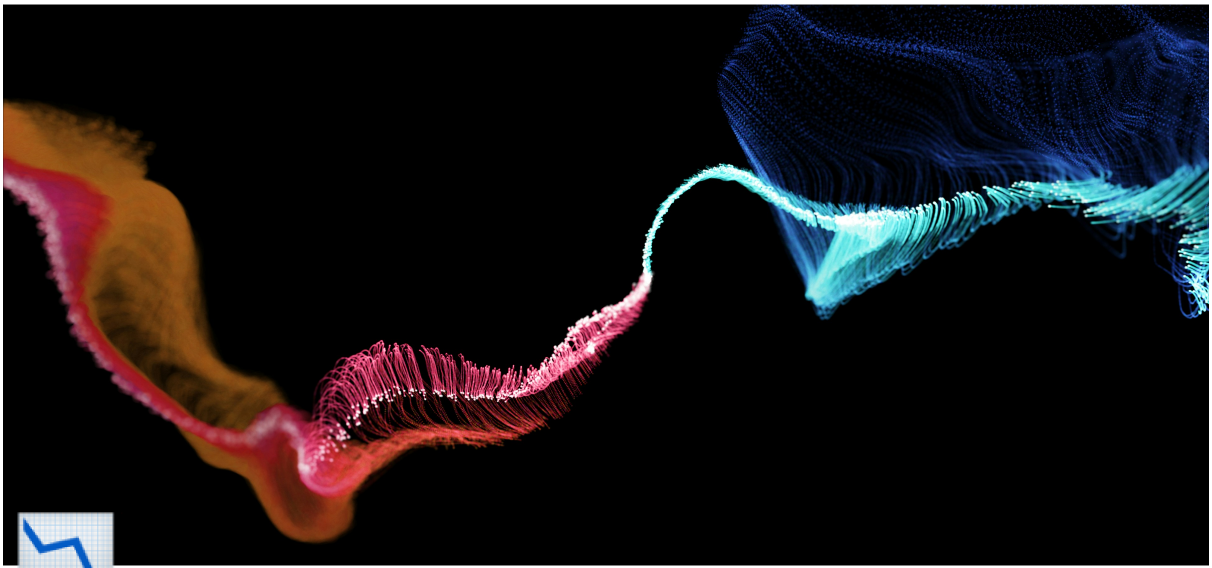


Creative Applications of Common Filters

Introduction

Filters are not just tools for removing unwanted elements. They are instruments for shaping, transforming, and extracting valuable information from signals. By manipulating the frequency content, filters can reveal hidden patterns, enhance specific features, and even create entirely new sounds or images.

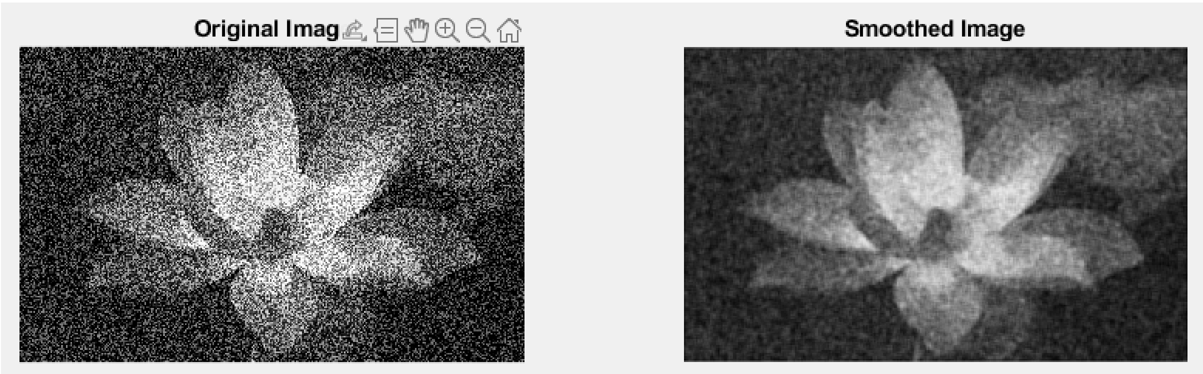
This report explores the diverse applications of filters in three key domains: image processing, audio processing, and financial signal processing. We will delve into specific examples of how filters are utilized to enhance, manipulate, and extract valuable information from signals in each of these areas, providing MATLAB code snippets to demonstrate their practical implementation.

Image Manipulation

Image processing is the digital manipulation and analysis of images using computer algorithms. It encompasses a wide range of techniques aimed at enhancing, transforming, or extracting information from visual data. These techniques can range from simple adjustments like brightness and contrast to complex operations like object recognition and image restoration. Image processing plays a crucial role in various fields, including photography, medicine, computer vision, and even art, enabling us to visualize, understand, and manipulate the visual world in ways that were previously unimaginable.

Noise Reduction (Low-Pass Filters)

Images often contain random variations in pixel values (noise) due to sensor imperfections or compression artifacts. Low-pass filters smooth out these variations by attenuating high-frequency components, resulting in a cleaner image.

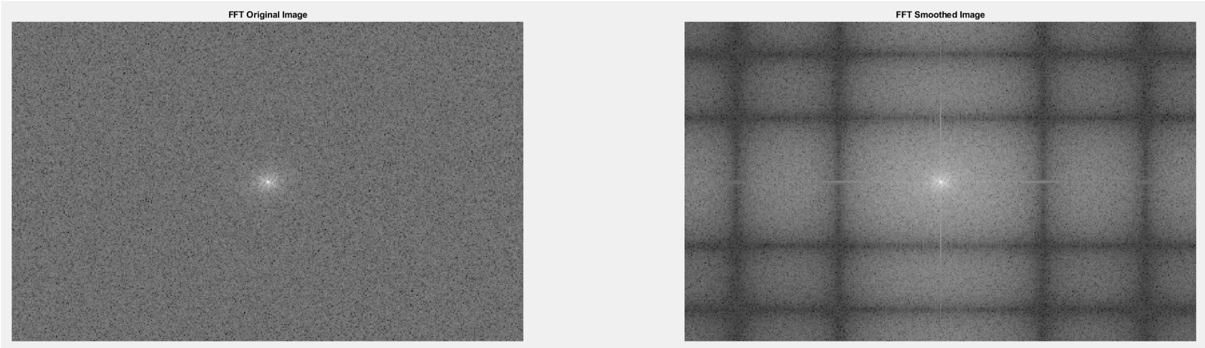


Frequency Domain Analysis

The Frequency Domain Analysis reveals the distribution of signal power across different frequencies. In this case:

- **Original Image:** The FFT (Fast Fourier Transform) of the original image shows a wide spread of energy across various frequencies. High-frequency components represent the noise, while lower frequencies typically correspond to the actual image content (edges, textures, etc.).
- **Smoothed Image:** After applying the low-pass filter, the FFT of the smoothed image demonstrates a significant reduction in the high-frequency content. This is because the low-pass filter attenuates or "blocks" higher frequencies, leaving primarily the lower frequencies that represent the underlying image structure.

