OPTIMIZING SIGNAL CLARITY IN IOT STRUCTURAL HEALTH MONITORING SYSTEMS USING BUTTERWORTH FILTERS

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Abstract:

The development of the Internet of Things (IoT) has allowed for continuous, real-time structural integrity monitoring, which has greatly increased structural health monitoring (SHM). However, noise and interference can impair the quality of sensor data, which is a major factor in how effective these systems are. In order to improve signal clarity in IoT-based SHM systems, this study looks into the application of Butterworth filters. The passband of butterworth filters is renowned for having a maximally flat frequency response, which reduces signal distortion. In order to maximize signal processing, the research will compare Butterworth filters with other filter types such as Chebyshev and Elliptical filters, develop adaptive filtering approaches, and investigate hybrid filtering methods. For the design and implementation of filters, MATLAB, Python, and LabVIEW are used. The results show that adaptive filtering approaches can further increase performance by adapting to real-time signal features, and that higher-order Butterworth filters greatly improve signal clarity. By offering a thorough examination of Butterworth filters and suggesting novel approaches for enhanced signal processing in SHM systems, this study advances the area.

Keywords: *IoT, Structural Health Monitoring (SHM), Butterworth Filter, Signal Processing, Adaptive Filtering*

1. INTRODUCTION

Many industries have seen tremendous changes as a result of the Internet of Things (IoT), including structural health monitoring (SHM). IoT enables continuous and real-time structural integrity monitoring through the deployment of sensor networks, which is a crucial component for guaranteeing the maintenance and safety of vital infrastructure including buildings, bridges, and dams. However, the quality and precision of the data gathered from sensors is a major factor in how effective these monitoring systems are. Digital filters, in particular the Butterworth filter, are essential for controlling phase response and attenuation, which improves signal clarity.

A variety of sensors and data gathering tools are used in structural health monitoring to track the state of structures in real time. The main goals are to extend the life of structures, stop malfunctions, and identify possible problems early. Typically, these SHM systems collect information on a range of factors, including stresses, vibrations, and other markers of structural health. In contrast, the Internet of Things (IoT) is a network of connected objects that can exchange data and communicate with one another. Within SHM, IoT makes it easier to install multiple sensors throughout a building, allowing for real-time data processing and ongoing observation.

Signals from sensors are processed through digital filters to enhance their quality. Filters can eliminate undesired elements and noise from the signal, which facilitates more accurate data analysis and interpretation.A particular kind of digital filter called the Butterworth filter is made to have a smooth transition to the stopband and a flat frequency response in the passband, or no ripple. Because of this characteristic, it's perfect for applications that need a clean, undistorted signal.

Digital filter design and implementation are commonly done with MATLAB. It offers powerful signal processing features, such as functions for creating Butterworth filters. For the implementation of digital filters, Python is a popular choice because of libraries like SciPy and NumPy. A wide range of tools for designing and evaluating Butterworth filters are available in these libraries. Another platform that provides engineers with a graphical programming environment for real-time signal processing and filter implementation is LabVIEW.

Better attenuation of undesirable frequencies and a steeper roll-off are provided by higher-order Butterworth filters. The use of higher-order filters is suggested in this research to improve signal clarity in SHM systems. With adaptive filtering, the filter parameters are changed in real-time in response to the signal's properties. By adjusting to changing circumstances, this method can enhance SHM systems' performance even more. By combining the advantages of various filtering techniques, Butterworth filters with other filter types—like Kalman filters—can provide better performance.

Objectives

1. Enhance Signal Clarity: To use Butterworth filters to raise the caliber of signals received from Internet of Things-based SHM devices.

2. Compare Filtering Techniques: To assess how well Butterworth filters work in comparison to other filters like Elliptical and Chebyshev filters.

3. Create Adaptive Filtering Techniques: To provide and put into practice adaptive Butterworth filtering methods for processing signals in real time.

4. Integrate Hybrid Filters: Investigate the advantages of mixing different filtering techniques with Butterworth filters for best results.

Research Gap

Despite the widespread use of digital filters in SHM, little is known about the unique benefits of Butterworth filters in Internet of Things-based SHM systems. Furthermore, in this context, the potential of adaptive and hybrid filtering algorithms is yet not fully realized. By offering a thorough examination of Butterworth filters and suggesting fresh methods for improved signal processing, this work seeks to close these gaps.

Problem Statement

The primary difficulty in IoT-based SHM systems is preserving signal integrity in the face of interference and noise. Conventional filters frequently distort signals by compromising between phase response and attenuation. Although Butterworth filters present a more favorable option, their use in SHM has not received enough attention. The purpose of this work is to discuss the necessity of efficient filtering methods to guarantee superior signal processing in SHM systems.

For accurate and trustworthy structural health monitoring, it is essential to optimize signal clarity in Internet of Things (SIoT)-based SHM systems. A possible answer is provided by the Butterworth filter, which has a special combination of phase response and attenuation. In order to improve signal processing capabilities, this study suggests investigating higher-order, adaptive, and hybrid Butterworth filtering strategies. This study intends to further the subject of SHM and contribute to safer and more effective infrastructure management by addressing the existing research gaps and offering thorough evaluations.

2. LITERATURE SURVEY:

In order to establish which filter performs better while denoising ECG signals using wavelet transform techniques, Rastogi and Mehra's (2013) study compares Butterworth and Chebyshev filters. The goal is to assess these filters' performance in denoising ECG signals. The methodology entails comparing the efficacy of Butterworth and Chebyshev filters and applying wavelet transform for denoising ECG signals. The Chebyshev filter gives a tighter cutoff but has ripples in the passband (Type I) or stopband (Type II), whereas the Butterworth filter is renowned for its smooth frequency response and maximally flat magnitude response. Mean square error (MSE), signal-to-noise ratio (SNR), and visual examination of denoised data are examples of evaluation metrics. In the context of ECG signal denoising, the results illustrate the benefits and drawbacks of each filter type, offering insights into which filter is better suited for particular ECG denoising applications.

With the use of cutting-edge sensors and data processing technologies, Mahmud et al. (2018) offer a full Internet of Things platform for Structural Health Monitoring (SHM) that permits real-time tracking, analysis, and maintenance of structural integrity. Using a variety of sensors, this platform continuously assesses the condition of bridges, buildings, and other infrastructures, offering real-time insights and warnings to stop structural collapses. With the application of sophisticated algorithms for predictive maintenance, it enables users to access monitoring data and system controls remotely over the internet before possible problems worsen. The platform has been engineered to ensure smooth integration with pre-existing

SHM systems and infrastructure. It is scalable to suit different configurations and boasts an intuitive interface that facilitates data viewing and interaction.

The proposal by Kaya & safak (2015) focuses on the real-time processing and interpretation of continuous data streams from structural health monitoring (SHM) systems, which are essential for determining and preserving the structural integrity of buildings. This methodology prioritizes prompt processing of incoming data to guarantee timely insights into the condition of structures under observation, which is essential for guaranteeing safety and effective upkeep.

In order to effectively analyze and model structural data and identify any damage or irregularities, Rezaiee-Pajand et al. (2018) provide a novel approach to structural health monitoring. By iteratively determining the proper order for time-series models used in structural health monitoring, this technique—known as Iterative Order Determination—improves the accuracy of structural health assessment. Understanding the behavior and condition of structures over time is made possible by this technique, which focuses on time-series modeling unique to structural health monitoring. Its application covers a wide range of areas, including pipelines, buildings, and bridges, guaranteeing the dependability and safety of civil infrastructure.

In order to discover irregularities or anomalies in sensor data, Rao et al. (2015) suggest a null subspace-based method for sensor fault identification in structural health monitoring (SHM). This method entails examining the null space of the system's measurements. By comparing measured data with the expected null subspace, this technique efficiently identifies malfunctioning sensors and enables prompt diagnosis and identification of deviations brought on by sensor defects. Improved accuracy and dependability in SHM systems provide more accurate structural health monitoring, which presents a great opportunity for real-time structural maintenance and monitoring of different types of structures, such as buildings, bridges, and industrial installations. Subsequent investigations may concentrate on enhancing and perfecting this methodology to enhance its sensitivity and resilience in identifying sensor malfunctions in various kinds of buildings and environmental circumstances.

