ISSN: 2976-7466

Journal of Biosensors and Bioelectronics Research

SCIENTIFIC Research and Community

Research Article

Open Access

Comparison of Short Fast Fourier Transform and Continuous Wavelet Transform in Study of Stride Interval

TH Lee[1]*, EF Shair[1], AR Abdullah[1], KA Rahman[1] and N Nazmi[2]

[1]Rehabilitation and Assistive Technology Research Group, Faculty of Electrical Technology and Engineering, Technical University Malaysia Melaka, Hang Tuah Jaya, 76100 Durian Tunggal, Melaka, Malaysia

[2]Malaysia-Japan International Institute of Technology, University of Technology Malaysia, Jalan Sultan Yahya Petra, 54100 Kuala Lumpur, Malaysia

ABSTRACT

Neurodegenerative diseases (NDD) are a heterogeneous group of complex diseases characterized by neuronal loss and progressive degeneration of different areas of the nervous system. Gait analysis presents an early recognition system for NDD which is important to increase the patient's awareness of their health conditions. However, it is very difficult to identify and formulate suitable digital biomarkers from the data collected from gait experiments such as stride interval and swing. The objective of this paper is to compare the result of Short - Time Fourier Transform (STFT) and Continuous Wavelet Transform (CWT) on the collected stride interval of healthy young people and healthy old people. In this paper, STFT and CWT are performed on the collected stride interval and from the result of the STFT and CWT, further features are extracted like instantaneous RMS and maximum RMS value. STFT is performed on the collected stride interval from a window length of 64 to 512 while CWT is performed on the collected stride interval from the scale of 128 to 2048. The processing time of the STFT and CWT with varied window lengths and scales respectively are collected. Besides, the actual maximum time from the time - frequency plot derived from STFT and CWT is also collected. Both STFT and CWT show that the young group has a higher maximum RMS, an indication of higher stride interval than the old group and higher variance, an indication of higher gait complexity. The suitable window lengths for STFT in analyzing the stride interval are 64 and 128 while the scale for CWT should be set to the lowest scale. Overall, STFT with a window length of 64 and 128 is better in analyzing the stride interval due to low processing time at the expense of slightly less accurate time - frequency representation.

***Corresponding author**

TH Lee, Rehabilitation and Assistive Technology Research Group, Faculty of Electrical Technology and Engineering, Technical University Malaysia Melaka, Hang Tuah Jaya, 76100 Durian Tunggal, Melaka, Malaysia.

Received: September 02, 2024; **Accepted:** September 05, 2024; **Published:** September 17, 2024

Keywords: Neurodegenerative Diseases (NDD), Gait Analysis, Digital Biomarkers, Short - Time Fourier Transform (STFT), Continuous Wavelet Transform (CWT)

Introduction

Gait analysis is important in diagnosing and rehabilitating gait abnormalities, as well as understanding the physiological changes associated with aging and treating injuries. Additionally, gait analysis can be used to improve the quality of life for patients with physical and neurological pathologies, as it helps in understanding the inner workings of the human nervous system [1, 2]. From 1990 to 2016, the number of people with Parkinson's Disease (PD) doubled to more than 6 million, with over 200,000 PD-related deaths globally which shows that the study of gait analysis is important [3]. One of the methods for gait analysis is analyzing the stride interval. Stride interval refers to the time between successive heel strikes of the same foot [4, 5]. From the literature review, many features are being used to formulate the digital biomarkers from the stride interval such as time feature, time-frequency feature, non–linear feature, and entropy [6-8]. There is no best feature for the data analysis as it depends on the type of cases and applications. Examples of time-frequency features include STFT and CWT. Each time-frequency feature has its advantages and disadvantages. STFT is suitable for analyzing non-stationary signals but uses fixed window lengths for all frequencies. Wavelet transform is sensitive to noise and has high computational complexity, but its upside is that it uses frequency - a dependent window [9].

Method

The stride interval of five healthy old people with a mean age of 74.6 and five healthy young people with a mean age of 24.4 are collected from the Gait in Aging and Disease Database in Physionet [10]. The healthy old people and healthy young people were asked to walk in a roughly circular path for 15 minutes. STFT and CWT are performed on the stride interval to identify the technique that gives the best visualization of the time-frequency plot.

The use of STFT is restrained by the uncertainty principle of time-frequency where a signal is divided into short pieces. The time resolution and frequency resolution in STFT are uniform because STFT has the same observation time width in all frequency ranges.

