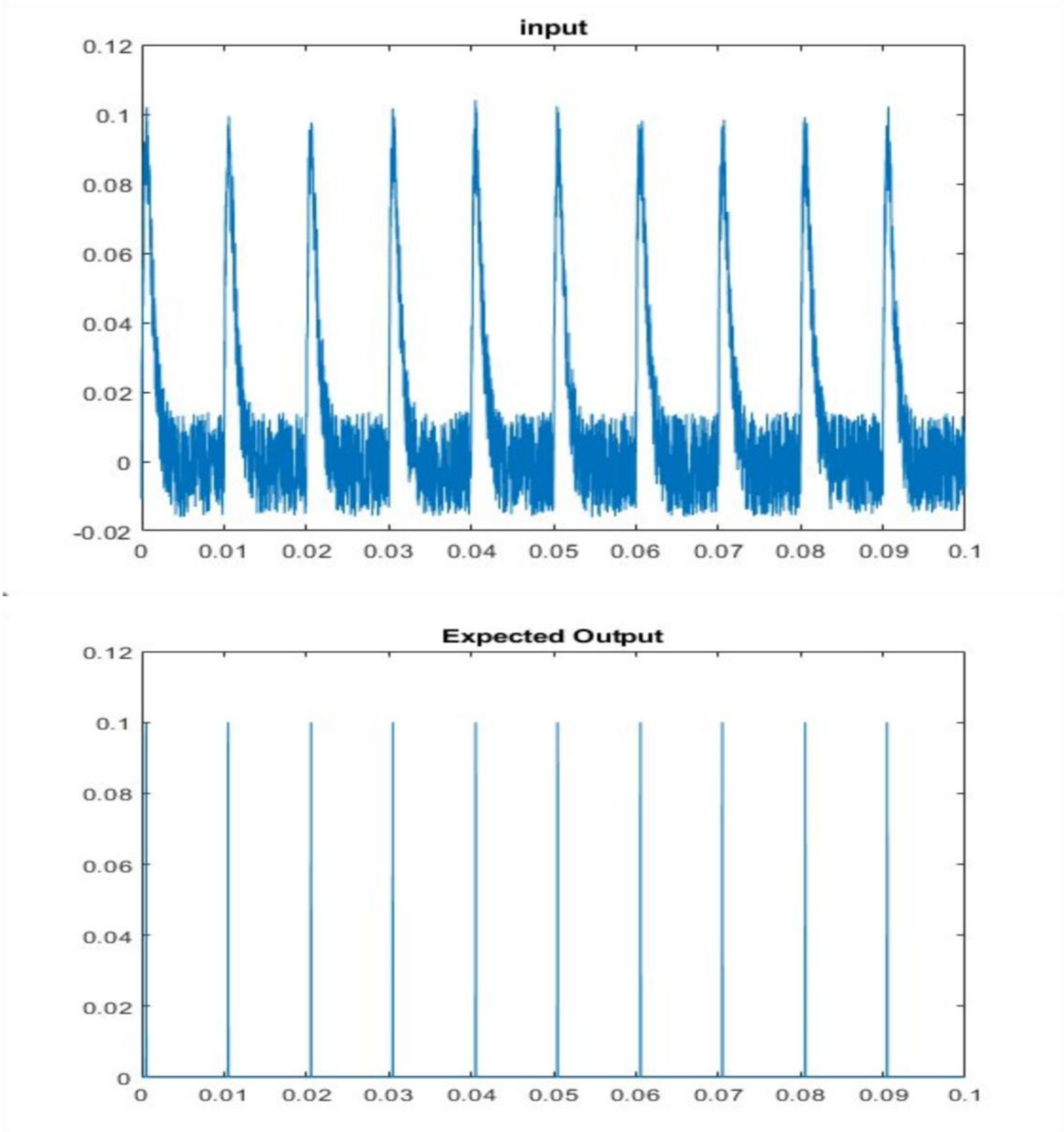


Figure 4.5 100 Hz training Dataset: input (noisy) and output (detected peaks)

As for the other signals, the input will be the signals with noise (figure 3.6) and the output will be 0 (figure 4.7):