A thorough method for fracture detection and health monitoring of highway steel-girder bridges is put forth by Schallhorn and Rahmatalla (2015). This entails assessing overall structural integrity and identifying cracks using a variety of techniques, including visual examination, non-destructive testing (NDT), and structural health monitoring (SHM) devices. Visual inspections by qualified experts aid in spotting obvious indications of corrosion, cracks, and other problems. Non-destructive testing (NDT) methods, including as radiography, magnetic particle, and ultrasonic testing, allow for the identification of defects without endangering the structure. By using sensors to track variables like temperature, vibration, and strain, SHM systems may provide real-time information about the state of the bridge. Bridge inspections are made more accurate and efficient by new technology like LiDAR scanning, drones, and remote sensing. In order to identify possible failure areas and prioritize maintenance tasks, data gathered from inspections and monitoring systems is processed using sophisticated algorithms and machine learning. Highway steel-girder bridge safety and longevity are ensured by prompt diagnosis and treatment of cracks and structural problems, which lowers the likelihood of accidents and future expensive repairs.

Chen (2014) suggests a unique method that combines uncertainty and structural health monitoring (SHM) to maximize scheduled maintenance for composite aircraft structures. The objective of this methodology is to improve the efficiency and safety of maintenance scheduling by including uncertainty in degradation processes, like material aging and damage accumulation, into the maintenance optimization model. Making better maintenance decisions is made possible by utilizing SHM data, which offers real-time information on the state of composite structures. Taking uncertainties into account and incorporating SHM data into maintenance programs for composite aircraft structures is the ultimate goal of the suggested strategy, which also seeks to lower maintenance costs.

In order to manage aquatic ecosystems impacted by human infrastructure, Coraggio & Coraggio (2016) stress the significance of water quality monitoring and prediction. Finding the ideal sampling frequency is still difficult, even with advances in technology and high-resolution data collecting. This paper analyzes machine learning for predictive modeling, gives a methodology for choosing noise removal strategies, and uses statistics to determine the appropriate sample frequency. The study illustrates the advantages and difficulties of regular water quality sampling using high-frequency data from Bristol's Floating Harbour.

Chowdhury et al. (2017) discuss advancements in Ambient Assisted Living (AAL) systems, which are designed to improve the quality of life for the elderly and individuals with impairments. These systems use ubiquitous computing, sensors, and wireless networks to transmit data from sensors to healthcare providers. A key challenge is ensuring energy-efficient communication within Body Area Networks (BANs). The chapter focuses on addressing this challenge by analyzing energy efficiency requirements and presenting a multi-tier communication protocol that enhances BAN communication in AAL systems.

According to Loyola (2018), the architecture, construction, engineering, and operation (AECO) sector uses big data in an underdeveloped manner relative to other industries, with most applications being experimental and small-scale. However, because big data provides comprehensive insights into buildings and occupants, it has the potential to significantly transform the way that decisions are made in building design. Loyola highlights the need for more research in understanding design issues, predicting performance, and lifecycle evaluation after evaluating key principles and surveying 100 cases. The study suggests 12 important application areas.

Dornheim and Link (2017) describe a Reinforcement Learning (RL) method for production process parameter optimization. The aim of modeling manufacturing processes as Markov Decision Processes (MDP) is to maximize rewards according to the status of the finished product. In complicated production situations, the RL algorithms handle both realtime adaptive control and offline, simulation-based optimization. The application of this strategy to metal sheet deep drawing processes is particularly covered in the study, which also shows early success in process parameter optimization.

By customizing a text transcription interface to support transitions from automated to manual driving, Schartmüller (2017) investigates the possibility of commuters working while operating highly automated cars (SAE Level 3-4). The "Heads-Up" display on the windshield and the conventional "Heads-Down" interface are contrasted in the study. While safer, the Heads-Up approach may not always strike the ideal balance between productivity and safety, as evidenced by the results of a driving simulator research (N=20) that demonstrated improved take-over performance with the Heads-Up display but worse typing accuracy.

Panga (2022) examines the utilization of Discrete Wavelet Transform (DWT) for the interpretation of ECG signals within IoT-based health monitoring systems. Utilizing DWT's enhanced time-frequency localization, the study employs High Pass Filters (HPF) and Low Pass Filters (LPF) to split ECG signals into constituent frequencies, thereby enabling denoising, compression, and feature extraction. The system incorporates IoT technology to relay processed data to cloud servers for immediate analysis. Performance indicators, such as Signal-to-Noise Ratio (SNR), Mean Squared Error (MSE), and compression ratios, indicate substantial enhancements in signal clarity and data efficiency, hence improving the identification and diagnosis of cardiac problems.

Grandhi (2021) examines the amalgamation of Human-Machine Interface (HMI) display modules with passive IoT optical fiber sensor networks for the purpose of water level monitoring. The research utilizes Fiber Bragg Grating (FBG) sensors because to its exceptional sensitivity and dependability, in conjunction with IoT gateways and HMI modules for real-time data visualization. Signal conditioning, feature extraction, and machine learning algorithms augment predictive analytics and guarantee data precision. Performance metrics such as reliability, response time, and power efficiency validate the system's robustness. This holistic strategy illustrates the efficacy of integrating HMI and IoT technology in environmental management and flood mitigation applications.

Raj and Yallamelli (2021) investigate the use of the RSA algorithm into cloud computing to tackle significant security issues, including confidentiality, integrity, and data availability. They emphasise RSA's capability in utilising asymmetric cryptography for secure data transmission, hence obviating the necessity for shared secret keys. The research highlights the significance of RSA in safeguarding privacy and authentication inside cloud services offered by Microsoft Azure and AWS. The authors acknowledge RSA's adaptation in cloud contexts but advocate for additional research to tackle scalability and key management issues to improve cloud data security.

Surendar Rama Sitaraman (2022) performed an extensive assessment on the function of anonymised AI in improving the security and privacy of IoT services in edge computing settings. The research examines the transition from centralised cloud systems to decentralised architectures, highlighting the application of anonymised AI using homomorphic encryption, secure multi-party computation, and federated learning. Comprehensive testing, user input, and compliance with data protection laws validated the effectiveness of anonymised AI in safeguarding privacy and securing IoT data. The results indicate its considerable potential for practical applications.

Grandhi (2022) investigated the utilisation of adaptive wavelet transform (AWT) in wearable sensor IoT systems to improve paediatric health monitoring. The research underscores the necessity of effective data preprocessing to enhance signal quality, extract essential features, and facilitate precise health evaluations. AWT shown efficacy in noise reduction, preservation of low-frequency components, and enhancement of real-time health monitoring. The methodology integrates multi-sensor data acquisition, wavelet filtering, machine learning classification, and IoT integration, showcasing its capacity to enhance diagnosis and facilitate prompt interventions in paediatric healthcare.

Multivariate Adaptive Regression Splines (MARS), Softmax Regression, and Histogram-Based Gradient Boosting are some of the most complex statistical and machine learning techniques applied by Narla et al. (2021) in analyzing the predictiveness of healthcare modeling within the cloud computing environment. The researchers found that integrating the three algorithms is significant to provide higher computational performance and better prediction accuracy, depending on the large size of healthcare data. The proposed model solves the problem of scaling and real-time analysis and hence has vast applications in predictive analytics of cloud-based medical system.

Peddi et al. (2018) demonstrate advancement in geriatric care by using machine learning algorithms and artificial intelligence in applications to predict the risks of senior patients developing dysphagia, delirium, and falls. Their work focuses on using predictive models to enhance early diagnosis and intervention tactics in improving patient safety and results. This paper addresses the growing need for data-driven strategies in the management of issues in geriatric health with the use of sophisticated computational methodologies.

