WAVELET TRANSFORM ANALYSIS

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Introduction:

Wavelet transform is a powerful mathematical tool for analyzing signals, particularly those that are non-stationary or exhibit time-varying characteristics. Unlike traditional methods such as the Fourier Transform (FT), which provide only frequency-domain information, the wavelet transform offers a time-frequency representation, enabling the simultaneous observation of how signal components evolve over time and across different frequencies. One of the key advantages of wavelet analysis is its ability to perform multi-resolution analysis capturing both coarse (low-frequency) and fine (high-frequency) signal details. This feature makes wavelets especially useful for detecting transients, singularities, trends, and discontinuities that might be overlooked by FT or even the Short-Time Fourier Transform (STFT).
In wavelet analysis, the signal is decomposed using a family of functions called wavelets, which are generated from a base wavelet (known as the "mother wavelet") by scaling and translating it. The Continuous Wavelet Transform (CWT) provides a redundant yet detailed representation of the signal, making it ideal for visualization and qualitative analysis.
This report explores the use of CWT specifically with the Morlet wavelet to analyze synthetic signals. The method demonstrates how frequency components in a signal change over time, highlighting the strengths of wavelet analysis over traditional approaches.

Methodology:

- A sinusoidal signal with a fixed frequency (10 Hz) and a randomly generated signal were created using Python after that we will bring signal from datasets.

- The duration and sampling rate of the signals were user-defined (e.g., 1 second at 1000 Hz).

- The CWT was performed using the Morlet wavelet ('morl') implemented via the PyWavelets library.

- Scales were chosen from 1 to 128 to capture a broad range of frequency behaviors.

Example of our code:

```python
def plot_wavelet(t, x, title="Wavelet Transform", filename="wavelet_plot.png"):
    """
    Compute and plot the Continuous Wavelet Transform (CWT) of the signal.
    A scalogram is produced showing the absolute coefficients of the CWT.
    """
    # Define scales. Adjust this range according to the expected frequency content.
    scales = np.arange(1, 128)

    # Using the Morlet wavelet ("morl") which works well for time-frequency analysis.
    coefficients, frequencies = pywt.cwt(x, scales, 'morl', sampling_period=t[1]-t[0])

    plt.figure(figsize=(12, 6))
    plt.imshow(np.abs(coefficients), extent=[t[0], t[-1], scales[-1], scales[0]],
               aspect='auto', cmap='jet')
    plt.colorbar(label='Magnitude')
    plt.title(title)
    plt.xlabel("Time (s)")
    plt.ylabel("Scale")
    plt.tight_layout()
    plt.savefig(filename)
    print(f"Wavelet transform plot saved to {filename}")
    plt.close()
```

Results:

The Continuous Wavelet Transform (CWT) was applied to two synthetic signals: a sinusoidal signal with a constant frequency and a randomly generated signal. The results were visualized using scalograms, which display how signal energy is distributed across time and frequency scales.

Figure 1 (a) shows the signal itself with its DFT and FFT plot.

Figure 1 (b) shows the scalogram of the sinusoidal signal with a fundamental frequency of 10 Hz. The energy is localized at a specific scale and remains consistent throughout the entire duration, which is indicative of a stationary signal with a single dominant frequency component.

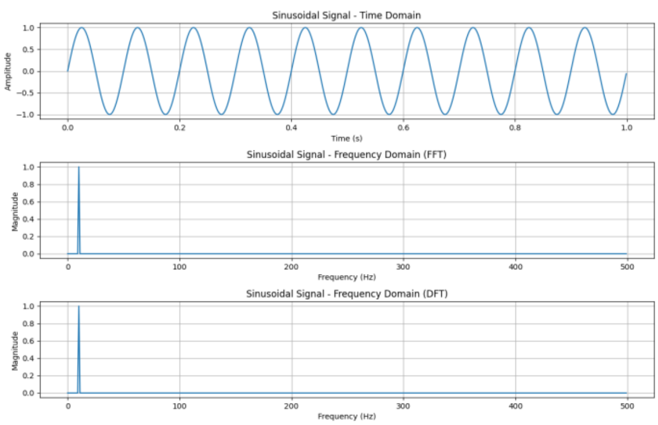

Fig 1 (a)