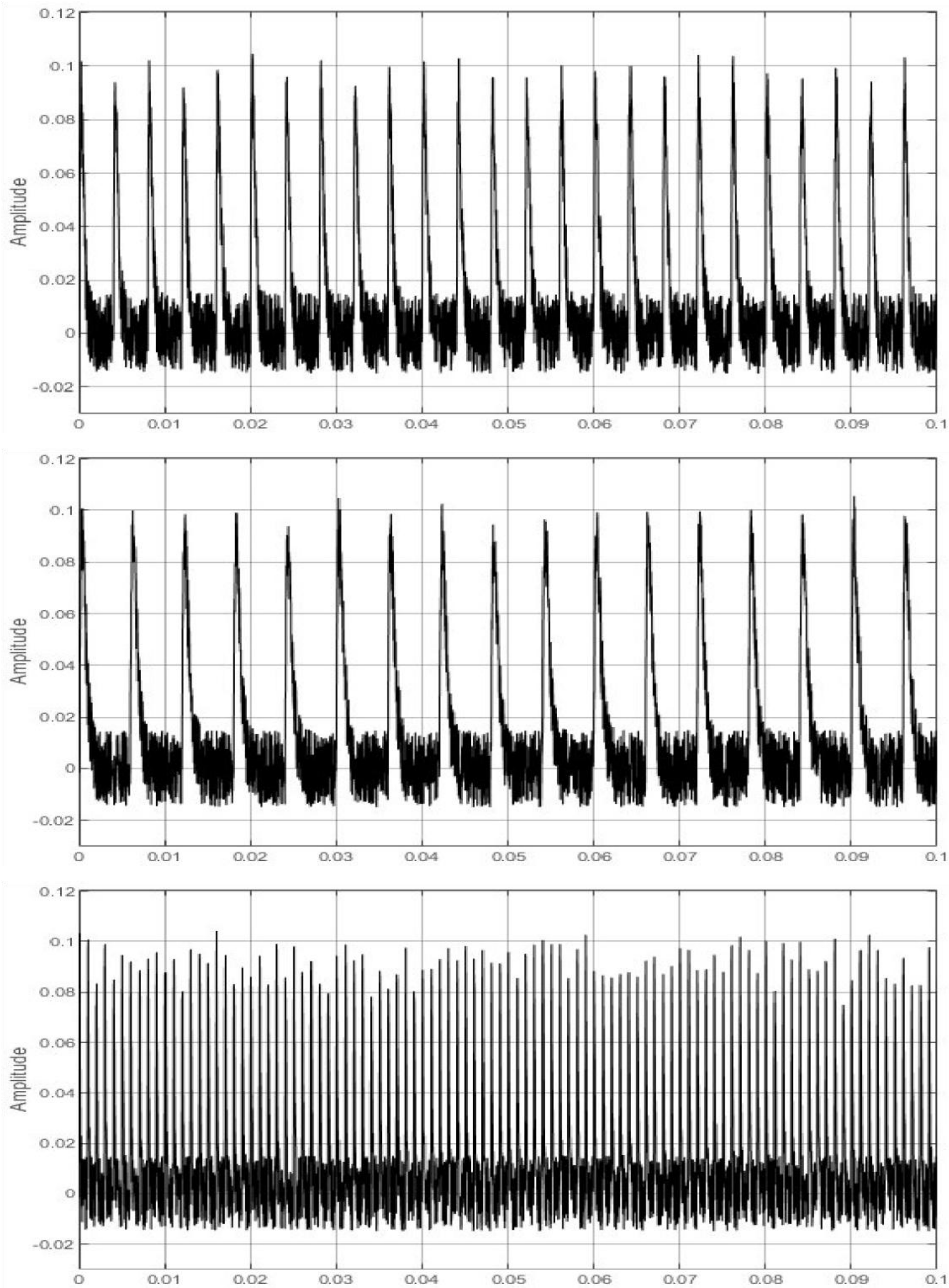


Figure 4.6 Signals (250 Hz, 150 Hz and 1 kHz respectively) Dataset: input noisy

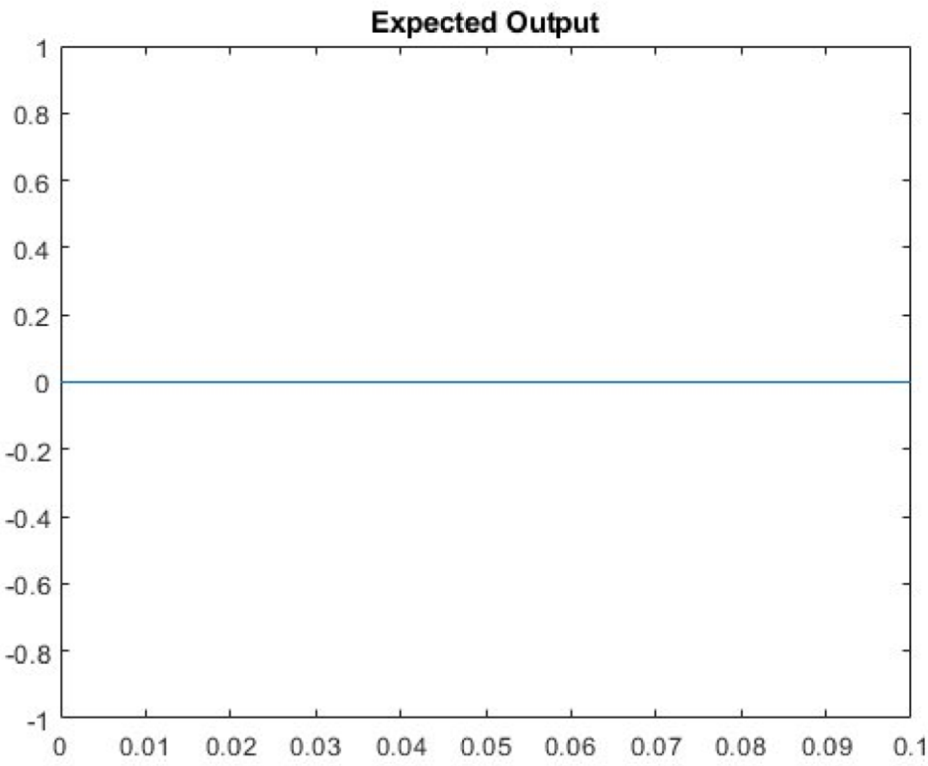


Figure 4.7 Signals (250 Hz, 150 Hz and 1 kHz) Dataset: output

We now have 260 samples with 3200x1 features each

4.5.2 Training Our ANN

Now that we have our training dataset, we begin training neural network, the training finishes with 14 Epochs and a gradient of $7*10^{-7}$, figure4.8

Training Progress

Unit	Initial Value	Stopped Value	Target Value
Epoch	0	14	1000
Elapsed Time	-	00:03:59	-
Performance	0.00483	1.74e-13	0
Gradient	0.203	7.1e-07	1e-06
Validation Checks	0	0	6

Figure 4.8 ANN Training final state

4.5.3 Testing Our Trained ANN

After finishing the training we plot the network's response to our data:

