Time-domain Frequency-domain analysis

Objective:

The primary objective is to conduct an in-depth analysis of the Gait Phase Database to uncover significant biomechanical adaptations and changes in human gait across various walking speeds. This investigation will encompass both time-domain and frequency-domain analyses to comprehensively characterize the dynamics of gait. Specifically, the time-domain analysis will focus on the temporal aspects of gait cycles, examining the durations of sub-phases such as stance, loading response, mid-stance, terminal stance, pre-swing, and swing, alongside variations in ground reaction forces and the synchronization of foot markers. The frequency-domain analysis will utilize Fourier analysis to identify dominant frequencies in marker trajectories and ground reaction forces, assessing how these frequencies and their harmonic components vary with walking speed and among different individuals, thereby providing insights into gait stability and efficiency. Through this multifaceted approach, the study aims to elucidate the complex interplay of biomechanical factors that contribute to human gait adaptability and performance.

Abstract:

This study leverages a dataset from a controlled laboratory setting where subjects' gait was recorded using infrared cinematography and instrumented treadmills. By analyzing ground reaction forces and marker positions at multiple walking speeds, we performed detailed time-domain and frequency-domain analyses to elucidate the patterns and variations in human gait. The time-domain analysis focused on statistical and waveform features such as mean, median, standard deviation, and root mean square, which depict gait cycle characteristics. Frequency-domain analysis using Fourier Transform techniques helped identify predominant frequencies, spectral energy distributions, and entropy, highlighting the rhythmic nature and stability of gait. These analyses contribute to a deeper understanding of gait mechanics, potentially aiding in the clinical assessment and treatment of gait disorders.

Introduction:

In this project, we undertake a comprehensive analysis of a Gait Phase Database, aimed at understanding the dynamics and variability of human gait across different walking speeds. The data, derived from 21 healthy subjects walking on a split-belt treadmill, encompasses ground reaction forces and 3D marker positions to capture the intricate biomechanics of gait. The focus is on both time-domain and frequency-domain characteristics of gait, providing insights into the normal functioning of gait mechanics under various conditions. Through this analysis, we aim to establish normative gait metrics and explore the influence of speed on gait phases such as stance and swing, which are crucial for diagnosing and improving clinical conditions related to gait abnormalities.

Time-domain and frequency-domain analysis are two fundamental approaches used to study and understand signals or data. Time-domain analysis looks at how a signal or data set changes over time. For example, in studying human gait, it involves examining the timing and duration of different phases of a walking cycle, like how long each foot is on the ground or in the air. Frequency-domain analysis, on the other hand, focuses on the different frequencies that make up a signal. This is done using techniques like Fourier analysis, which breaks down a complex signal into simpler parts to see the dominant frequencies. This can help identify patterns and rhythms, such as the repetitive movements in walking, and understand how these patterns change with speed or between individuals. Both methods are crucial for gaining a comprehensive understanding of dynamic systems like human gait.

Literature Review:

Problem Addressed:

The study tackles the challenge of accurately detecting gait phases, which is crucial for monitoring neurological and musculoskeletal disorders and for controlling lower limb assistive devices.

Methodology Used:

The researchers recruited eight healthy participants and used wireless EMG sensors attached to four muscles in each lower extremity to collect data during walking. The EMG signals were segmented and labeled for two-class (stance and swing) and three-class (weight acceptance, single limb support, and limb advancement) gait phases. Non-negative matrix factorization (NNMF) was applied to identify muscle synergies. The gait phases were classified using four machine learning algorithms: decision tree (DT), k-nearest neighbors (KNN), support vector machine (SVM), and neural network (NN).

Final Outcomes:

The study found that muscle synergy features provided better classification accuracy for gait phases compared to traditional EMG features. This supports the hypothesis that muscle synergies, which reflect the co-activation of muscle groups, can enhance the accuracy of gait phase detection. The use of NNMF to identify muscle synergies was validated as a useful approach for understanding the functional organization of the neuromuscular system in gait analysis.

Gaps Identified:

The study acknowledges that while muscle synergy features improved classification accuracy, further research is needed to explore their application in pathological gait conditions and in populations with neurological and musculoskeletal disorders. Future studies could also investigate the integration of muscle synergy features with other sensor modalities to further enhance gait phase detection accuracy.

Time Domain Analysis and Frequency Domain Analysis:

Time Domain Analysis:

Time domain analysis in the context of gait phase data involves examining the raw temporal data as it evolves over time. This analysis focuses on understanding the patterns, sequences, and durations of the gait cycle. Time domain metrics can include:

Stride Duration: The time taken for a complete cycle of the gait, from one foot contact to the next of the same foot.