When $x(n)$ is an input signal, the time-axis sampling function of STFT can be denoted by equation (1).

$$x(n) \otimes W_n(n - k.S_n) \qquad (1)$$

Equation (1) is transformed into Equation (2) after a Fourier Transform is applied.

$$X(k, i\omega) = [\textstyle\sum_{n=-\infty}^{+\infty} x(n).\exp(-jn\omega)].[\textstyle\sum_{n=-\infty}^{+\infty} W_n(n-k.S_n).\exp(-jn\omega)] \quad (2)$$

Based on Equation (1) and (2), W_n is the window function, N is the FFT number, S_n is the time interval shift and k is an integer [11].

In CWT, the observation time-width changes according to the frequency. When the frequency is low, the observation time-width is lengthened which results in a small frequency resolution. When the frequency is high, the time resolution becomes small which results in a large frequency resolution. The time resolution and the frequency resolution of the wavelet transform are not uniform.

The CWT of a discrete-time signal with uniform time intervals is determined by calculating the inner product with a scaled and shifted mother wavelet as described in Equation (3) [12].

$$W_n(s) = \sum_{n'=0}^{N-1} x'_n \psi * \left[\frac{((n'-n)\delta_t)}{s}\right] \quad (3)$$

Based on Equation (3), discrete-time signal is denoted as x_n, uniform time intervals are denoted as δ_t, inner product is denoted as x_n and a scaled and shifted mother wavelet is denoted as ψ. n' and n are sequence positions.

Results & Discussion

To ensure the result of STFT has a good time - frequency resolution and can derive the instantaneous RMS value accurately, it is important to select the appropriate window length. The sampling frequency, f_s for STFT in this project is defined by the reciprocal of the difference of consecutive time as shown in Equation (4).

$$f_s = \frac{n-1}{\sum_{i=1}^{n-1}(x_{i+1} - x_i)} \quad (4)$$

Based on Equation (4), n is the number of data points, x is the data.

Table 1 shows the time - frequency plot of STFT (hanning window), derived instantaneous RMS of STFT and recorded processing time with varied window lengths from Old Subject 1. The window length is adjusted from 64 to 512. When the window length is increased from 64 to 512, the derived instantaneous RMS of STFT converges slowly from a maximally flat amplitude to a single peak. It can also be seen that when the window length increases from 128, the maximum x - value (time) has increased and deviated significantly from the original maximum x - value which is 869.79s. Table 2 shows the actual maximum x - value (time) that is derived from the result of STFT of varied window lengths from Old Subject 1. There is no noticeable change in recorded processing time when the window length is increased.

Table 1: The Time - Frequency Plot of STFT (Hanning Window), Derived Instantaneous RMS of STFT and Recorded Processing Time with Varied Window Length from Old Subject 1

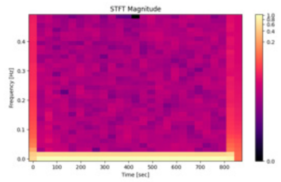
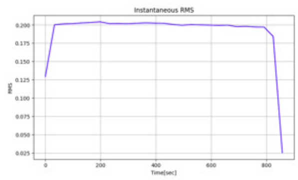
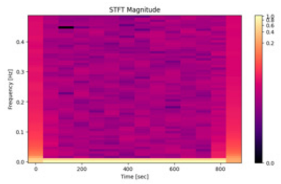
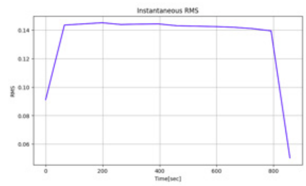
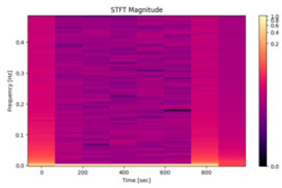
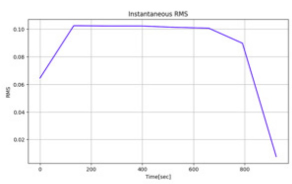
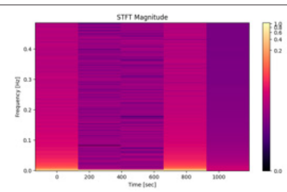
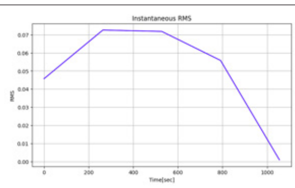
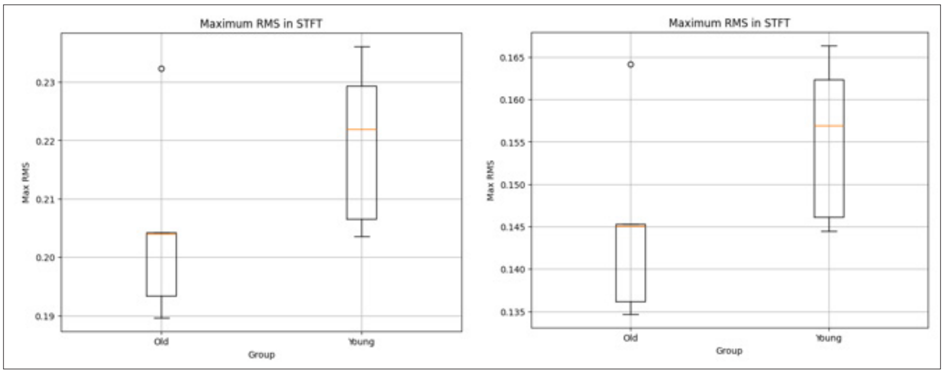
Window Length	Time - frequency Plot of STFT	Derived Instantaneous RMS of STFT	Recorded Processing Time [sec]
64			0.0656
128			0.0645
256			0.0704
512			0.0611