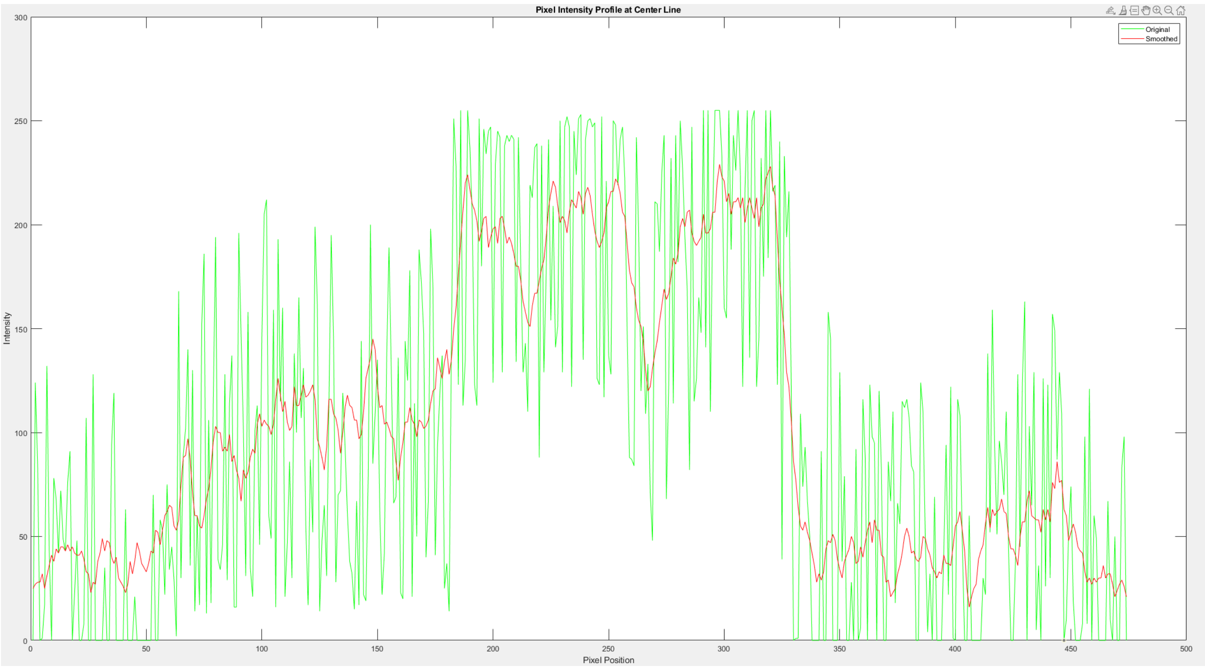
This can be observed in the FFT plots as a more concentrated energy distribution towards the center (low frequencies) and a darker (less intense) region in the outer areas (high frequencies) for the smoothed image compared to the original.



Time-Domain Analysis

The Time Domain Analysis examines the signal's amplitude over time. In the context of images, this translates to pixel intensities along a particular line or path.

- **Original Image:** The pixel intensity profile along the center line shows rapid fluctuations and variations due to the presence of noise.
- **Smoothed Image:** After filtering, the intensity profile appears much smoother. The peaks and valleys caused by noise are reduced, resulting in a more consistent intensity pattern that better represents the underlying image features.



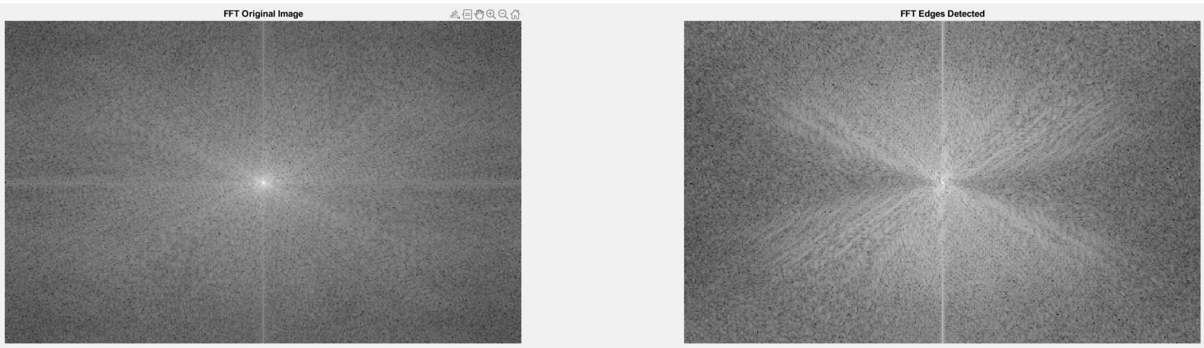
Edge Detection (High-Pass Filters)

Edges are abrupt changes in pixel intensity, representing boundaries between objects or regions. High-pass filters emphasize these changes by amplifying high-frequency components, making edges more prominent.

Frequency Domain Analysis

The FFT plots visually represent the distribution of frequencies in the original and edge-detected images. Here's what we can observe:

- **Original Image (Left):** The FFT of the original image shows a concentration of energy at the center, which represents lower frequencies. This is expected, as natural images typically have more gradual changes in intensity (corresponding to low frequencies) than abrupt changes. There's a gradual decrease in energy towards the outer edges of the plot, indicating less presence of high frequencies.
- **Edges Detected (Right):** The FFT of the edge-detected image reveals a stark difference. There's a significant increase in energy towards the outer regions, indicating a much stronger presence of high-frequency components. This makes sense, as the Sobel operator emphasizes sharp changes in intensity (edges), which manifest as high frequencies in the Fourier domain. The brighter, more pronounced "cross" pattern in the FFT highlights the directional nature of the Sobel operator, which detects both horizontal and vertical edges.



Key Insights:

- **Edge Enhancement:** The Sobel filter effectively enhances edges in the image by amplifying high-frequency components, as evident in the brighter outer regions of the "Edges Detected" FFT.
- **Directional Emphasis:** The cross-like pattern in the "Edges Detected" FFT reveals the Sobel filter's bias towards horizontal and vertical edges, as it is designed to detect gradients in these directions.
- **Frequency Distribution:** While the original image's FFT shows a more even distribution of energy across frequencies, the edge-detected image's FFT is dominated by high frequencies, highlighting the filter's focus on abrupt intensity changes.