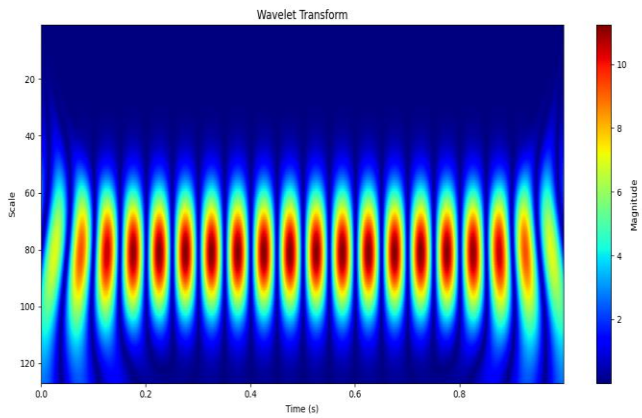

Fig 1 (b)

Figure 2 (a) shows the signal itself with its DFT and FFT plot.
In contrast, the scalogram of the random signal Figure 2 (b) displays a broad and irregular distribution of energy across multiple scales and time intervals. This behavior is characteristic of a broadband or noisy signal, lacking any dominant frequency component and exhibiting non-stationary properties.

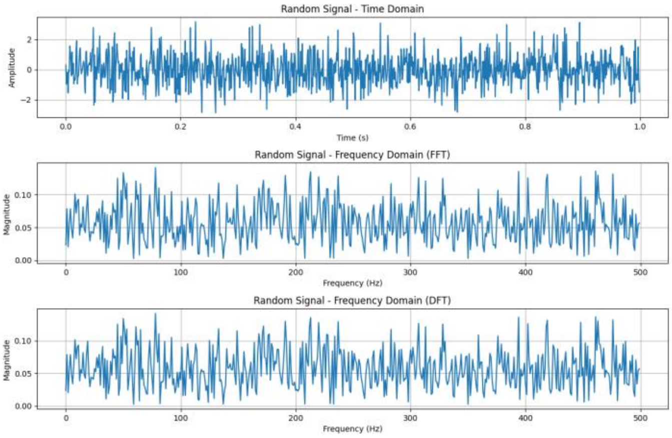

Fig 2 (a)

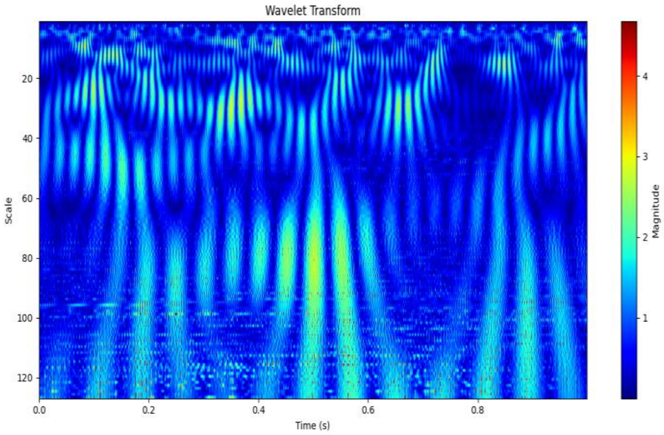

Fig 2 (b)

Conclusion:

The wavelet transform has proven to be a powerful tool for analyzing signals with time-varying frequency content. Unlike the Fast Fourier Transform (FFT), which offers only a global frequency perspective, the Continuous Wavelet Transform (CWT) provides both time and frequency localization. This dual resolution makes CWT particularly well-suited for examining non-stationary signals, where changes in frequency content occur over time. The experimental results demonstrated how CWT effectively isolates stable frequencies in stationary signals and reveals the complex structure of broadband, non-stationary signals. As such, wavelet analysis serves as a valuable complement to traditional spectral methods, especially in fields requiring high temporal resolution.