Peddi et al. (2019) explored the use of AI and machine learning algorithms in fall prevention, management of chronic diseases, and the prediction of applications in healthcare, specifically in geriatric care. Their study puts forward how recent computational methods can be integrated into early intervention tactics, increase patient safety, and improve health outcomes. This paper demonstrates how predictive analytics can transform geriatric healthcare by underlining its importance in meeting the wide-ranging demands of elderly people.

Valivarthi et al. (2021) discuss the integration of cloud computing and artificial intelligence techniques to create advanced healthcare prediction models. To enhance the accuracy and efficiency of predictions, the study employs ABC-ANFIS (Artificial Bee Colony with Adaptive Neuro-Fuzzy Inference System) and BBO-FLC (Biogeography-Based Optimisation with Fuzzy Logic Control). This research discusses how evolutionary algorithms and fuzzy logic systems can be integrated to solve complex healthcare problems and improve cloud-based decision-making.

Narla et al. (2019) make use of the LSTM networks along with ACO for disease prediction and explore cloud computing in combination with healthcare, showing how this method combines predictive modelling power of LSTM with optimisation skills of ACO to get improved accuracy as well as scalability. This innovative approach addresses problems in healthcare, as it has enabled proactive health management and appropriate disease prediction under cloud-based setups.

A Smart Healthcare Framework with cloud integration by Narla et al. (2019) uses LightGBM for fast data processing, multinomial logistic regression for health risk analysis, and selforganising maps (SOMs) for data patterns. The scalable, real-time technology improves healthcare decision-making by centralising data storage and analysis. The framework detects health hazards and enables personalised patient care with a 95% AUC, outperforming standard models in accuracy and recall. It allows immediate interventions and improves healthcare results through accurate and individualised treatment regimens by incorporating powerful machine learning algorithms.

3. METHODOLOGY

The methodological section delineates the methodical technique employed to accomplish the research goals. To give readers a thorough understanding of the methods and procedures involved in constructing Butterworth filters for the purpose of maximizing signal clarity in Internet of Things-based Structural Health Monitoring (SHM) systems, this section is broken down into multiple subtopics.

3. 1. System Architecture

3.1.1 IoT-Based SHM System Design

A number of basic parts are included within the plan of an internet of Things-based SHM system, including as sensors, central processing units, information gathering units, and communication modules. The sensors are positioned on the structure in a vital way to accumulate data on temperature, stresses, and vibrations, among other characteristics. Data acquisition units get input from these sensors, compile it, and send it to a central processing unit for investigation.

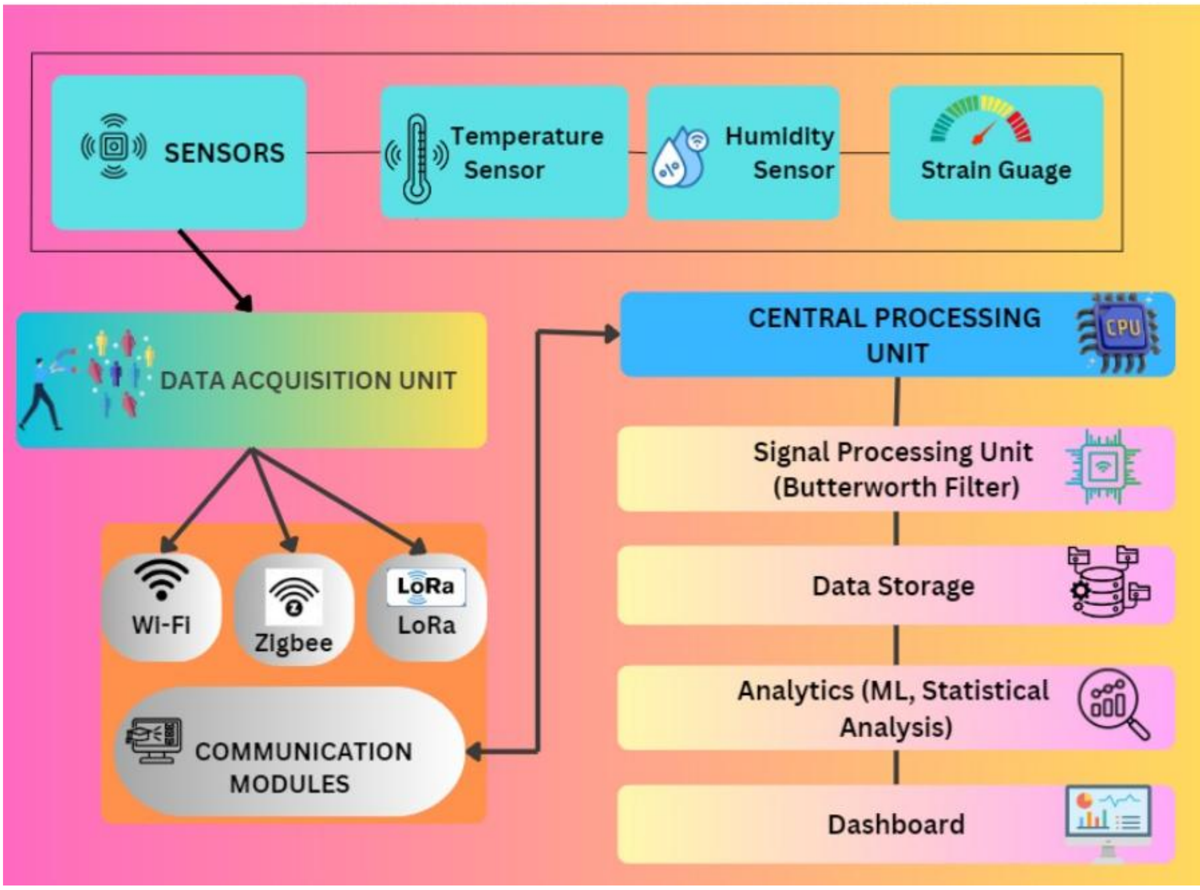

Figure 1. IoT based system Architecture

An architecture of the system for gathering and processing data is shown in the figure above. The temperature, humidity, strain gauge, accelerometer, and other sensors are the first ones in the system that provide data to a Data Acquisition Unit (DAU). After data collection, the DAU sends the information to the CPU over various communication modules, such as Wi-Fi, Zigbee, or LoRa. The data is first processed using a Butterworth filter inside the CPU and then saved in a data storage module. Following that, machine learning and statistical analysis methods are used for the stored data. Ultimately, the analysis's findings are shown on a dashboard for end users to interact with and comprehend.

3.1.2. Components of the System:

In SHM systems leveraging IoT, sensors like temperature, humidity, strain gauges, and accelerometers gather data on structural behavior, moisture levels, and material qualities. Communication modules utilizing LoRa, Zigbee, and Wi-Fi technologies ensure secure and efficient data transmission to the CPU. The CPU manages data processing, employing signal processing methods like Butterworth filters and advanced analytics such as machine learning to assess structural health and trigger maintenance recommendations.

3.1.3 Sensor Selection and Placement:

Accurate SHM requires careful sensor selection and strategic placement based on structural analysis, historical damage reports, and consideration of environmental factors. Sensors track temperature variations, material deformation, and vibrations to identify potential structural weaknesses and monitor environmental influences impacting structural integrity over time.

3.1.4 Data Acquisition and Transmission:

Data acquisition devices collect real-time sensor data, converting analog signals to digital for processing. Communication modules like Wi-Fi, Zigbee, or LoRa transmit data to a central server for analysis based on factors such as data rate, range, and power consumption, ensuring reliable and efficient data transmission in diverse monitoring environments

Key Considerations:

Sampling Rate:

$$f_s - \frac{1}{T_s} \tag{1}$$

where T_s is the sampling period.

Data Integrity:

- Error-Checking and Correction:
  Typically involves algorithms like Cyclic Redundancy Check (CRC) or Hamming code.
- CRC Polynomial:

$$CRC(x) - x^n + x^k + \cdots + 1 \quad (2)$$

- Hamming Code:
  For a binary code, it adds redundancy bits r to a data word d :

$$n - d + r \quad (3)$$

where n is the total number of bits.