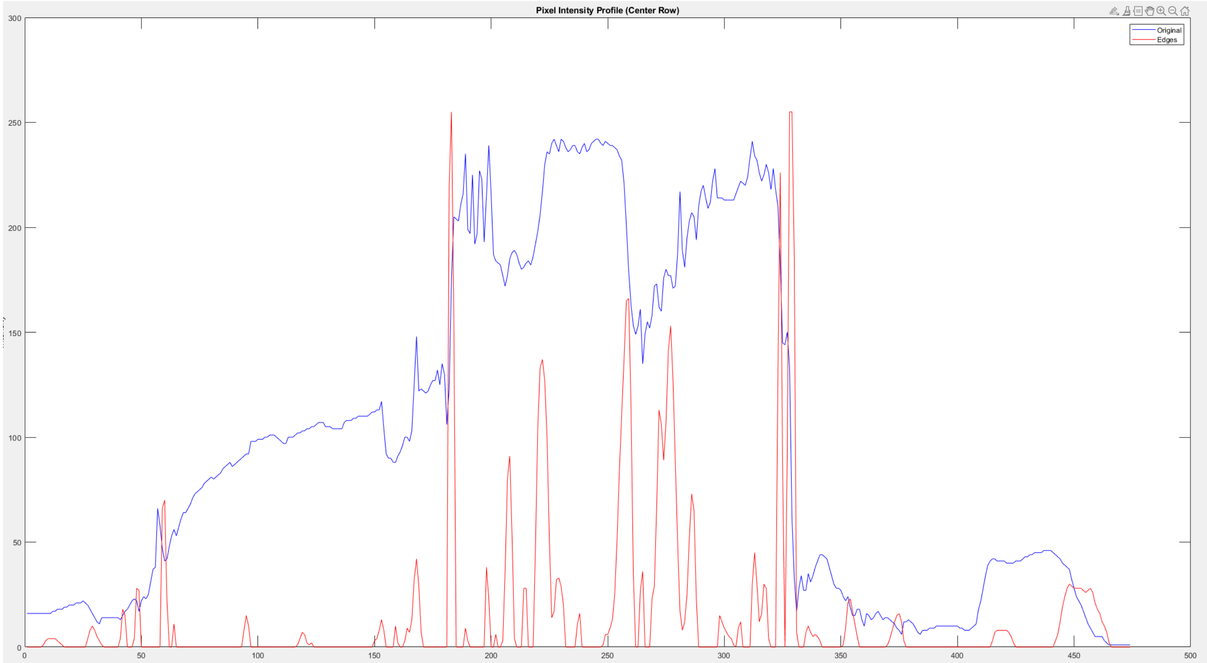
Additional Considerations:

- **Noise Amplification:** While the Sobel filter excels at edge detection, it can also amplify noise in the image. This is because noise often manifests as high-frequency fluctuations, and the Sobel filter's emphasis on high frequencies can inadvertently boost the noise signal as well.
- **Choice of Filter:** Depending on the specific application, different edge detection filters might be more suitable. For example, the Canny edge detector is known for its ability to detect weak edges while minimizing false positives.

Time-Domain Analysis

This plot shows the pixel intensities along the center row of your original and edge-detected images. Here's what we can observe:

- **Original Image (Blue):** The blue line represents the intensity profile of the original image. It shows smooth variations in intensity, corresponding to different regions of the flower image (petals, stem, leaves, etc.). There are some gradual transitions, indicating subtle changes in color and texture.
- **Edges Detected (Red):** The red line represents the intensity profile of the edge-detected image after applying the Sobel filter. Notice the dramatic difference compared to the original profile. The red line has very sharp peaks and valleys. These sharp peaks correspond to the locations of edges in the original image. The higher the peak, the more abrupt the change in intensity, indicating a stronger or sharper edge.



Key Insights:

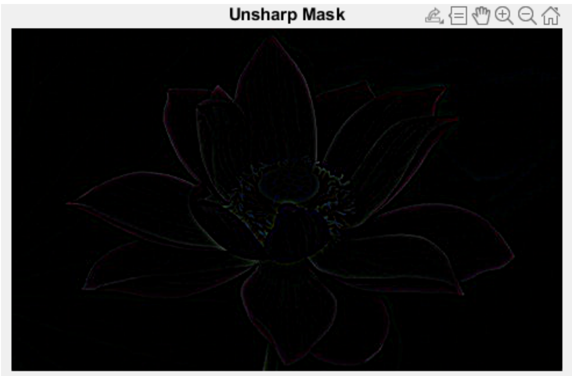
- **Edge Locations:** The peaks in the red line pinpoint the exact locations of edges in the image. You can correlate these peaks with the visual edges you see in the original image.
- **Edge Strength:** The height of the peaks in the red line gives you a sense of the relative strength of the edges. Taller peaks indicate sharper edges, while smaller peaks represent more subtle or gradual transitions.
- **Noise Amplification:** Notice that the red line also has many small peaks and fluctuations that don't correspond to obvious edges in the original image. These are likely due to the Sobel filter amplifying noise present in the original image.

Additional Considerations:

- **Center Row:** This plot only shows a single row from the image. To get a more complete picture, you could analyze profiles from other rows or columns, or even create a 3D visualization of the intensity values across the entire image.
- **Filter Parameters:** The strength of the edges detected can be influenced by the parameters of the Sobel filter. You can experiment with different kernel sizes or thresholds to fine-tune the edge detection results.

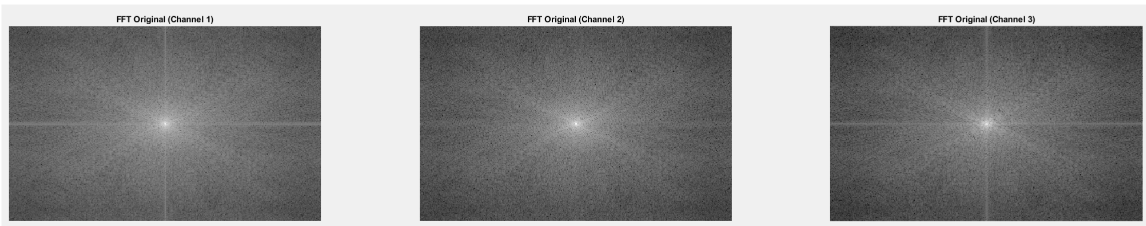
Sharpening (Unsharp Masking)

Unsharp masking is a technique that enhances image details by subtracting a blurred version of the image from the original. This effectively creates a high-pass filtered image, which is then added back to the original with some scaling to increase sharpness.

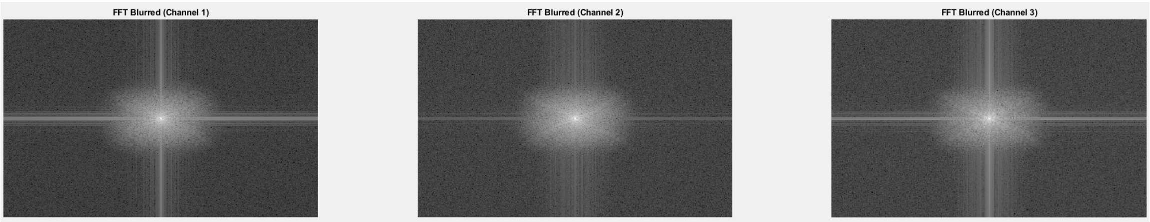


Frequency Domain Analysis

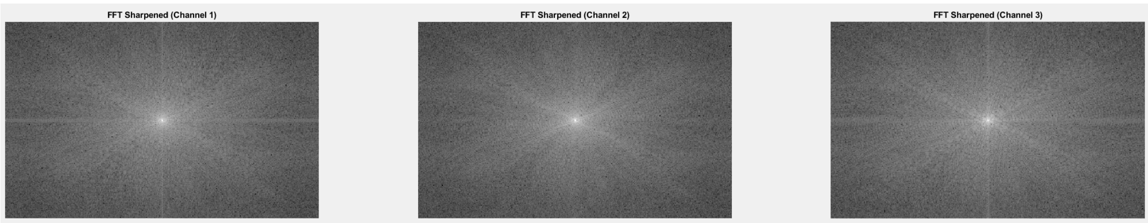
- **Original Image:** The FFT of the original image shows a concentration of energy at lower frequencies, representing the overall structure and large-scale features of the image. There's also some spread to higher frequencies, corresponding to finer details and textures.



- **Blurred Image (Mask):** The FFT of the blurred image exhibits a significant reduction in high-frequency energy. This is expected, as blurring essentially removes sharp edges and fine details, which are represented by high frequencies. The spectrum is more concentrated around lower frequencies, reflecting the smoother nature of the blurred image.