Stance Duration: Time during which the foot remains in contact with the ground.

Swing Duration: Time during which the foot is in the air.

Double Support Duration: Time when both feet are on the ground, usually occurring between the end of one leg's swing phase and the start of its stance phase.

Frequency Domain Analysis:

Frequency domain analysis, on the other hand, involves transforming time-domain data into the frequency domain using mathematical techniques such as Fourier Transform. This analysis provides insights into the periodicity and the dominant frequencies within the gait cycle, which can be particularly revealing in cyclic activities like walking. Metrics and applications include:

Dominant Frequencies: Identifying the main frequencies at which components of the gait cycle repeat. This can highlight consistent oscillations in gait mechanics that might not be evident in time domain.

Harmonics: Higher frequencies that occur at integer multiples of the fundamental frequency of the gait. These can indicate subtle patterns like limb stiffness or asymmetry.

Power Spectrum: Analysis of how the power (squared magnitude of the signal) is distributed across different frequencies.

Time-domain Analysis Features:

Mean (μ):

The mean provides the average value of the dataset, which represents the central tendency of the data points over the duration of the gait cycle. This helps in understanding the general level around which data points fluctuate.

Formula:

$$\mu = \frac{1}{N}\sum_{i=1}^{N} x_i$$

where x_i represents individual data points and N is the total number of observations.

Median:

The median is the value separating the higher half from the lower half of the data points. For gait analysis, this can provide insights into the central tendency of the data that is not skewed by outliers or extreme values, which may affect the mean.

Formula:

If the number of observations N is odd, the median is the middle value. If N is even, it is the average of the two middle numbers.

Standard Deviation (σ):

Standard deviation measures the amount of variation or dispersion present in the gait data from the mean. A low standard deviation indicates that the data points tend to be close to the mean, while a high standard deviation indicates that the data points are spread out over a wider range of values.

Formula:

$$\sigma = \sqrt{\frac{\sum (x_i - \mu)^2}{N}}$$

Variance (σ²):

Description: Variance is the square of the standard deviation and similarly measures the dispersion of the data points in the dataset. It's useful for providing a squared scale which can sometimes be more interpretable in terms of the units of the original data.
Formula:

$$\sigma^2 = \frac{\sum (x_i - \mu)^2}{N}$$

Range:

Description: Range provides the difference between the maximum and minimum values within the dataset. In gait analysis, this helps in understanding the total amplitude of variation through the gait cycle.
Formula:

$$\text{Range} = \max(x_i) - \min(x_i)$$

Root Mean Square (RMS):

RMS is particularly useful in gait analysis as it provides a measure of the magnitude of a varying quantity. It can be interpreted as the effective value of the total gait force or position over time.

Formula:

$$RMS = \sqrt{\frac{1}{N}\sum_{i=1}^{N} x_i^2}$$

Zero Crossing Rate (ZCR):

ZCR is the rate at which the signal changes sign from positive to negative or back. This is indicative of the frequency of gait cycles or steps, reflecting changes in the direction of the gait force or movement.

Formula:

$$ZCR = \frac{1}{T-1}\sum_{i=1}^{T-1} |\operatorname{sgn}(x_i) - \operatorname{sgn}(x_{i+1})|$$

Signal Magnitude Area (SMA):

SMA sums the absolute values of the signal, providing a cumulative measure of the amplitude over time. In the context of gait, it indicates the overall activity level, capturing the dynamic range and movement intensity.

Formula:

$$SMA = \frac{\sum |x_i|}{N}$$

Frequency-domain Analysis Features:

FFT Coefficient:

Fast Fourier Transform (FFT) coefficients are complex numbers representing the amplitude and phase of sinusoids that compose the original time-domain signal. This transformation decomposes gait data into its constituent frequencies, revealing the periodic nature of the gait cycle.

Formula:

Applied directly as FFT(x) on the time-domain signal x.

Power Spectral Density (PSD):

PSD measures how power (variance) of the signal is distributed across different frequencies. It is particularly useful in identifying dominant frequencies and analyzing the energy contributions across the frequency spectrum of the gait.

Formula:

$$PSD = |FFT(x_i)|^2$$

where `|FFT(x_i)|` is the magnitude of the FFT at frequency bin `i`.

Fundamental Frequency:

The fundamental frequency is the lowest frequency in the Fourier Transform that is not zero. It represents the primary frequency component of the gait cycle, corresponding to the basic repeat rate of the stride.

Formula: Identified as the lowest non-zero peak in the FFT spectrum.