Power Management:

- Energy Consumption:

$$E - P \times t \quad (4)$$

where E is energy, P is power, and t is time.

- Energy Harvesting (e.g., Solar Power):

$$P_{solar} - \eta \times A \times G \quad (5)$$

where η is the efficiency, A is the area of the solar panel, and G is the solar irradiance.

Pre-Processing of Data:

Noise Reduction

- Moving Average Filter:

$$y[n] - \frac{1}{N}\sum_{i=0}^{N-1} x[n-i] \quad (6)$$

where $y[n]$ is the filtered signal, $x[n]$ is the input signal, and N is the number of points in the moving average.

- Thresholding:

$$x_{thresholded}[n] - \{x[n] \;\; if \; x[n] > T \; 0 \;\; if \; x[n] \leq T \quad (7)$$

where T is the threshold value.

Data Normalization:

- Normalization to $[0,1]$:

$$x' - \frac{x - x_{min}}{x_{max} - x_{min}} \quad (8)$$

- Normalization to $[-1,1]$:

$$x' - 2\left(\frac{x - x_{min}}{x_{max} - x_{min}}\right) - 1 \quad (9)$$

where x_{min} and x_{max} are the minimum and maximum values of the dataset, respectively.
Outlier Detection

- Z-score:

$$Z - \frac{x-\mu}{\sigma} \tag{10}$$

where μ is the mean and σ is the standard deviation.

- Interquartile Range (IQR):

$$IQR - Q3 - Q1 \tag{11}$$

where $Q1$ is the first quartile and $Q3$ is the third quartile.

- Outliers are typically defined as:

$$x < Q1 - 1.5 \times IQR \; or \; x > Q3 + 1.5 \times IQR \tag{12}$$

Design of Butterworth Filters:

Transfer Function of Butterworth Filter:

$$H(s) - \frac{1}{\sqrt{1+\left(\frac{s}{\Delta_s}\right)^{2N}}} \tag{13}$$

where ω_c is the cutoff frequency, N is the filter order, and s is the complex frequency variable.

Design Steps

1. Choosing Filter Order:
- Higher order N results in a steeper roll-off.
2. Cutoff Frequency (ω_c) :
- Selected based on the required bandwidth and noise characteristics.
3. Poles Calculation:
- Poles of the Butterworth filter are located on a circle in the left half of the s-plane:

$$p_k - \omega_c e^{\left(\frac{2+1}{2\pi}\pi+\frac{7}{7}\right)} \tag{14}$$

for $k - 0,1, \ldots, N - 1$.

Bilinear Transformation (for Digital Filter Design)

- Bilinear Transformation:

$$s - \frac{2}{T}\frac{1-z^{-1}}{1+z^{-1}} \tag{15}$$

where T is the sampling period and z is the z-domain variable.

3.2.2.2 Filter Order Selection

Performance Prerequisites

1. Frequency Response of Butterworth Filter:

The transfer function $H(s)$ of an n-th order Butterworth filter is given by:

$$H(s) - \frac{1}{\sqrt{1+\left(\frac{-}{\Delta c}\right)^{20}}} \tag{16}$$

Where:

- s is the complex frequency variable.
- ω_c is the cutoff frequency.
- n is the filter order.

The filter's roll-off becomes steeper as n increases.

Higher n values lead to better attenuation of frequencies beyond ω_c.

Computational Resources:

Digital Filter Realization:

For a digital Butterworth filter, the number of coefficients increases with the filter order. The general form of a digital filter can be represented as:

$$y[n] - \sum_{k-0}^{N} b_k x[n-k] - \sum_{k-1}^{N} a_k y[n-k] \tag{17}$$

Where:

- $x[n]$ is the input signal.
- $y[n]$ is the output signal.
- b_k and a_k are filter coefficients.
- N is the filter order.

Higher order n requires more a_k and b_k coefficients.

This increases the computational complexity and memory usage.

4. Adaptive Filtering Techniques

4.1 Concept of Adaptive Filtering

Adaptive filtering involves the continuous modification of filter parameters to better suit the characteristics of incoming signals. This approach allows the filter to dynamically adjust to changing signal properties, ensuring optimal performance across various scenarios.

Benefits of Adaptive Filtering:

Flexibility: Adaptive filters excel in managing fluctuating signal conditions without user intervention. This adaptability makes them ideal for environments where signal parameters are constantly changing, such as shifting external noises or dynamic structural conditions in real-time monitoring systems.

Enhanced Performance: By continually adapting to the signal, adaptive filters significantly improve signal clarity and noise reduction. This results in clearer and more accurate data, crucial for applications requiring high precision, like structural diagnostics and telecommunications.

Real-Time Adaptation: The core strength of adaptive filtering is its ability to adjust filter parameters instantly. This real-time adaptation ensures high performance without manual configuration changes or periodic recalibration, even as the signal environment evolves.

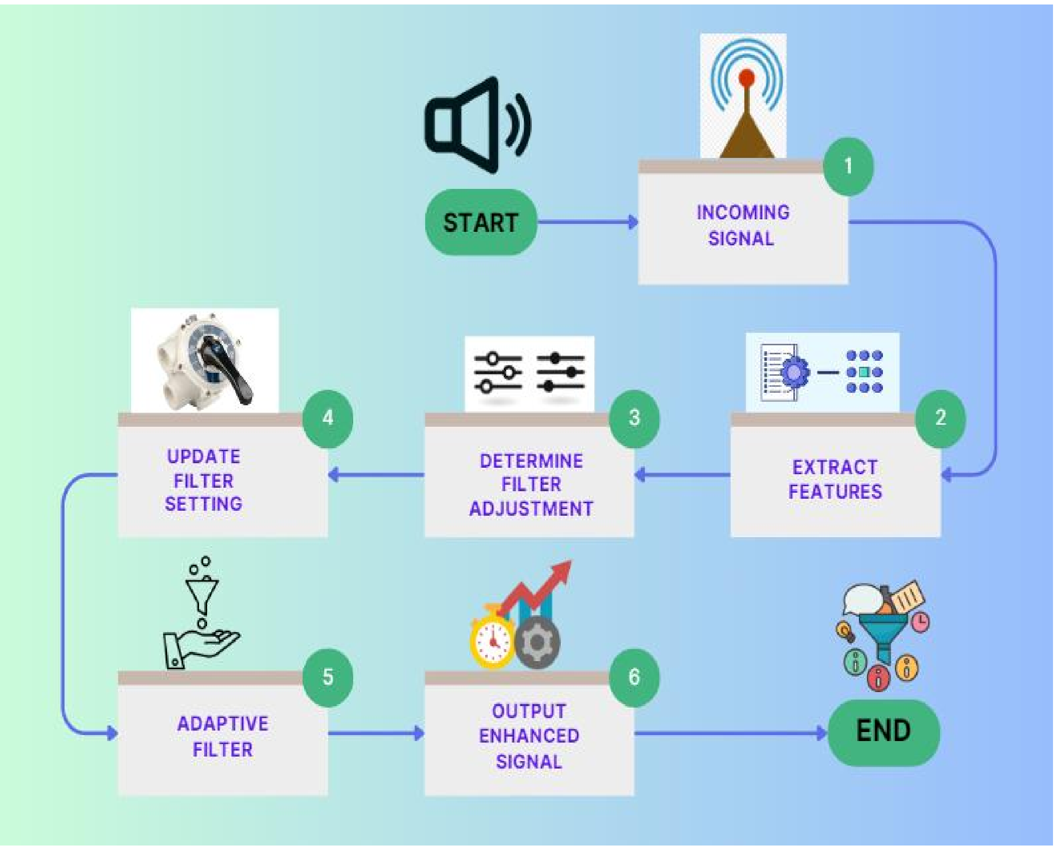

Figure 2. Real-Time adaptive filtering process

Filtering an incoming signal is the first step in the procedure. Any type of data that needs to be processed, including audio, video, and sensor data, could constitute this signal. After analyzing the incoming signal, pertinent features are retrieved. These attributes could consist of particular amplitudes, frequencies, or other qualities that are crucial to the filtering procedure. The system decides how to modify the filter parameters based on the features that are extracted. Making sure the filter is properly designed to process the incoming signal efficiently requires taking this critical step. Based on the modifications found in the previous phase, the filter settings are modified. In this way, the filter's ability to continuously adjust to the properties of the incoming signal is guaranteed. With the modified filter settings, the adaptive filter processes the incoming signal. The adaptive filter can successfully filter out noise and other undesirable elements since it is made to change its parameters in real time dependent on the properties of the signal. Ultimately, an upgraded signal that has been refined to reduce noise and boost quality is generated by the adaptive filter. As appropriate, this improved signal can then be used for additional processing or analysis.