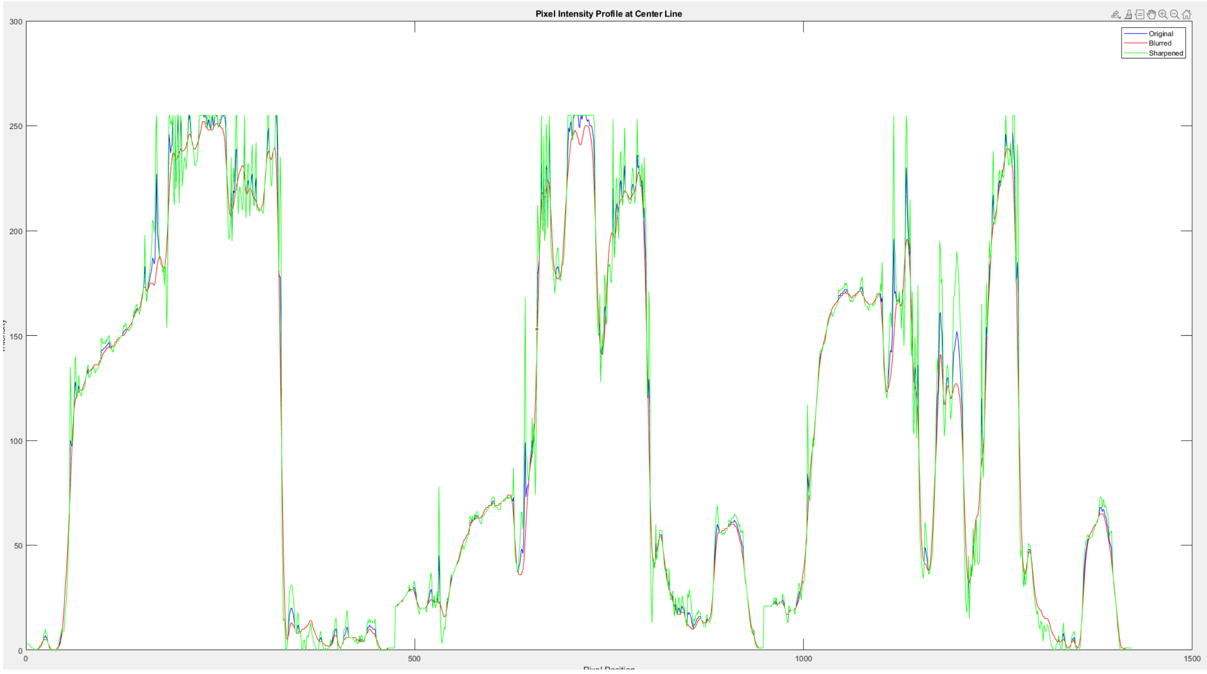
- **Sharpened Image:** The FFT of the sharpened image reveals an enhancement of high-frequency content compared to the original. This is because unsharp masking effectively boosts the edges and fine details that were attenuated in the blurred image. The spectrum now exhibits a greater spread towards higher frequencies, indicating a more detailed and sharper image.



Time-Domain Analysis

- **Original Image:** The intensity profile at the center line of the original image shows variations corresponding to different objects and textures. The transitions between these areas might be relatively smooth, representing gradual changes in intensity.
- **Blurred Image (Mask):** The intensity profile of the blurred image is smoother, with less pronounced peaks and valleys. This reflects the loss of high-frequency detail and the overall reduction in contrast. The transitions between different areas are more gradual due to the blurring effect.
- **Sharpened Image:** The intensity profile of the sharpened image exhibits exaggerated peaks and valleys compared to the original. This is a result of the unsharp masking process, which amplifies the differences between

neighboring pixels, emphasizing edges and fine details. The transitions between areas become sharper and more abrupt.

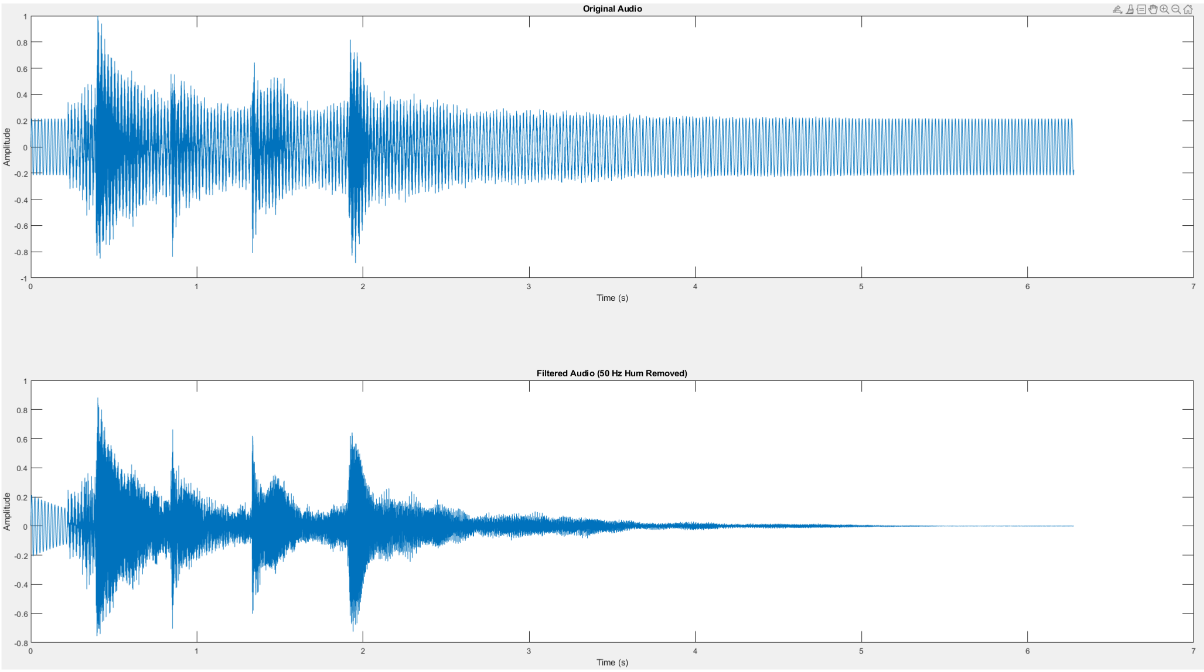


Audio Manipulation

Audio processing is the electronic manipulation of audio signals, transforming sound waves into a digital format for enhancement, alteration, or analysis. This multi-faceted field encompasses techniques like filtering, equalization, compression, and effects processing to improve sound quality, create artistic soundscapes, or extract information from audio data. Audio processing is fundamental to music production, film sound, telecommunications, and scientific research, enabling us to shape, understand, and interact with sound in unprecedented ways.