Low Frequency Band Energy and High Frequency Band Energy:

These metrics quantify the total energy contained within specific low and high frequency bands of the spectrum. They can provide insights into how different parts of the gait cycle contribute to the overall movement, with low frequencies often representing major body movements and high frequencies capturing finer adjustments and corrections.

Formula:

$$\text{Band Energy} = \sum |FFT(x_i)|^2 \text{ for } f_i \in [\text{band}]$$

Spectral Centroid:

The spectral centroid is a measure used to characterize the "center of mass" of the power spectrum, providing a perception of where the "center" of the sound or motion is located frequency-wise. In gait analysis, this can indicate the overall balance of frequency components in the movement.

Formula:

$$\text{Spectral Centroid} = \frac{\sum_{n=0}^{N-1} f(n) \cdot |X(n)|}{\sum_{n=0}^{N-1} |X(n)|}$$

where `f(n)` is the frequency at bin `n` and `|X(n)|` is the magnitude of the FFT at bin `n`.

Spectral Rolloff:

Spectral rolloff is the frequency below which a specified percentage (commonly 85% or 95%) of the total spectral energy is contained. This measure helps in understanding how spread the energy distribution is across the frequency spectrum.

Formula:

$$\text{Spectral Rolloff} = \min\left\{ f : \frac{\sum_{i=0}^{f} |X(i)|}{\sum_{i=0}^{N} |X(i)|} \geq k \right\}$$

where `k` is typically 0.85 or 0.95, representing the cumulative percentage threshold.

Spectral Entropy:

Spectral entropy measures the randomness or unpredictability of the power distribution across the frequency spectrum. A lower spectral entropy indicates a more predictable or concentrated frequency distribution, typically associated with rhythmic or periodic signals.

Formula:

$$\text{Spectral Entropy} = -\sum p_i \log p_i$$

where p_i is the normalized power spectral density at frequency bin `i`.

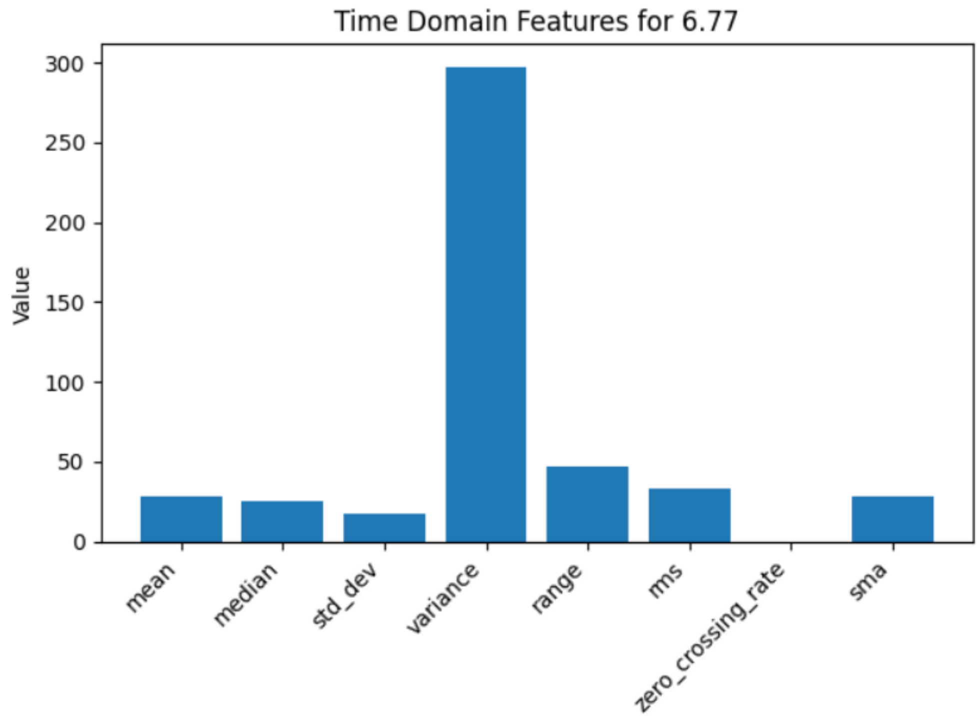
Results:

For the data GP2_1.2_oversteps.csv

```
Please enter the path to the CSV file: /content/GP2_1.2_oversteps.csv
     6.77
0   7.825
1  19.515
2  31.070
3  54.440
```