Table 2: The Actual Maximum Time Derived from STFT of Varied Window Length from Old Subject 1

Window Length	Actual Maximum Time [sec]
64	857.546
128	857.546
256	923.511
512	1055.441

Since the result of STFT of the window length above 128 does not come out with the accurate span of time in time - frequency plot, the window lengths of 64 and 128 will be chosen for further analysis because the maximum time derived from STFT is nearest to 869.79s. Figure 1 shows the comparison of the boxplot of maximum RMS in STFT versus the old group and young group with window lengths of 64 and 128. There is no difference in the overall pattern and trend of the boxplot in window lengths of 64 and 128. The difference lies in the magnitude of the maximum RMS. The higher the window length, the smaller the magnitude of the maximum RMS. Therefore, any of the two window lengths, 64 and 128 can be used to analyze the stride interval in this project with almost the same processing time.

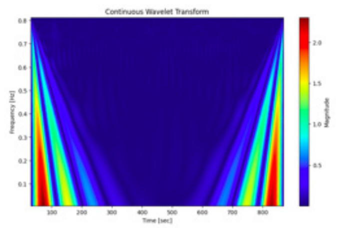
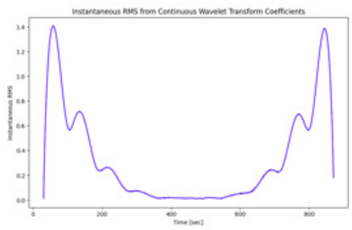
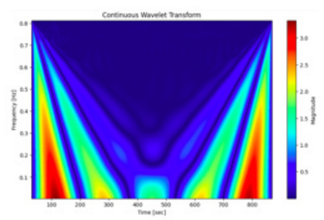
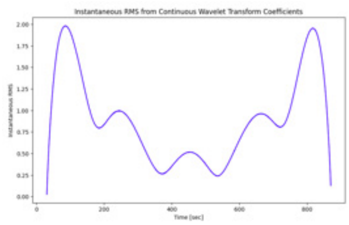


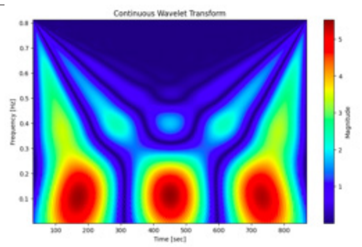
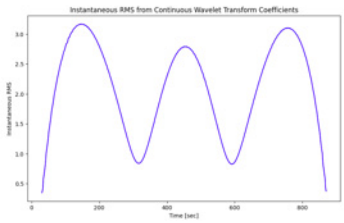
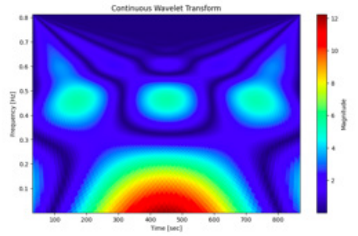
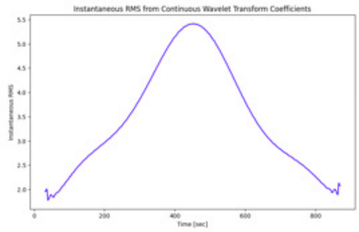
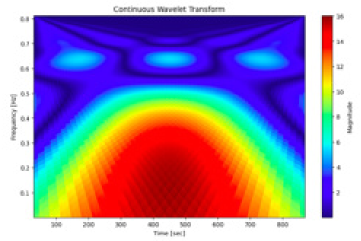
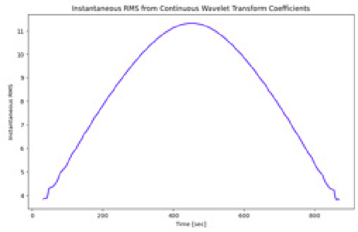
(a) **(b)**