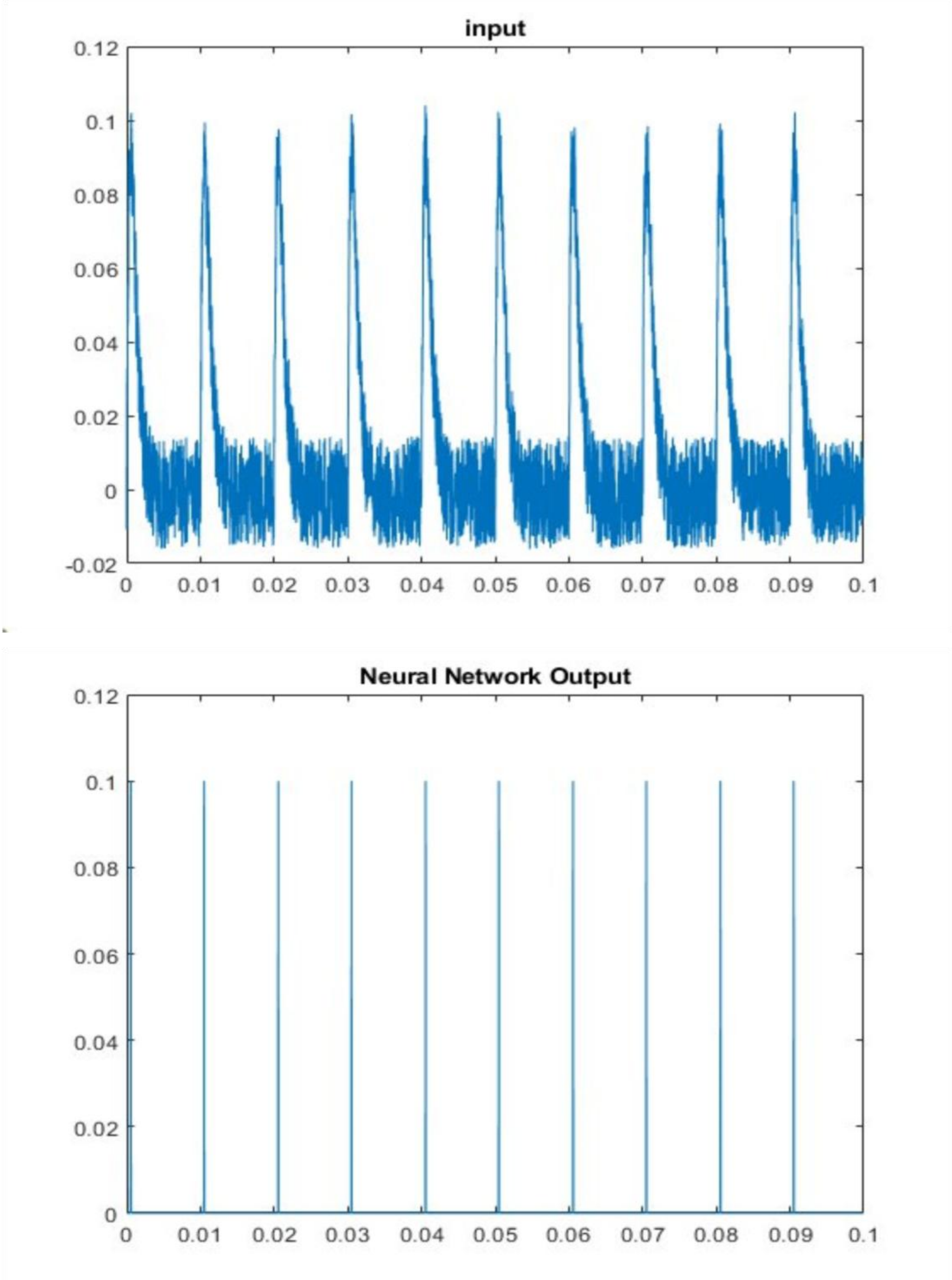


Figure 4.9 ANN Response to desired signal

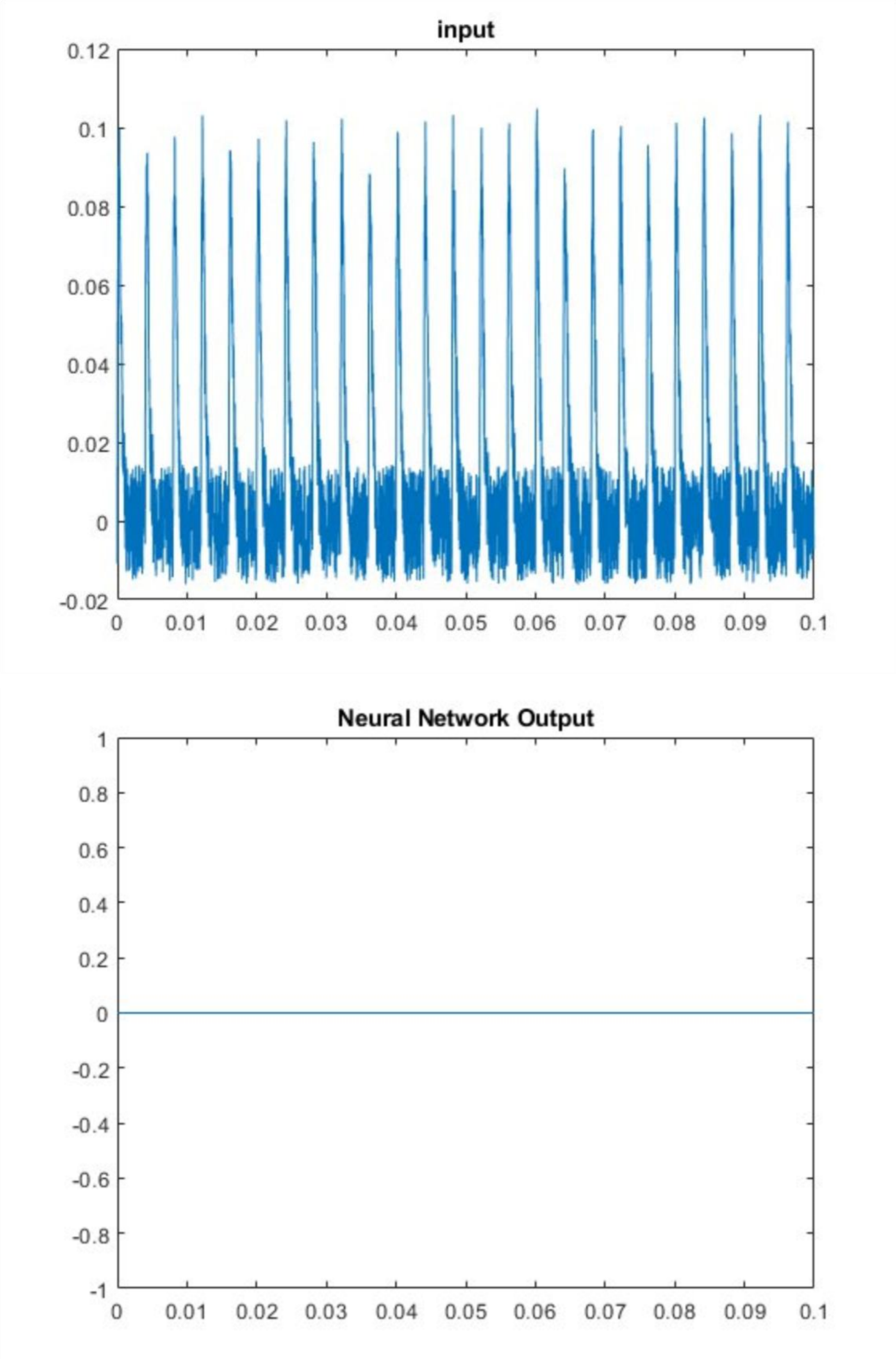


Figure 4.10 ANN response to 250 Hz signal

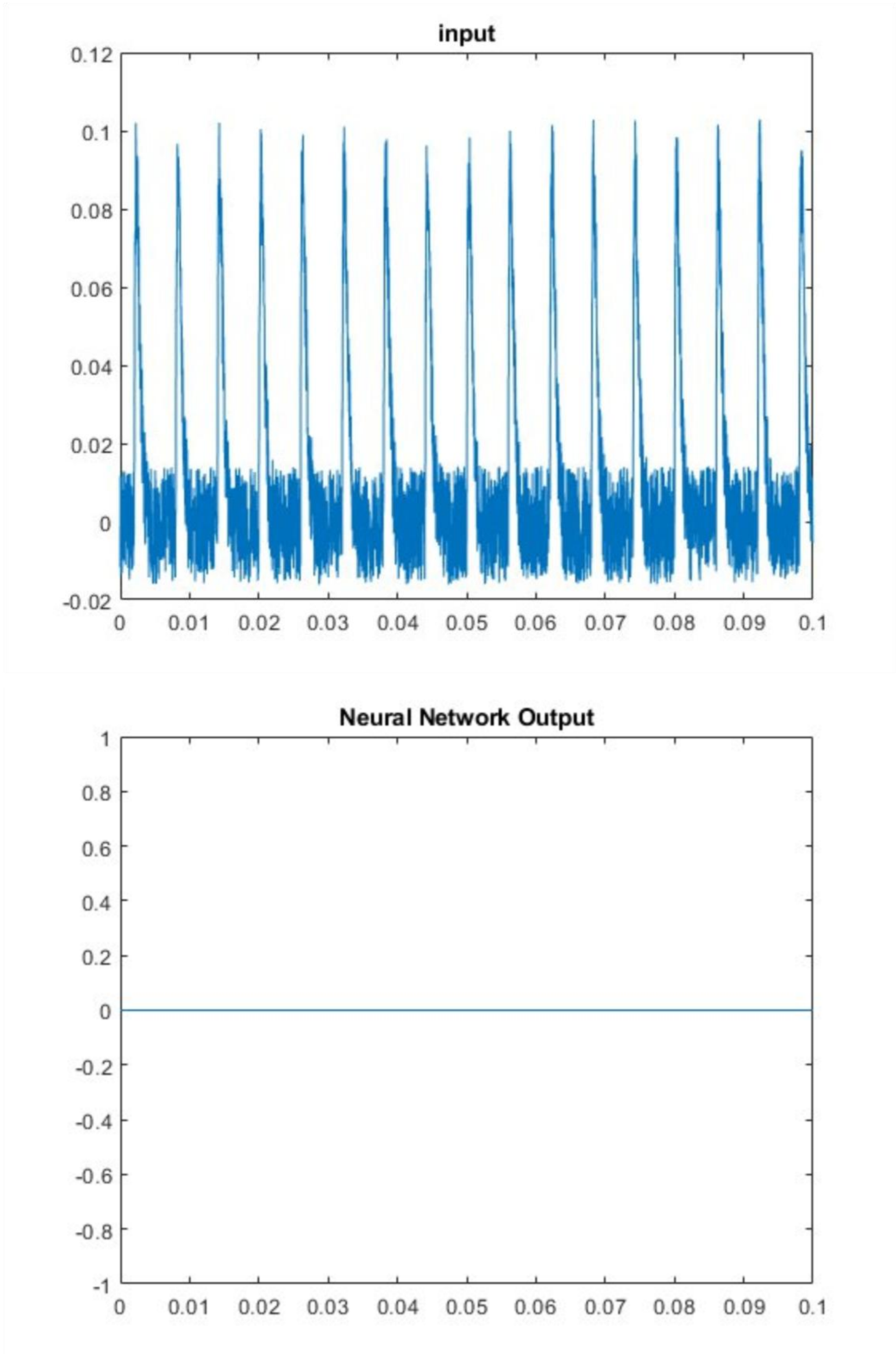


Figure 4.11 ANN response to 150 Hz signal

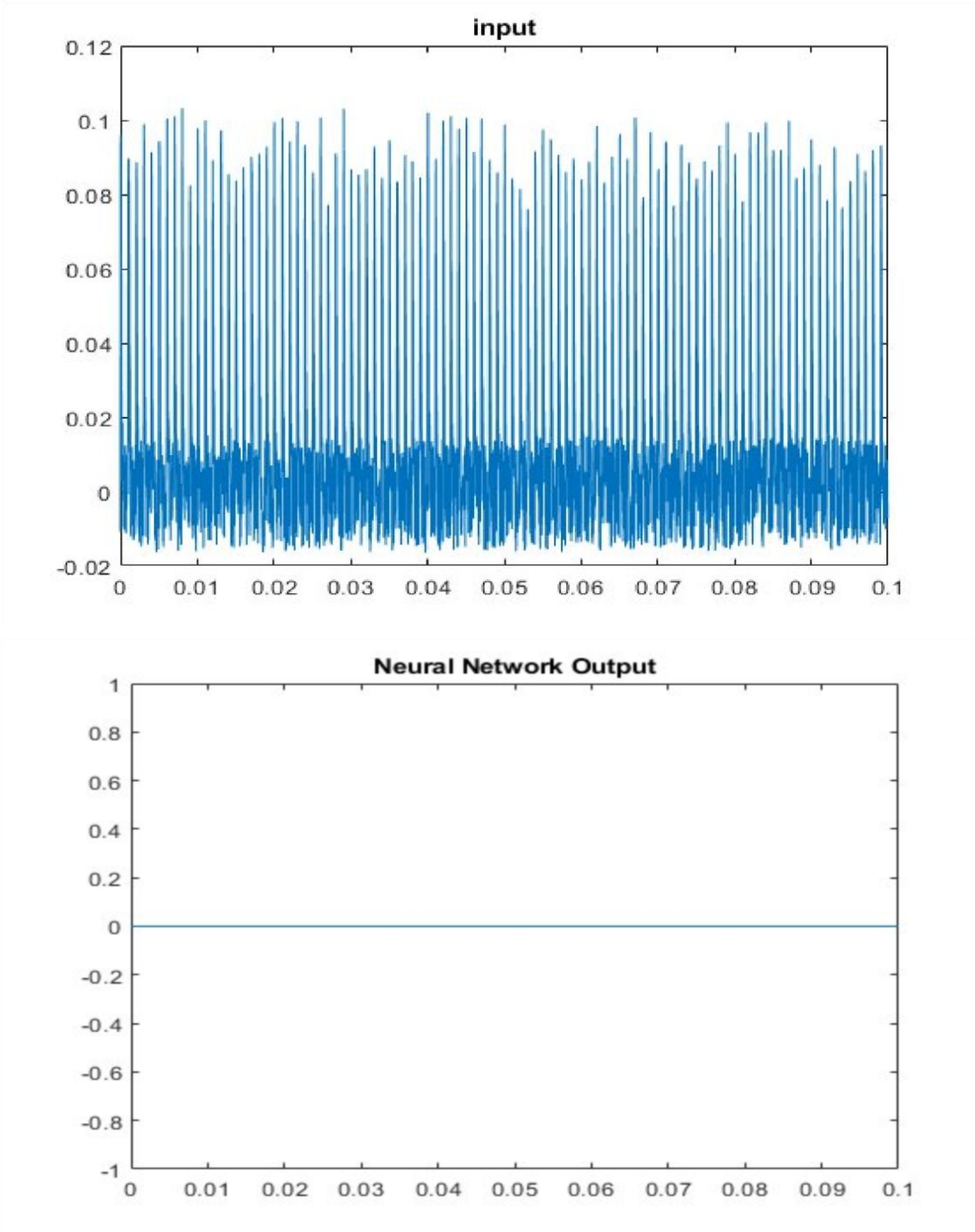


Figure 4.12 ANN response to 1 kHz signal

The result is a non-linear ANN that detects only our target 100 Hz AP signal and rejects other signals.

Chapter Five

Conclusion and Recommendations

5.1 Conclusion

In this project, a comprehensive system for detecting action potentials in neural signals was designed and implemented. The approach integrated a bandpass filter to isolate the frequency range associated with action potentials, followed by a time-series Artificial Neural Network (ANN) for signal analysis and classification.

The utilization of the bandpass filter proved to be effective in isolating the specific frequency components corresponding to action potentials, enhancing the accuracy and reliability of subsequent analysis. The time-series ANN, trained on labeled data sets, demonstrated its capability in accurately detecting and classifying action potentials in real-time neural recordings.

Through rigorous testing and validation, the system showcased robust performance metrics, including high sensitivity and specificity in identifying action potentials amidst noise and background activity. The integration of signal processing techniques with machine learning methodologies enabled the development of a sophisticated tool for neurophysiological research and clinical applications.

Moving forward, the insights gained from this project lay the foundation for further advancements in neural signal processing, with potential applications in neuroprosthetics, brain-computer interfaces, and understanding neural dynamics in health and disease. Continued refinement and optimization of the system hold promise for contributing to the broader field of neuroscience and fostering innovations in neural engineering.

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APPENDICES

APPENDIX A: Graphs

APPENDIX B: Computer Programme Listing

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