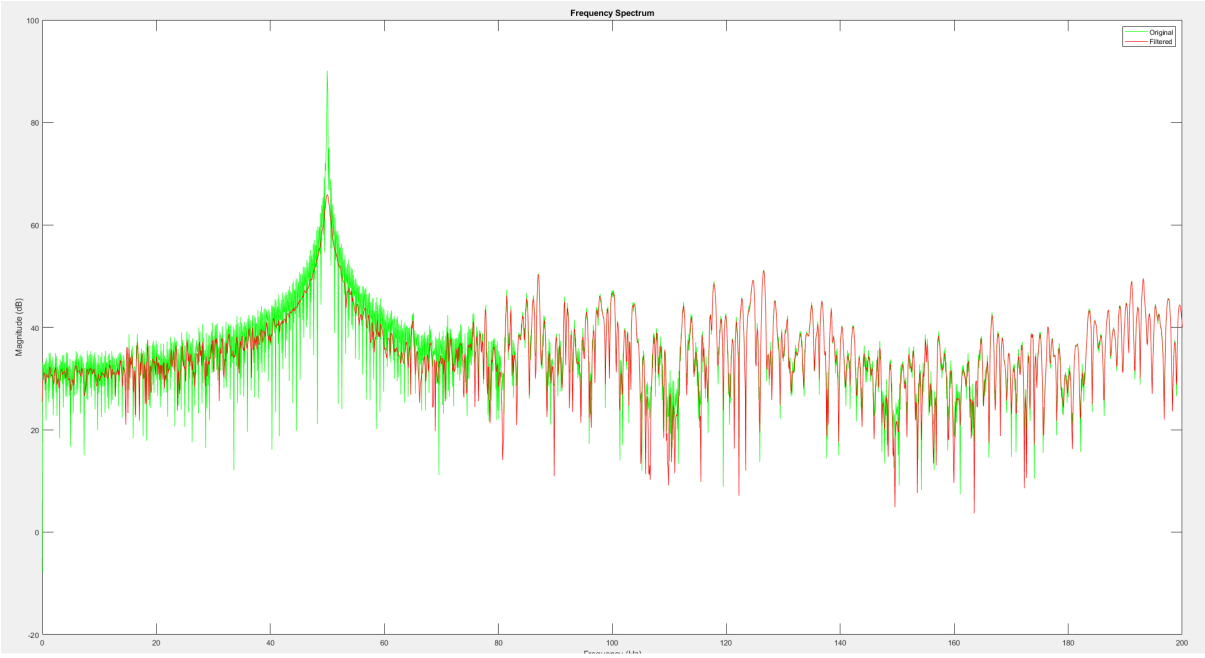
Audio Signal Enhancement (Notch Filter)

Notch filters are a powerful tool in audio processing for addressing specific problem frequencies. They can be used to remove unwanted hums, resonances, or feedback, while preserving the overall character of the audio signal.



Frequency Domain Analysis

- **Original Audio (Blue):** The spectrum of the original audio signal exhibits a prominent peak around 50 Hz, indicating the presence of the 50Hz hum. Additionally, there's a broader range of frequencies representing the harmonic content of the piano notes and other background noise.
- **Filtered Audio (Red):** The spectrum of the filtered audio shows a significant reduction in the magnitude around 50 Hz. This is the clear result of the notch filter effectively attenuating the hum. While the overall shape of the spectrum remains similar (preserving the piano notes and other frequencies), the 50Hz peak is notably suppressed.



Key Insights

- **Successful Hum Removal:** The notch filter has successfully targeted and attenuated the unwanted 50Hz hum, as evidenced by the significant reduction in the corresponding peak in the frequency spectrum.
- **Minimal Impact on Other Frequencies:** The filter has largely preserved the harmonic content of the piano notes and other frequencies, ensuring that the overall musicality and tonal quality of the audio are not significantly altered.
- **Notch Filter Effectiveness:** The width of the "notch" in the red curve around 50 Hz indicates the filter's selectivity. A narrower notch means the filter is more precise in targeting the specific frequency, while a wider notch might affect a broader range of frequencies.

Further Analysis

- **Quantitative Assessment:** To quantify the effectiveness of the notch filter in removing the 50 Hz hum, the difference in magnitude (in dB) between the original and filtered signals at 50 Hz can be calculated.

```
%% Quantitative Assessment

% Find the index corresponding to the frequency closest to 50
[~, idx_50Hz] = min(abs(f - 50));
```

```
% Extract magnitudes at closest frequency to 50 Hz
mag_original_50Hz = fftOriginal_mag(idx_50Hz);
mag_filtered_50Hz = fftFiltered_mag(idx_50Hz);

% Handle the case where the filtered magnitude is zero (or ve
if mag_filtered_50Hz < eps
    hum_reduction_dB = Inf;  % Infinite dB reduction (complet
else
    hum_reduction_dB = 20 * log10(mag_original_50Hz / mag_fil
end

% Display the result
fprintf('Hum reduction at closest frequency to 50 Hz (%.2f Hz
```

```
>> audio_enhancement
Hum reduction at closest frequency to 50 Hz (49.99 Hz): 24.24 dB
```

Key Insights

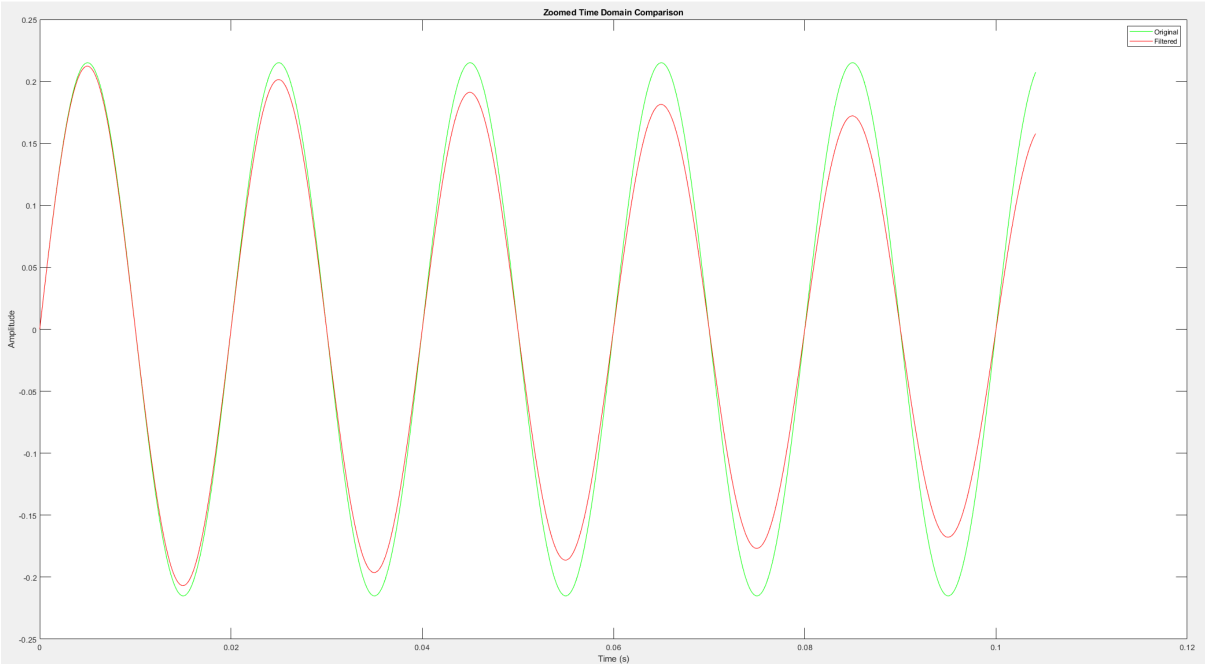
- Your notch filter has been very effective in attenuating the 50Hz hum.
- The 24.24 dB reduction indicates a significant decrease in the power of the hum component.
- This improvement should be readily noticeable in the filtered audio, resulting in a cleaner sound.