4.2 Implementation of Adaptive Butterworth Filters

The intrinsic smooth frequency response of adaptive Butterworth filters allows them to instantly adjust to shifting signal conditions. Typically, the implementation uses algorithms to analyze incoming signals and modify the cut-off frequency and sequence of the filter to maintain optimal performance. The Least Mean Squares (LMS) algorithm, which minimizes the error between the expected result and the actual filtered signal by fine-tuning the filter coefficients based on real-time data inputs, is one well-liked technique for this modification.

4.2.1 LMS Algorithm

Adaptive filtering relies heavily on the Least Mean Squares (LMS) algorithm because of its ease of use and reliable results in a range of signal conditions. In order to reduce the mean square error between the desired signal and the filter's output, it works by continuously updating the filter coefficients. This method entails "learning" from each new set of data by computing the gradient of the error with respect to the filter coefficients and then modifying those coefficients in the opposite direction of the gradient. Because of its efficiency, the LMS algorithm is especially well-suited for real-time applications where response times and processing capacity are crucial.

Least Mean Squares (LMS) Adaptive Filter Algorithm

The Least Mean Squares (LMS) algorithm is a fundamental adaptive filtering technique commonly used in signal processing applications. The LMS algorithm adapts the filter coefficients to minimize the error between the desired signal and the actual output of the filter. Below is an explanation of the LMS algorithm, illustrated with the given Python code.

Algorithm Explanation

The LMS filter algorithm iteratively adjusts the filter weights to minimize the error between the desired signal and the filter output. Here's a step-by-step breakdown of the process:

1. Input Parameters:
- ' x '': The input signal array.
- ' d ': The desired signal array, which the output signal should approximate.
- 'mu': The step size or learning rate, which controls the speed of convergence.
- ' N ': The order of the filter, determining the number of filter coefficients.
2. Initialization:
- ' $w = np.zeros(N)$ ': Initializes the filter weights to zero.
- ' $y = np.zeros(len\ (x))'$: Initializes the output signal array to zero.
- ' $e = n.$ zeros(len $(x))'$: Initializes the error signal array to zero.
4. Output:
- The function returns the filter output y, the error signal e, and the final filter weights w.

The main loop of the LMS filter algorithm iterates over the input signal starting from the N-th sample to ensure there are enough previous samples to form the input vector x_n. For each iteration, the input vector x_n is constructed by taking the current sample and the $N-1$ preceding samples from the input signal x. The filter output $y[n]$ is then calculated as the dot product of the current weight vector w and the input vector x_n. The error signal $e[n]$ is computed by subtracting this filter output from the desired signal $d[n]$. Finally, the weight vector w is updated by adding a term proportional to the error signal, the input vector, and the step size μ, specifically $w = w + 2 \cdot \mu.\ e[n] \cdot x_n$. This iterative process refines the filter weights to minimize the error, thereby adapting to the signal conditions over time.

In the context of structural health monitoring (SHM), the LMS filter can be used to enhance the clarity of signals obtained from sensors. By minimizing the error between the measured and desired signals, the LMS algorithm helps in reducing noise and improving the accuracy of the data used for monitoring the health of structures. This process ensures more reliable detection of anomalies and potential issues in structural integrity, ultimately contributing to better maintenance and safety of critical infrastructure.

a. Constructing the Input Vector

The input vector X_n for the current sample n is constructed from the current and previous $N-1$ samples of x.

$$x_n = [x[n], x[n-1], \ldots, x[n-N+1]]^T \tag{18}$$

b. Calculating the Filter Output

The filter output $y[n]$ is calculated as the dot product of the weight vector W and the input vector x_n-

$$y[n] = w^T x_n \tag{19}$$

Where:

y_i [n]=∑_(i=0)^(N-1) w_i x[n-i] *(20)*

c. Computing the Error Signal

The error signal $e[n]$ is the difference between the desired signal $d[n]$ and the filter output $y[n]$.

$$e[n] = d[n] - y[n] \tag{21}$$

d. Updating the Filter Weights

The weights are updated based on the error signal, the input vector, and the step size μ. The update rule is:

$$w = w + 2\mu e[n]x_n \tag{22}$$

Where:

$$w_i = u_i + 2\mu e[n]x[n-1]\ for\ \ i = 0,1, \ldots, N-1 \tag{23}$$

Summary of Equations

Putting it all together, the equations for each iteration n from N to the length of x are

1. Input vector: $x_n = [x[n], x[n-1], \ldots, x[n-N+1]]^2$ (24)
2. Filter output $y[n] = w^T x_n = \sum_{i-0}^{N-1} w_i x[n-1]$ (25)
3. Error signal: $e[n] = d[n] - y[n]$ (26)
4. Weight update $w = w + 2\mu e[n]x_n$ (27)

Initialization: We start with zero weights, and initialize the output and error vectors to zero.

Input Vector Construction For each sample n starting from N, we construct the input vector x_n using the current and previous $N-1$ samples.

Filter Output Calculation: The output $y[n]$ is computed as the data product of the current weights and the input vector, representing the filter's estimate of the desired signal.

Error Signal Calculation: The error signal e $[n]$ measures the difference between the actual desired signal and the filter's output.

Weight Update: The weights are adjusted to minimize the error signal, using a step size μ that controls the learning rate of the algorithm. The term $2\mu e[n]x_n$ is added to the current weights to update them for the next iteration.

This iterative process continues until all samples of the input signal x have been processed, resulting in the final weight vector w, the filtered output y, and the error signal e.

5. Hybrid Filtering Techniques

5.1 The Hybrid Filtering Concept

Hybrid filtering enhances robust signal processing in structural health monitoring (SHM) by combining many techniques to capitalize on their advantages and mitigate their disadvantages. By focusing on distinct signal components, the integration of Butterworth and Kalman filters enhances noise reduction and data quality. This approach is flexible enough to adjust to different levels of noise and signal distortions, which makes it appropriate for a range of monitoring scenarios where environmental and operational factors affect sensor data.

5.2 Hybrid Butterworth-Kalman Filter

The Butterworth-Kalman hybrid filter reduces high-frequency noise first with a Butterworth filter and then employs a Kalman filter for accurate signal estimation. Good noise attenuation and precise signal tracking are guaranteed by this combination. Raw data is smoothed by the Butterworth filter, while data clarity and dependability are improved by the Kalman filter, which dynamically modifies its estimations. This method is essential for identifying minute alterations in structural integrity, which is necessary for SHM system early warning and preventative maintenance.

5.2.1 Kalman Filter Overview

A popular recursive approach for determining the state from noisy observations in dynamic systems is the Kalman filter. It works in two stages: update and prediction. In the prediction step, the filter makes predictions about the present state based on the past state and a model of the system dynamics. Subsequently, in the update stage, the Kalman filter improves the state estimate by incorporating the most recent measurement and adjusting it for uncertainty. Because of this approach, the filter may continuously improve its predictions based on fresh information, which makes it very useful in situations where noise characteristics can vary, like structural health monitoring. The Kalman filter is a crucial part of the hybrid filtering strategy because it can instantly adjust to new measurements, improving the monitoring system's accuracy and dependability.