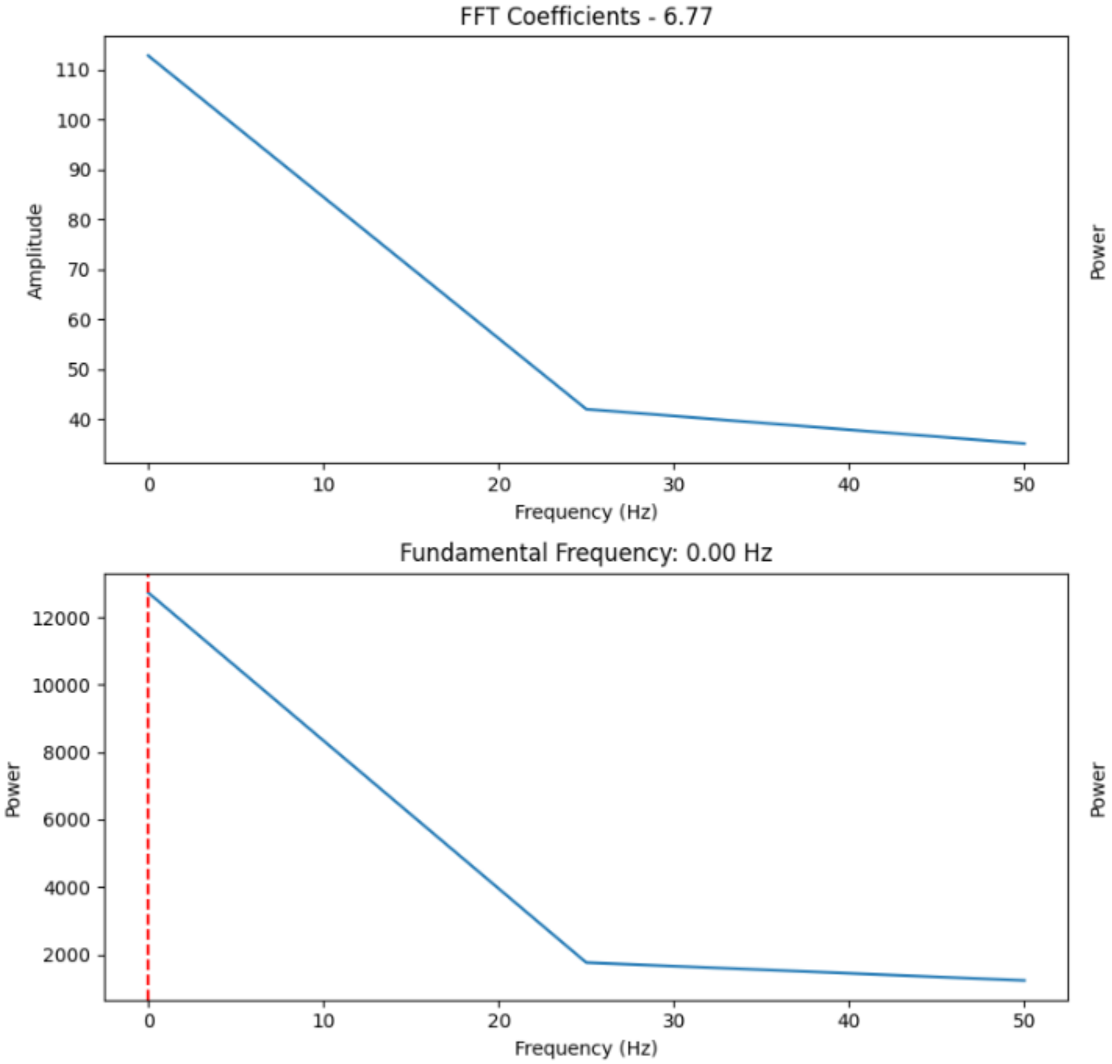
<u>Result of Time Domain Analysis Features:</u>