Time-Domain Analysis

This plot visualizes the amplitude of the audio signals (original in green, filtered in red) as a function of time. Here's what we can observe:

- **Original Signal (Green):** The green waveform shows a clear periodic pattern, representing the main musical notes being played. However, there's also a subtle, higher-frequency oscillation superimposed on top of the main waveform. This is likely the 50Hz hum that you're trying to remove.
- **Filtered Signal (Red):** The red waveform, representing the audio after applying the notch filter, is very similar to the original in terms of the overall shape and periodicity of the musical notes. However, the subtle high-frequency oscillation present in the original signal is significantly reduced in

the filtered signal. This indicates that the notch filter has successfully attenuated the 50Hz hum.



Key Insights:

- **Hum Reduction:** The time-domain plot visually confirms the effectiveness of the notch filter in removing the 50Hz hum. The filtered signal (red) is smoother and less "noisy" than the original signal (green).
- **Preservation of Musical Content:** The overall shape and periodicity of the waveforms are largely preserved, indicating that the notch filter has not significantly altered the musical content of the audio. This is a crucial aspect of audio enhancement, as the goal is to remove unwanted noise without compromising the desired signal.
- **Subtle Differences:** Upon closer inspection, you might notice slight differences in the amplitude of the two waveforms at certain points in time. These subtle variations are likely due to the phase shift introduced by the notch filter. However, in most cases, these phase shifts are not perceivable to the human ear and do not significantly affect the audio quality.

Simulating Vintage Equipment (Vintage Gramophone)

Vintage audio equipment, particularly from the analog era, often had subtle imperfections in their frequency response due to component limitations, circuit design, and manufacturing tolerances. These imperfections could include:

- **Roll-offs:** Gradual attenuation of frequencies at the high or low end of the spectrum, leading to a warmer or darker sound.
- **Resonances:** Peaks or dips in the frequency response at specific frequencies, adding character or "color" to the sound.
- **Notches:** Narrow frequency bands where the signal is significantly attenuated, sometimes due to component interactions or transformer resonances.

While these were technically flaws, they often contributed to a unique and desirable sonic signature. Modern digital audio systems tend to be more precise and linear, lacking these imperfections. Notch filters, however, can be strategically employed to reintroduce some of these vintage characteristics to recordings.

Gramophone Sonic Characteristics:

- **Limited Frequency Response:** Gramophones had a limited frequency response, typically rolling off sharply in the high frequencies and often lacking very low frequencies as well.
- **Surface Noise:** Gramophones produced a significant amount of surface noise due to the physical interaction of the needle with the record groove. This noise often included crackling, hissing, and popping sounds.
- **Wow and Flutter:** These are pitch variations caused by inconsistencies in the rotation speed of the turntable. Wow refers to slow, gradual changes in pitch, while flutter refers to rapid, tremolo-like fluctuations.

Simulating Gramophone Sound with Filters and Effects:

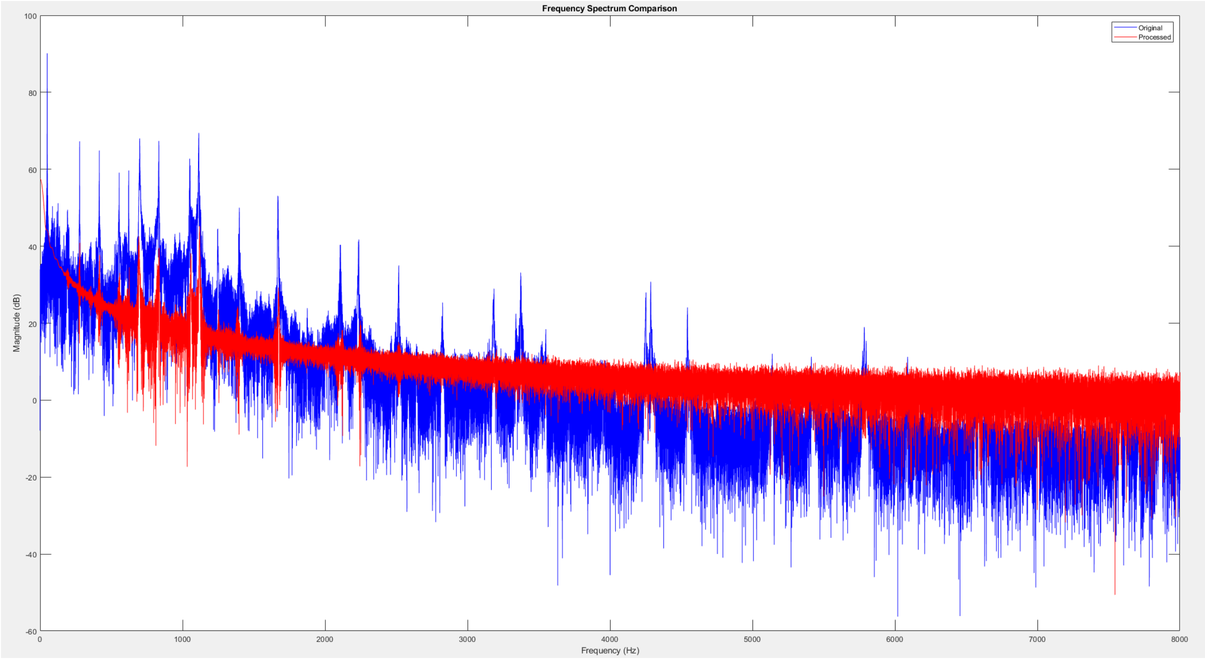
- **Frequency Response Shaping:**
    - **High-pass Filter:** Use a high-pass filter with a gentle slope (e.g., 6 dB/octave) and a cutoff frequency around 100-200 Hz to remove the very low frequencies that gramophones couldn't reproduce.
    - **Low-pass Filter:** Use a low-pass filter with a steeper slope (e.g., 12 dB/octave or more) and a cutoff frequency around 3-5 kHz to simulate the sharp high-frequency roll-off.
- **Surface Noise Emulation:**

    - **White Noise Generator:** Add a low-level white noise signal to the audio to simulate the hiss and background noise of a gramophone.
    - **Impulse Generator:** Introduce occasional impulse sounds (clicks and pops) to mimic the sound of dust or scratches on a record.
    - **Bitcrushing:** Applying a bitcrusher effect can introduce quantization noise, similar to the distortion found in early recordings.
- **Wow and Flutter Simulation:**
    - **Low-Frequency Oscillator (LFO):** Use an LFO to modulate the pitch of the audio signal subtly. A slow LFO rate (e.g., 0.1-0.5 Hz) will create a wow effect, while a faster rate (e.g., 4-10 Hz) will simulate flutter.