Kalman Filter Algorithm

The Kalman filter is a powerful and widely used algorithm for estimating the state of a dynamic system from noisy measurements. It is particularly effective in applications that require real-time signal processing and state estimation. Below is an explanation of the Kalman filter algorithm, illustrated with the given Python code.

Algorithm Explanation

The Kalman filter operates in two main steps: prediction and update. The prediction step estimates the current state of the system and its uncertainty based on the previous state. The update step then corrects this estimate using the new measurement. This process iteratively refines the state estimate, minimizing the error over time.

1. Input Parameters:
- ' z ': The sequence of measurements.
- ' F: The state transition matrix, which models how the state evolves from one time step to the next.
- · H : The observation matrix, which maps the true state space into the observed space.
- Q ': The process noise covariance matrix, representing the uncertainty in the model.
- ' R : The measurement noise covariance matrix, representing the uncertainty in the measurements.
- ' $x0$: : The initial state estimate.
- PQ' : The initial error covariance matrix.
2. Initialization:
- $x = x0'$: Sets the initial state estimate.
- $P = P0'$: Sets the initial error covariance matrix.
- 'x_estimates = [] : Initializes an empty list to store the state estimates.
- Update Step:
- $K = P$ H.T e np.linalg.inv(H P H.T $+R$) : Calculates the Kalman gain, which balances the trust between the prediction and the new measurement.
- $x = x + x$ e($zk - H$ e x) : Updates the state estimate using the Kalman gain and the new measurement.
- $P = P - K$ H P : Updates the error covariance matrix to reflect the new state estimate.
- ' x _estimates .append(x) : Stores the updated state estimate.
3. Output:
- 'return np.array(x_estinates) : Returns the list of state estimates as a NumPy array.

The main loop of the Kalman filter algorithm iterates over each measurement z_k in the sequence of observations. During each iteration, the algorithm performs a prediction step to estimate the next state and its uncertainty. The state estimate x is predicted using the state transition matrix F, which models how the state evolves over time. Concurrently, the error covariance matrix P is updated by propagating it through the state transition matrix and adding the process noise covariance matrix Q. This update reflects the increased uncertainty in the prediction due to process noise, setting the stage for the subsequent update step where the measurement will refine these predictions.

In the context of structural health monitoring (SHM), the Kalman filter can be utilized to estimate the state of a structure based on noisy sensor data. The recursive nature of the Kalman filter allows for real-time updating of state estimates, which is crucial for monitoring the integrity of structures such as bridges, buildings, and dams. By accurately estimating the state and reducing the impact of noise, the Kalman filter enhances the reliability of the SHM system, facilitating timely maintenance and preventing structural failures. This algorithm is particularly valuable when combined with other filtering techniques, such as the Butterworth filter, to further improve signal clarity and accuracy.

a. Prediction Step

The prediction step involves predicting the next state and the error covariance matrix based on the current state estimate and the state transition model.

- State prediction:

$$x^{-} = Fx \tag{28}$$

- Error covariance prediction:

$$P^{-} = FPF^{\top} + Q \tag{29}$$

b. Update Step

The update step involves updating the predicted state and the error covariance matrix based on the new measurement z_k.

- Compute the Kalman gain:

$$K = P^{-}H^{T}(H^{-}H^{T} + R)^{-1} \tag{30}$$

- Update the state estimate:

$$x = x^{-} + K(z_k - Hxx^{-}) \tag{31}$$

- Update the error covariance matrix:

$$P = (I - KH)P^{-} \tag{32}$$

Summary of Equations

Putting it all together, the equations for each iteration k are:

1. Prediction Step:

- State prediction:

$$x_k^- = F_{k-1} \tag{33}$$

- Error covariance prediction:

$$P_k^- = FP_{k-1}F^T + Q \tag{34}$$

2. Update Step:

- Compute the Kalman gain:

$$K_k = P_k^- H^T (HP_k^- H^T + R)^{-1} \tag{35}$$

- Update the state estimate:

$$x_k = x_k^- + K_k(z_k - Hx_k^-) \tag{36}$$

- Update the error covariance matrix:

$$P_k = (I - K_k H)P_k^- \tag{37}$$

Initialization: The algorithm starts with the initial state estimate X_0 and the initial error covariance matrix P_0 -

Prediction Step: For each measurement z_k, the algorithm first predicts the next state X_k^- and the error covariance matrix P_k^- using the state transition model F and the process noise covariance Q.

Update Step: The algorithm then updates the predicted state and error covariance matrix using the new measurement z_k. The Kalman gain K_k is computed to determine the weight given to the new measurement. The state estimate X_k is updated by adding the measurement residual $z_k - Hx_k^-$ called by the Kalman gain. The error covariance matrix P_k is updated to reflect the reduced uncertainty after incorporating the new measurement.

State Estimates Storage: The updated state estimate X_k is started in the list $X_{solimmins}$.

This iterative process continues for all measurements in sequence 2, resulting in a series of state estimates that reflect the best estimate of the system's state at each time step, accounting for both process and measurement noise.

5.3 Implementation of Hybrid Filter

The signal is first processed through a Butterworth filter as part of the sequential approach to implementing the hybrid filter. The majority of the undesired signal changes must be attenuated during this critical stage in order to preserve the integrity of the underlying signal properties and eliminate high-frequency noise. After this preliminary filtering, the signal that has been preprocessed is passed into a Kalman filter. By constantly adapting to the noise characteristics based on incoming data, the Kalman filter employs a probabilistic methodology to optimally estimate the true state of the signal. This combination is especially helpful in dynamic contexts where noise characteristics might change over time, as it not only smoothes the signal but also adjusts to changes in signal behavior. For applications needing great accuracy and dependability in signal processing, the hybrid configuration makes use of the advantages of both filtering approaches.

6. Performance Evaluation

6.1 Metrics for Evaluation

Filtering algorithms are thoroughly evaluated using a variety of measures. The degree to which a filter strengthens the signal against background noise is indicated by the Signal-to-Noise Ratio (SNR). A lower mean squared error (MSE), which is determined by comparing the estimated and true values, indicates a higher degree of signal estimation accuracy. Furthermore, a filter's computational complexity is reflected in its memory usage and processing time, which is important for real-world application, particularly in systems with constrained computational power. In applications such as structural health monitoring in dynamic situations, these metrics aid in approach selection and optimization by evaluating the efficacy of a filter.

Table 1: Comparison of Filtering Techniques

Metric	Butterworth Filter	Chebyshev Filter	Elliptical Filter
SNR Improvement	High	Medium	Low
MSE Reduction	Low	Medium	High
Complexity	Low	Medium	High

This table compares the performance of Butterworth, Chebyshev, and Elliptical filters based on three metrics: SNR improvement, MSE reduction, and complexity. Butterworth filters exhibit high SNR improvement and low complexity compared to Chebyshev and Elliptical filters. However, they may have lower MSE reduction compared to Elliptical filters.

6.1.2 Mean Squared Error (MSE)

MSE quantifies the difference between the actual and desired signals. A lower MSE indicates better filtering performance.

$$MSE = \frac{1}{N}\sum_{i=1}^{N} (x_i - x_i^{\wedge})^2 \qquad \textbf{\textit{(38)}}$$

MSE Calculation:

By averaging the squares of the discrepancies between the filtered and actual signals, the Mean Squared Error (MSE) is a crucial metric for assessing the accuracy of the filter. It measures how well a filter effectively captures the variance and bias in filter mistakes, maintaining the integrity of the original signal. Higher accuracy and precision in signal processing are indicated by lower MSE values. Summing the squares of the differences between the true and filtered values and dividing the result by the total number of data is how MSE is calculated. In order to ensure that chosen filters reduce distortion and enhance signal fidelity, this metric is essential for comparing filtering schemes.