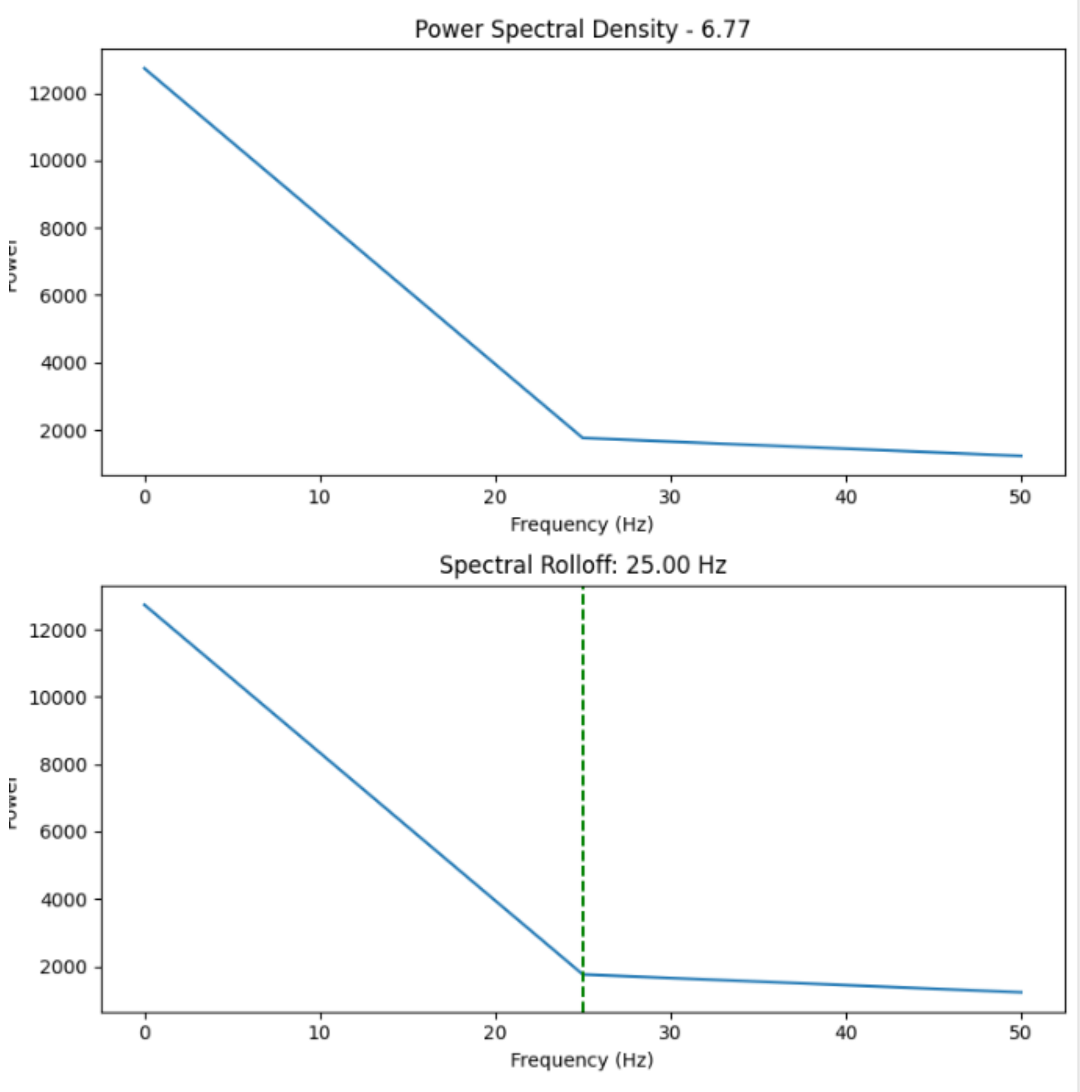
```
Enter the CSV file path: /content/GP2_1.2_oversteps.csv

Time Domain Analysis for 6.77:
mean: 28.2125
median: 25.2925
std_dev: 17.2289
variance: 296.8359
range: 46.6150
rms: 33.0572
zero_crossing_rate: 0.0000
sma: 28.2125
<ipython-input-4-1e7729dcbf08>:42: UserWarning: FixedFormatter
  ax.set_xticklabels(feature_names, rotation=45, ha='right')
```



Results of Frequency Domain Analysis Features:

```
Please enter the CSV file path: /content/GP2_1.2_oversteps.csv

Frequency Domain Analysis for 6.77:
fft_coefficients: Array of 3 elements
power_spectral_density: Array of 3 elements
fundamental_frequency: 0.0000
low_freq_band_energy: 0.0000
high_freq_band_energy: 2989.2892
spectral_centroid: 6.7069
spectral_rolloff: 25.0000
spectral_entropy: 0.8874
```





Conclusion:

Through meticulous time-domain and frequency-domain analyses of the gait phase data, this project provides significant insights into the biomechanics of walking at varying speeds. The statistical measures from the time-domain analysis reveal variability and central tendencies of gait cycles, while the frequency-domain analysis offers a detailed look at the energetic and spectral properties. This dual perspective enhances our understanding of gait dynamics, aiding in the development of diagnostic and therapeutic strategies for gait-related disorders. The findings also underscore the importance of controlling walking conditions in experimental setups to achieve reliable and reproducible gait analysis outcomes.