Frequency Domain Analysis

The plot shows the magnitude spectrum of the original (blue) and processed (red) audio signals, revealing several key differences:

1. **High-Frequency Roll-off:** The most noticeable change is the significant reduction in high-frequency content in the processed audio (red). The original signal (blue) exhibits energy extending to higher frequencies, while the processed signal drops off sharply after about 4000 Hz. This is consistent with the intended simulation of a gramophone's limited frequency response, which typically struggled to reproduce high frequencies.
2. **Low-Frequency Emphasis:** There's a subtle increase in energy in the low-frequency range (below 200 Hz) in the processed audio. This could be due to the combined effects of the high-pass filter (removing very low frequencies), the added surface noise (which might have some low-frequency content), and the wow/flutter modulation (which could introduce some low-frequency artifacts).
3. **Overall Smoothing:** The processed audio's spectrum appears slightly smoother than the original. This is likely due to the low-pass filtering, which not only rolls off high frequencies but also helps smooth out some of the finer details in the original signal.
4. **Noise Floor:** The noise floor (the level of background noise) seems slightly higher in the processed audio, particularly in the mid-frequency range. This is expected due to the addition of white noise, crackles, and pops to simulate the surface noise of a gramophone record.



Interpreting the Results

The frequency domain analysis confirms that the applied processing steps are successfully emulating the characteristics of a vintage gramophone:

- The high-frequency roll-off and subtle low-frequency emphasis create a warmer, more "vintage" sound.
- The increased noise floor and slight spectral smoothing contribute to the overall "lo-fi" character of a gramophone recording.

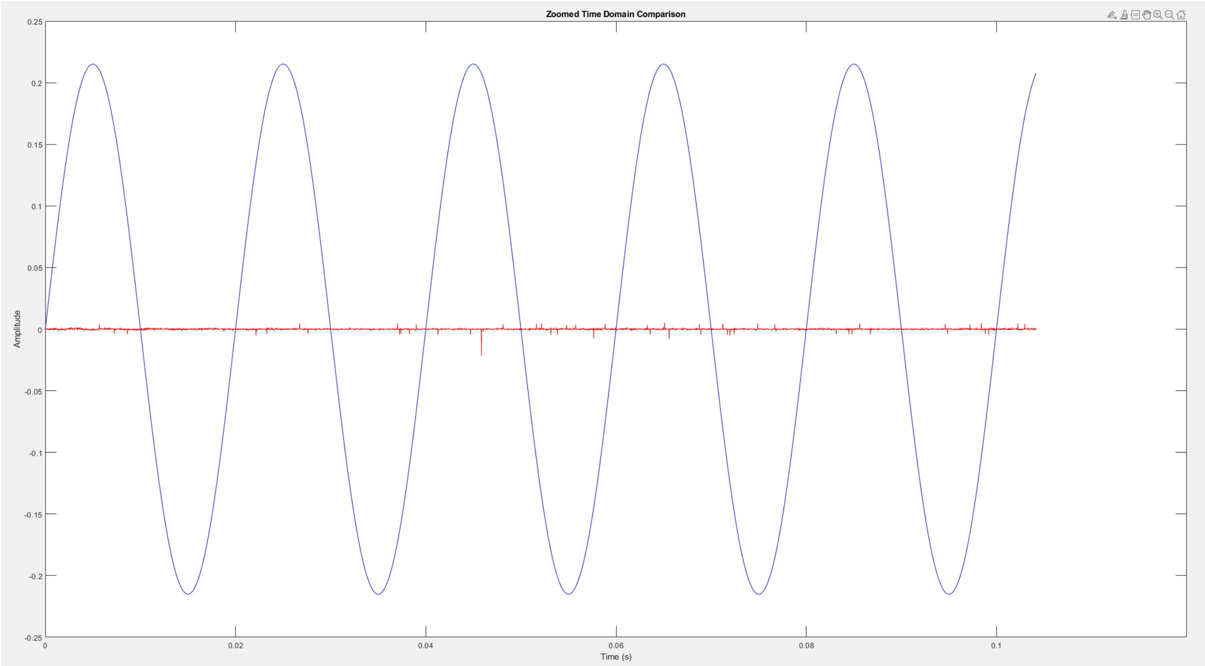
Time-Domain Analysis

This plot visualizes the amplitude of the audio signals (original in blue, processed in red) over a short time segment. Here's what we can observe:

- **Original Signal (Blue):** The blue waveform exhibits a clean, smooth sinusoidal pattern, representing the original pure tone in your audio file (likely a piano note). There are no visible imperfections or noise in this signal.
- **Processed Signal (Red):** The red waveform, representing the audio after applying the gramophone simulation effects, shows several key differences:
    - **Wow and Flutter:** There are noticeable fluctuations in the pitch of the waveform. The peaks and troughs of the red waveform are not perfectly aligned with the blue waveform, indicating subtle variations in the

frequency over time. This is the wow and flutter effect, simulating the irregularities in the rotation speed of a gramophone turntable.

- **Surface Noise:** The red waveform also exhibits a significant amount of high-frequency noise superimposed on top of the main signal. This noise is a combination of the white noise, crackles, and pops that were added to simulate the surface noise of a gramophone record.



Key Insights:

- **Successful Simulation:** The time-domain plot visually confirms that the processing steps you've applied are successfully emulating the imperfections of a vintage gramophone. The wow and flutter effect, as well as the surface noise, are clearly visible in the processed signal.
- **Impact on Signal Clarity:** The added noise and pitch variations make the processed signal less "clean" than the original. This is consistent with the lo-fi character of gramophone recordings, which were known for their warm but somewhat noisy sound.

Signal Processing in Finance

Financial Signal Processing (FSP) is an interdisciplinary field that applies signal processing techniques, originally developed for fields like telecommunications and engineering, to analyze financial data. This involves filtering, transforming, and interpreting time series data such as stock prices, market indices, and economic indicators to extract meaningful insights. By leveraging these techniques, FSP enables traders, investors, and analysts to identify trends, forecast volatility, detect anomalies, and develop sophisticated trading strategies. FSP plays a pivotal role in modern finance, empowering decision-makers to navigate complex markets with greater precision and confidence.

Trend Analysis (Apple Stock 2023)

In financial markets, prices of assets like stocks, commodities, or currencies fluctuate constantly. These fluctuations can be caused by various factors, such as news, economic events, or even random market noise. While these short-term price movements are important, traders and investors are often more interested in the underlying trends that reveal the overall direction of the market.

Moving average filters are a simple yet powerful tool for identifying and analyzing trends in financial time series data. They work by averaging a set of recent prices over a specified window of time. This smoothing process reduces the impact of short-term fluctuations, revealing the underlying trend more clearly.