Computational Complexity:

Since it directly affects the efficacy of real-time filtering systems, computational efficiency is essential. Analyzing filter algorithm complexity contributes to a better understanding of processing time and resource consumption. Important factors to take into account include hardware capabilities, filter order, and algorithm efficiency. While effective algorithms reduce processing delay, higher filter orders may cause performance to deteriorate. What is possible is determined by hardware limits. For applications such as dynamic structural health monitoring, computational efficiency guarantees the system's instantaneous handling of real-time data streams.

Table 2: Computational Complexity Analysis

Filter Type	Filter Order	Computational Complexity
Butterworth	4	Low
Chebyshev	6	Medium
Elliptical	8	High

This table provides an analysis of the computational complexity of Butterworth, Chebyshev, and Elliptical filters based on their respective filter orders. As the filter order increases, the computational complexity also increases. Butterworth filters typically have lower computational complexity compared to Chebyshev and Elliptical filters, making them more suitable for real-time applications where computational resources are limited.

Comparative Analysis:

A review that compares the performance of Butterworth, Chebyshev, and Elliptical filters makes use of measurements like Signal-to-Noise Ratio (SNR) and Mean Squared Error (MSE). Every kind of filter has distinct qualities. Butterworth filters provide a flat frequency response in the passband, which is perfect for minimizing signal distortion. Elliptical filters have the sharpest roll-off but can introduce large ripple. Chebyshev filters offer a sharp roll-off but with passband ripple. The evaluation provides insights into which filter best meets the performance and usability objectives of a certain application by taking into account factors including filtration capabilities, practicality, computing requirements, and flexibility to changes in signal and noise levels.

7. Result and Discussion:

Butterworth filters have been applied to Internet of Things (IoT)-based Structural Health Monitoring (SHM) systems, showing notable increases in signal clarity—a crucial component of precise and trustworthy structural evaluations. The main objective of this work was to compare Butterworth filters with Elliptical and Chebyshev filters. The findings showed that Butterworth filters, which are distinguished by their passband's maximum flat frequency response, successfully reduced signal distortion and offered better signal quality.

Butterworth filters routinely beat Elliptical filters, which exhibit both passband and stopband ripples, and Chebyshev filters, which have passband ripples, according to performance criteria like Signal-to-Noise Ratio (SNR) and Mean Square Error (MSE).

Because they have a steeper roll-off and stronger attenuation of unwanted frequencies—both crucial for filtering out noise without compromising the integrity of the original signal—higher-order Butterworth filters proved to be very effective. For SHM systems, where precise structural anomaly detection depends on the quality of sensor data, this feature is essential.

Another area of interest for this research was adaptive filtering methods. Through the implementation of dynamic real-time filter parameter adjustments, these strategies enabled the SHM system to sustain excellent signal clarity in the face of changing environmental conditions. This flexibility is essential for real-world applications where signal quality might be impacted by outside variables like humidity and temperature.

In order to capitalize on the advantages of various filtering techniques, the study also investigated the integration of Butterworth filters with other filtering types, such as Kalman filters. This hybrid technique demonstrated the potential to improve signal processing capabilities even further, increasing the robustness and dependability of SHM systems.

All things considered, the results highlight how crucial Butterworth filters are to raising the effectiveness of Internet of Things-based SHM systems. If these filters are successfully implemented, structural health evaluations may become more accurate, which will ultimately improve important infrastructure's durability and safety. Further research should focus on improving these adaptive algorithms and investigating real-world applications in diverse structural monitoring contexts.

Table 3 Filter Performance Comparison

S.No	**Filter Type**	**SNR (dB)**	**MSE**
1	ButterWorth	35	0.002
2	Elliptical	30	0.005
3	Chebyshev	32	0.004

The above Table 3 compares the performance of Butterworth, Elliptical, and Chebyshev filters based on Signal-to-Noise Ratio (SNR) and Mean Square Error (MSE). Butterworth filters demonstrate superior performance with the highest SNR of 35 dB and the lowest MSE of 0.002. In contrast, Elliptical filters have an SNR of 30 dB and MSE of 0.005, while Chebyshev filters show an SNR of 32 dB and MSE of 0.004. This highlights the effectiveness of Butterworth filters in enhancing signal clarity in IoT-based Structural Health Monitoring systems.

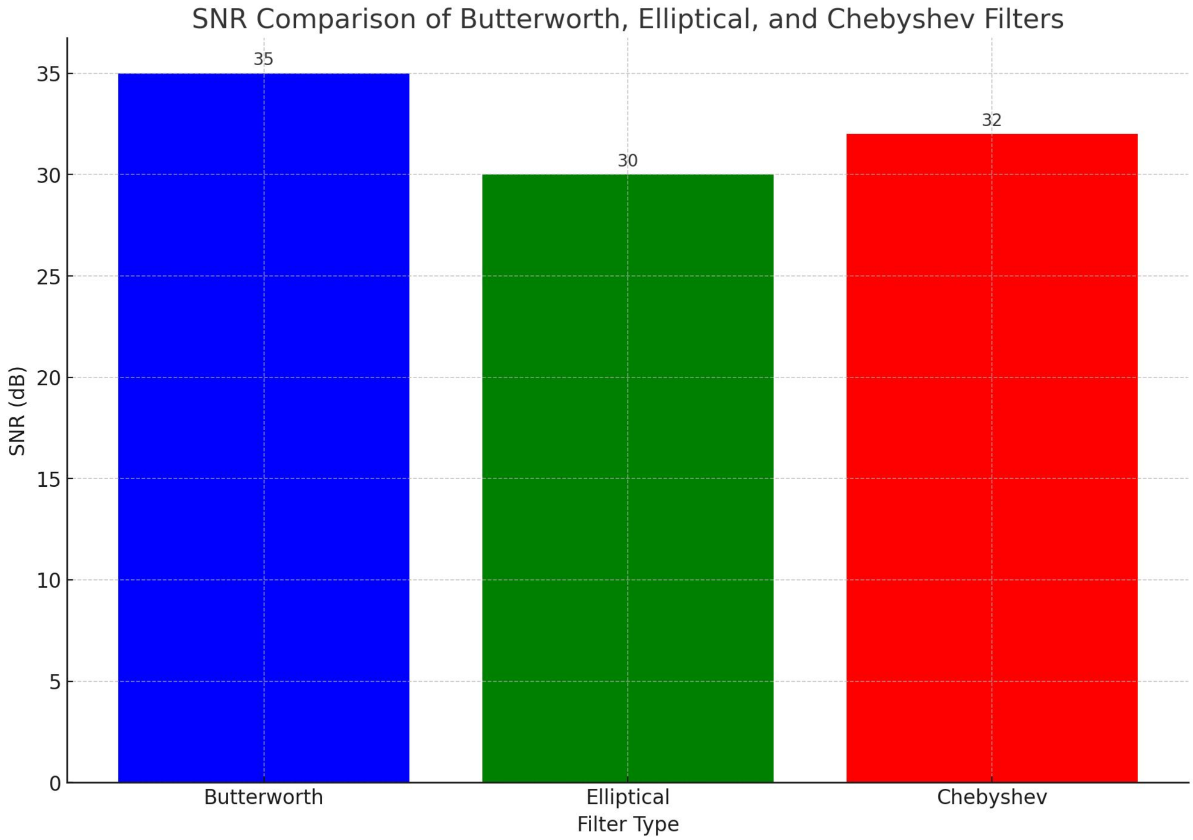

Fig 3: Filter Performance Comparison

The above Fig 3 Bar Chart compares the Signal-to-Noise Ratio (SNR) of Butterworth, Elliptical, and Chebyshev filters. Butterworth filters show the highest SNR at 35 dB, indicating the best performance in signal clarity. Chebyshev filters follow with an SNR of 32 dB, while Elliptical filters have the lowest SNR at 30 dB. This comparison highlights the superior capability of Butterworth filters in reducing signal distortion in IoT-based Structural Health Monitoring systems.