Figure 1: The Box Plot of Maximum RMS in STFT versus Old Group and Young Group with (a) Window Length of 64 and (b) Window Length of 128

Table 3 shows the time - frequency plot of CWT, Derived Instantaneous RMS of CWT and recorded processing time with varied scales from 128 to 2048 from Old Subject 1. When the scale increases, the derived instantaneous RMS of CWT converges slowly from multiple peaks to a single peak. Also, the recorded processing time increases when the scale increases.

Table 3: The Time - Frequency Plot of CWT, Derived Instantaneous of CWT and Recorded Processing Time with Varied Scale from Old Subject 1

Scale	Time – frequency Plot of CWT	Derived Instantaneous RMS of CWT	Recorded Processing Time [sec]
128			0.695
256			0.825

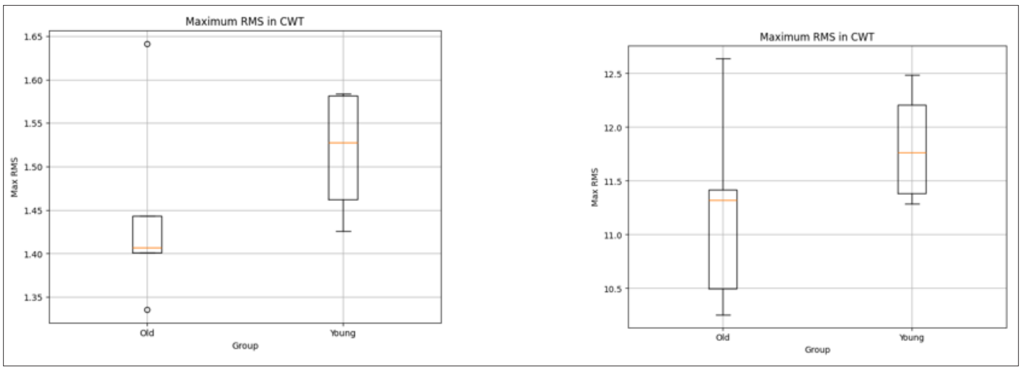
512			1.107
1024			2.188
2048			6.409

Based on Table 4, the actual maximum time derived from CWT of varied scale from 128 to 2048 from Old Subject 1 is all the same which is 869.03s which is nearer to 869.79s than STFT. It shows that CWT produces slightly more accurate time - frequency visualization than STFT.

Table 4: The Actual Maximum Time Derived from CWT of Varied Scale from Old Subject 1

Scale	Actual Maximum Time [sec]
128	869.043
256	869.043
512	869.043
1024	869.043
2048	869.043

Figure 2 shows the comparison of the boxplot of maximum RMS in CWT versus the old group and young group with a scale of 128 and 2048. The variance of maximum RMS in CWT of the old group is higher on the scale of 2048 than in 128. Other than that, there are no differences in the overall pattern and trend on a scale of 128 and 2048. The higher the scale, the higher the magnitude of maximum RMS in CWT. It is better to use the lower scale for CWT because the processing time increases with the scale and there are no significant differences between lower scale and higher scale in terms of overall pattern and trend.



(a) **(b)**

Figure 2: The Box Plot of Maximum RMS in CWT versus Old and Young Group on a scale of (a) 128 and (b) 2048

From the result of STFT and CWT, the young group has a higher maximum RMS than the old group. The higher maximum RMS indicates that the stride interval of the young group is larger than the old group. In STFT, the young group has a higher variance of maximum RMS than the old group at both window lengths of 64 and 128. In CWT, the young group has a higher variance at a low scale and has almost the same variance as the old group at a high scale. The higher variance of the stride interval indicates higher complexity in the gait of the young group. The complexity of the gait of the young group had been studied extensively using Detrended Fluctuation Analysis (DFA) in the past that showed gait complexity increased during young adulthood and declined with aging [13-15].

STFT and CWT are both capable of distinguishing the gait of old people and young people using the feature, maximum RMS value. The suitable window lengths for STFT in analyzing the stride interval are 64 and 128 while for CWT, the scale should be set to the lowest which is 128. However, in terms of processing time, STFT can be performed in a significantly shorter time than CWT. CWT at any scale produces a slightly more accurate time - frequency representation than STFT.