Types of Moving Averages

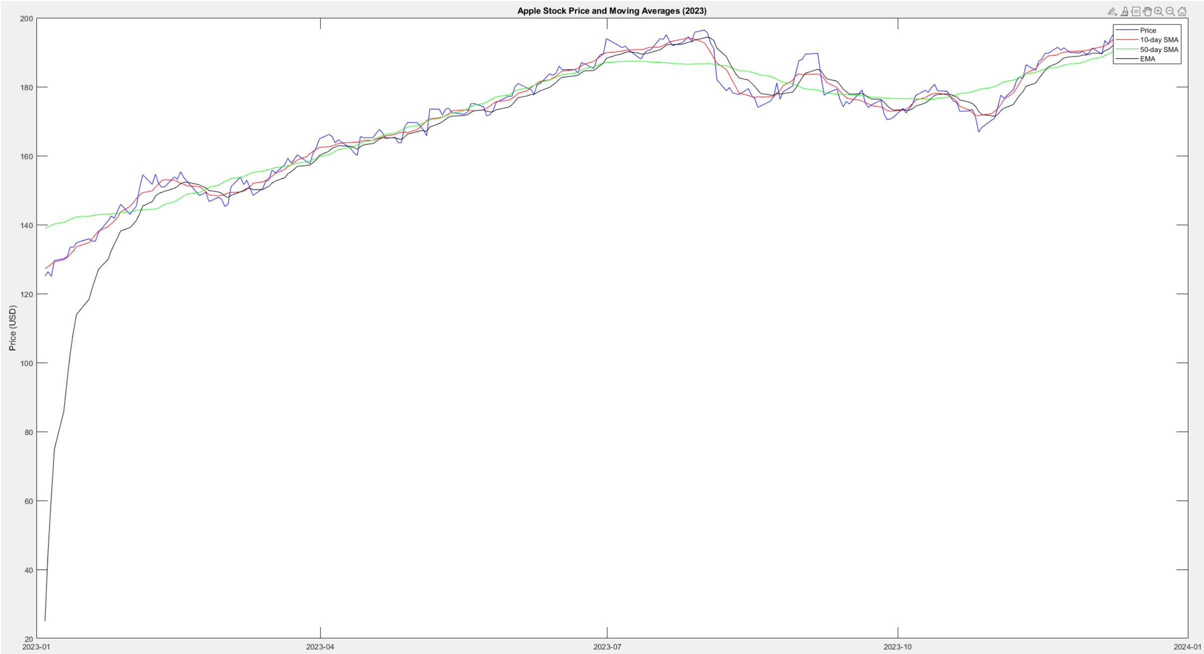
There are two main types of moving averages used in financial analysis:

1. **Simple Moving Average (SMA):** This is the most basic type, calculated by simply averaging the closing prices over a specified number of periods. For example, a 10-day SMA would average the closing prices of the last 10 days.

2. **Exponential Moving Average (EMA):** This type gives more weight to recent prices, making it more responsive to current market conditions. The EMA is calculated using a smoothing factor that determines the weighting of past prices.

Analysis of Apple Stock Price and Moving Averages (Filter Perspective)

The plot illustrates the application of different filtering techniques to Apple's daily stock prices throughout 2023. These filters act to smooth out the raw price data (blue) and reveal underlying trends, providing valuable insights for traders and investors.



- **Original Price Data:** The unfiltered price data exhibits high-frequency fluctuations, representing short-term market noise and volatility. This unfiltered signal is akin to a raw audio signal containing unwanted noise or a high-resolution image with fine details.
- **Moving Averages as Filters:** The three moving averages act as low-pass filters with varying degrees of aggressiveness.
  - **10-day SMA (Red):** This filter has the shortest window and, therefore, the weakest low-pass effect. It removes some high-frequency noise but retains most of the medium-term fluctuations, making it useful for identifying short-term trends and potential reversals.
  - **50-day SMA (Green):** With a longer window, this filter more effectively attenuates higher frequencies, resulting in a smoother curve that represents the medium-term trend more clearly. It's less responsive to short-term fluctuations, making it a more stable indicator.
  - **20% EMA (Black):** This exponential filter places more weight on recent data points, making it more responsive to current market conditions than the SMAs. It strikes a balance between responsiveness and smoothness, allowing for early identification of trend changes while filtering out some noise.

Key Filter-Based Observations:

- **Smoothing Effect:** Each moving average progressively removes higher-frequency components, resulting in smoother curves that reveal the underlying trend more clearly.
- **Trend Identification:** The filtered signals help identify the overall direction of the market and filter out short-term noise. The longer the moving average period, the more stable and reliable the trend indication.
- **Responsiveness:** The EMA, being an exponential filter, is more responsive to recent price changes than the SMAs, which can be advantageous for capturing short-term trends and reversals.

Filter Choice and Interpretation:

The choice of which moving average to use depends on the trader's or investor's time frame and objectives:

- **Short-term Traders:** Might prefer the 10-day SMA or EMA for quick reaction to market changes.
- **Medium-term Investors:** Might find the 50-day SMA more suitable for identifying established trends.
- **Combination:** Many traders use a combination of moving averages to gain insights into both short-term and medium-term trends.

Overall in this particular example the date set used contains only one price per day. This make the data not as suited as necessary to show the full potential of these moving average filters.

Limitations and Challenges

Despite their widespread utility, filters in signal processing present certain limitations and challenges that must be considered in their application.

- **Image Processing:**
  - **Artifact Introduction:** Aggressive filtering can introduce artifacts like ringing or blurring, especially with sharp filters.
  - **Loss of Information:** Over-filtering can lead to the loss of fine details or subtle textures in an image.
  - **Computational Complexity:** Some sophisticated filters can be computationally expensive, particularly for real-time applications.

- **Audio Processing:**
  - **Phase Issues:** Filters can introduce phase shifts, which can alter the perceived stereo image or create comb filtering effects.
  - **Transients:** Filters can smear transients (sharp attacks in sound), affecting the clarity and punch of percussive sounds.
  - **Overprocessing:** Excessive filtering can lead to unnatural or sterile-sounding audio.
- **Financial Signal Processing:**
  - **Non-stationarity:** Financial markets are dynamic and non-stationary, meaning their statistical properties change over time. This can make it difficult to design filters that perform consistently well.
  - **Overfitting:** Models based on filtered data can be overfitted to historical data, leading to poor performance on new data.
  - **Black Swan Events:** Extreme, unpredictable events can disrupt financial models and render filters ineffective.

Future Directions

Despite these challenges, ongoing research and technological advancements are paving the way for exciting future directions in filter applications.

- **Image Processing:**
  - **Deep Learning-Based Filters:** Neural networks are increasingly being used for image filtering, offering improved performance in tasks like noise reduction and super-resolution.
  - **Adaptive Filters:** Filters that can adapt to the local image content hold promise for more sophisticated and context-aware image enhancement.
  - **Real-Time Processing:** With the increasing power of mobile devices, we can expect more real-time image processing applications using filters.
- **Audio Processing:**
  - **Artificial Intelligence:** AI-powered tools are emerging that can analyze audio content and automatically apply appropriate filtering and processing for optimal sound quality.

    - **Personalized Audio:** Filters could be used to tailor audio experiences to individual preferences or hearing profiles.
    - **Spatial Audio:** The use of filters in immersive audio formats like Dolby Atmos and Ambisonics will continue to evolve, creating more realistic and engaging listening experiences.
- **Financial Signal Processing:**
    - **Machine Learning in Finance:** The integration of machine learning with FSP will likely lead to more sophisticated models for forecasting, risk management, and algorithmic trading.
    - **Alternative Data:** The use of non-traditional data sources like social media sentiment or satellite imagery, combined with advanced filtering techniques, could uncover new trading insights.
    - **Explainable AI:** As FSP models become more complex, there will be a growing need for techniques to interpret and explain their decisions, especially in the context of regulatory compliance.

Conclusion

The applications of filters in signal processing across image, audio, and financial domains demonstrate their power to reveal hidden information and manipulate signals for various purposes. In image processing, filters enhance clarity by reducing noise and highlighting edges. In audio, notch filters can eliminate unwanted frequencies while low-pass and high-pass filters can be used to create vintage effects, as seen in the gramophone simulation. In finance, moving averages smooth price data to reveal trends, aiding in investment decisions. These examples underscore the versatility and importance of filters in extracting valuable insights and shaping signals for desired outcomes.