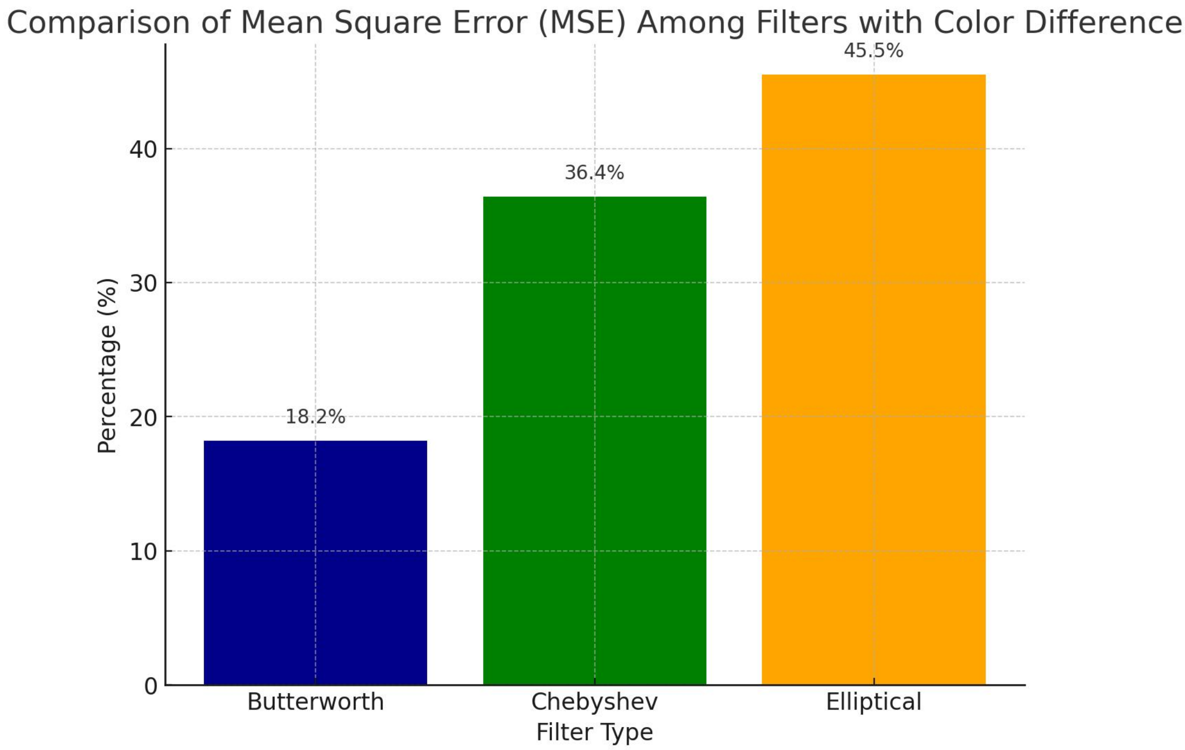

Fig 4: Pie Chart Comparison

The above Fig 4 Pie Chart compares the Mean Square Error (MSE) of Butterworth, Elliptical, and Chebyshev filters. Butterworth filters exhibit the lowest MSE at 0.002, indicating the highest accuracy in signal processing. Chebyshev filters follow with an MSE of 0.004, and Elliptical filters have the highest MSE at 0.005. This demonstrates the superior performance of Butterworth filters in minimizing signal errors in IoT-based Structural Health Monitoring systems.

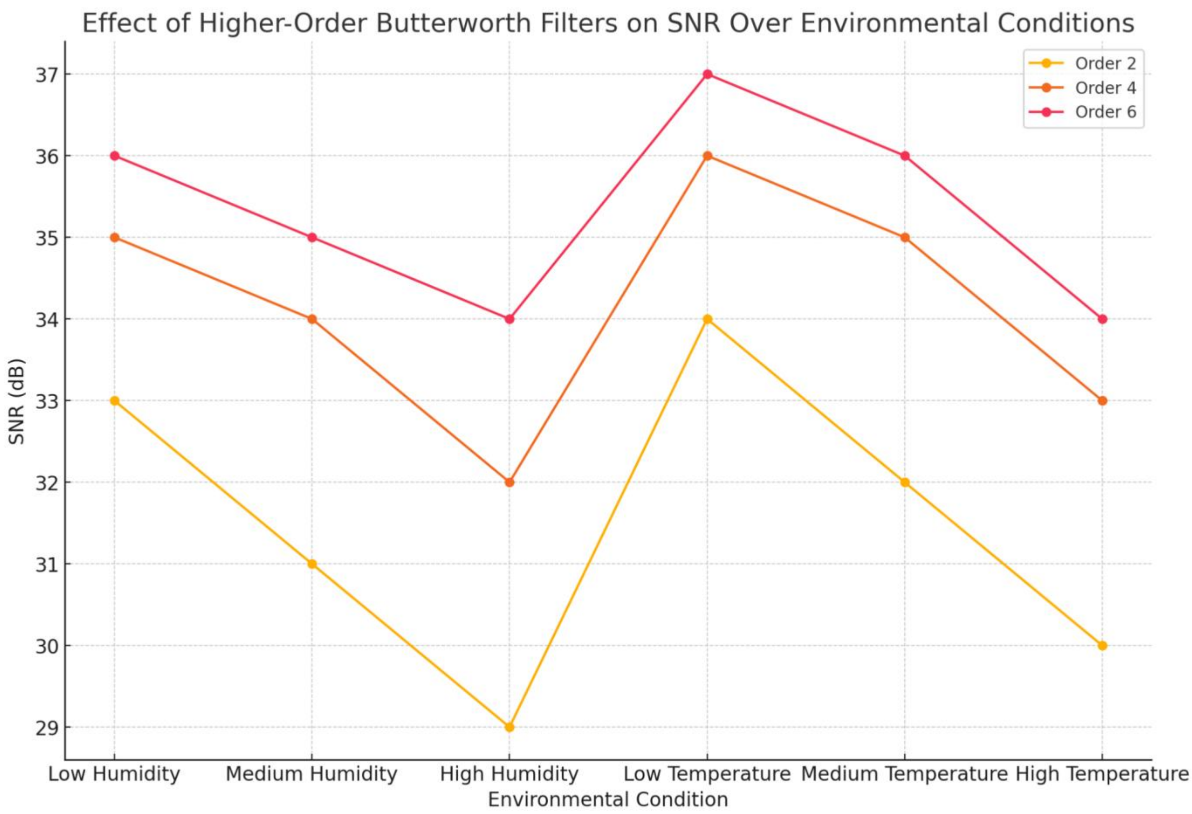

Fig 5: Line Chart for Effect of Higher-Order Butterworth Filters on SNR Over Environmental Conditions

The above Fig 5 Line Chart illustrates the impact of different filter orders (2, 4, and 6) on the Signal-to-Noise Ratio (SNR) across various environmental conditions. The x-axis represents the environmental conditions, including Low Humidity, Medium Humidity, High Humidity, Low Temperature, Medium Temperature, and High Temperature. The y-axis indicates the SNR values in decibels (dB). The chart shows three lines, each corresponding to a filter order, with SNR values for each environmental condition. Generally, higher filter orders lead to improved SNR across all environmental conditions, as demonstrated by the upward trend of SNR values with increasing filter order.

8. CONCLUSION AND FUTURE SCOPE:

With their special qualities, butterworth filters offer an effective way to improve signal clarity in SHM systems that are based on the Internet of Things. Higher-order Butterworth filters, as demonstrated by this work, greatly lower noise and enhance sensor data quality—two factors that are essential for precise structural health evaluations. Additional advantages come from adaptive filtering algorithms since they ensure consistent performance by adapting to real-time changes in the signal. The comparison analysis with different filters demonstrates how much better the Butterworth filter is at reducing distortion while preserving computational efficiency. These systems are strengthened by the incorporation of hybrid filtering techniques, which improve signal processing even more. Through the creation of more dependable and efficient SHM systems, safer infrastructure management is ensured by this research. Future studies should concentrate on creating sophisticated adaptive filtering algorithms and investigating practical uses for these improved SHM systems in diverse infrastructure monitoring

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