Overall, STFT with window lengths of 64 and 128 is better in analyzing the stride interval due to low processing time at the expense of slightly less accurate time - frequency representation.

Conclusion

The result of STFT and CWT, both show that the young group has a higher maximum RMS value than the old group which indicates a higher stride interval. The result of STFT shows that the young group has a higher variance of maximum RMS than the old group at both window lengths of 64 and 128. The result of CWT shows that the young group has a higher variance of maximum RMS at a low scale and almost the same variance as the old group at a high scale. The suitable window lengths for STFT in analyzing the stride interval are 64 and 128 while for the CWT, the lowest scale which is 128 should be chosen to reduce the processing time. Overall, STFT with window lengths of 64 and 128 is better in analyzing the stride interval due to low processing time at the expense of slightly less accurate time - frequency representation.

Acknowledgements

The authors acknowledge the support and funding provided by the Ministry of Higher Education (MOHE) of Malaysia and Technical University Malaysia Melaka (UTeM) through the Fundamental Research Grant Scheme (FRGS), No: FRGS/1/2023/SKK06/UTEM/02/1.

References

1. P Ren, S Tang, F Fang, L Luo, Lei Xu, et al. (2017) Gait Rhythm Fluctuation Analysis for Neurodegenerative Diseases by Empirical Mode Decomposition. IEEE Trans Biomed Eng 64: 52-60.
2. G Cicirelli, D Impedovo, V Dentamaro, R Marani, G Pirlo, et al. (2022) Human Gait Analysis in Neurodegenerative Diseases: A Review. IEEE J Biomed Heal Informatics 26: 229-242.
3. KR Chaudhuri, JP Azulay, P Odin, S Lindvall, J Domingos, et al. (2024) Economic Burden of Parkinson's Disease: A Multinational, Real-World, Cost-of-Illness Study. Drugs Real World Outcomes 0123456789.
4. M Akhtaruzzaman, AA Shafie, MR Khan (2016) GAIT ANALYSIS: SYSTEMS, TECHNOLOGIES, and IMPORTANCE. J Mech Med Biol 16: 1-45.
5. K Okamoto, I Obayashi, H Kokubu, K Senda, K Tsuchiya, et al. (2022) Contribution of Phase Resetting to Statistical Persistence in Stride Intervals: A Modeling Study. Front Neural Circuits 16: 1-11.
6. VT Sai Sandeep Raju, M Belwal (2021) Driver Drowsiness Detection. Lect Notes Data Eng Commun Technol 58: 975-983.
7. SM Cai, PL Zhou, HJ Yang, T Zhou, BH Wang, et al. (2007) Diffusion entropy analysis on the stride interval fluctuation of human gait. Phys A Stat Mech its Appl 375: 687-692.
8. V Alcan (2022) Nonlinear Analysis of Stride Interval Time Series in Gait Maturation Using Distribution Entropy. Irbm 43: 309-316.
9. EF Shair, SA Ahmad, MH Marhaban, SBM Tamrin, AR Abdullah (2017) EMG processing-based measures of fatigue assessment during manual lifting. Biomed Res Int 2017.
10. A Goldberger, L Amaral, L Glass, J Hausdorff, PC Ivanov, et al. (2000) Physio Bank, Physio Tool kit, and PhysioNet: Components of a new research resource for complex physiologic signals. Circulation 101: e215-e220.
11. T Baba (2012) Time-Frequency Analysis Using Short Time Fourier Transform. Open Acoust J 5: 32-38.
12. N Ji, H Zhou, K Guo, OW Samuel, Z Huang, et al. (2019) Appropriate mother wavelets for continuous gait event detection based on time-frequency analysis for hemiplegic and healthy individuals. Sensors 19: 1-18.
13. K Jordan, JH Challis, KM Newell (2006) Long range correlations in the stride interval of running. Gait Posture 24: 120-125.
14. JM Hausdorff, SL Mitchell, R Firtion, CK Peng, ME Cudkowicz, et al. (1997) Altered fractal dynamics of gait: Reduced stride-interval correlations with aging and Huntington's disease. J Appl Physiol 82: 262-269.
15. S Yano, L Dimalanta, Y Suzuki, T Nomura (2019) Fluctuation of stride time intervals during walking with smartphone. 2019 IEEE 1st Glob Conf Life Sci Technol Life Tech 296-297.