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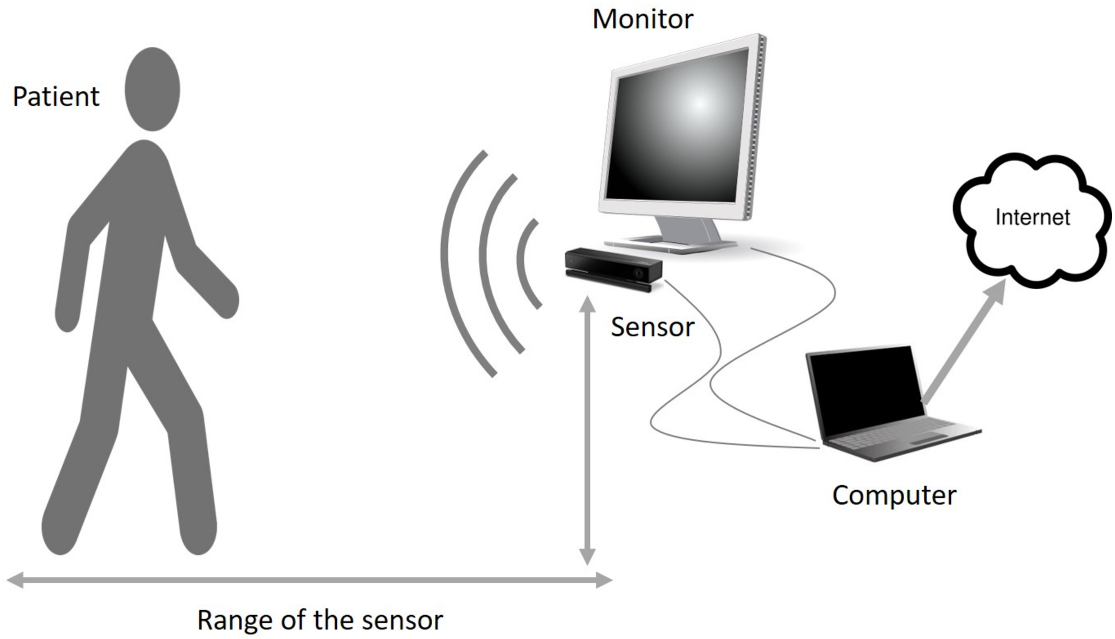

Motor Functions Assessment for Parkinson Disease via Radar Sensors

Focusing on Finger Tapping Test

Master's Thesis in Electrical Engineering

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CHALMERS UNIVERSITY OF TECHNOLOGY
Gothenburg, Sweden 2024
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Abstract

This thesis investigates the assessment of motor functions using a radar sensor, focusing on the finger tapping test. The primary goal is to help healthcare professionals in accurately detecting and analyzing finger tapping test, which is essential for effective treatment and management of Parkinson's disease (PD). Data of several finger tapping scenarios was collected by mimicking them by healthy individuals using the radar sensor, followed by comprehensive data and signal processing.
The developed model achieved a promising accuracy of 93.18% on the dataset collected by students. It successfully identified and scored the cases with interruptions, as well as amplitude and frequency decrements, although it does not provide a severity score for decrement cases. However, the model's inability to handle cases involving combinations of interruptions and decrements was identified as a limitation. Tests conducted by physiotherapists resulted in lower accuracy, primarily due to the radar sensor's high sensitivity to motion and distance changes.
This thesis explores the potential of radar sensor technology in monitoring motor functions while highlighting the challenges associated with data collection and sensor sensitivity.

Keywords: Parkinson's disease, finger tapping test, radar sensor, motor function assessment, FMCW radar sensor,

Acknowledgements

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Thank you all for being part of this journey.

Gustav Isaksson and Seyedehnaghmeh Mosaddeghi, Gothenburg, June 2024

List of Acronyms

Below is the list of acronyms that have been used throughout this thesis listed in alphabetical order:

Analog to Digital Converter	ADC
Central Nervous System	CSN
Discrete Fourier Transform	DFT
Dopaminergic	DA
Excessive Daytime Sleepiness	EDS
Frequency Modulated Continuous Wave	FMCW
Fast Fourier Transform	FFT
Finger Tapping Quantification Algorithm	FTQA
Fourier Transform	FT
Intermediate Frequency	IF
International Parkinson and Movement Disorder Society	MDS
Magnetic Resonance Imaging	MRI
Parkinson Disease	PD
Positron Emission Tomography	PET
Postural Instability	PI
Postural Instability and Gait Difficulty	PIGD
Predicted Interruption Pulse Graph	PIPG
Radio Detection and Ranging	Radar
Short Time Fourier Transform	STFT
Single Photon Emission Computed Tomography	SPECT
Texas Instrument	TI
True Interruption Pulse Graph	TIPG
Transcranial Sonography	TCS
User Datagram Protocol	UDP
Unified Parkinson's Disease Rating Scale	UPDRS
World Health Organization	WHO

Contents

List of Figures

List of Tables

1
Introduction

Parkinson's Disease (PD), the most common movement disorder, is characterized by disruptions in body movement, which can significantly impact patients' ability to engage in activities and participate in daily life. Parkinson's disease (PD) impacts roughly 1.47% of individuals aged 60 years or above [1]. In 2015, Parkinson affected more than 6 million people globally [2], and now there are more than 10 million people suffer from PD, making it the neurological disorder with the fastest-growing prevalence [3].

PD is a common Neurodegenerative diseases associated with the loss of dopaminergic terminals in the basal ganglia and the loss of neurons in the substantia nigra. Diagnosis, reliable monitoring of patients, and assessment of the effectiveness of medications are crucial aspects of managing PD. Diagnosing PD is particularly challenging because there is no specific physical test available; it is primarily diagnosed based on clinical observations. And monitoring of PD is significantly important as it contributes to enhancing patients' quality of life. By closely monitoring medication effectiveness and symptom progression, healthcare teams can collaborate with patients to make informed decisions and explore alternative treatments.

Motor function assessment is the evaluation of patient's ability to perform specific movements. These assessments are crucial as they are designed to measure various aspects of motor functions. They help physiotherapists in several ways: diagnosing conditions, monitoring progress, designing treatment plans, and measuring the outcomes of treatments. Motor function assessment covers the main characteristics of PD, including bradykinesia, rigidity, tremor, and gait and balance abnormalities. And finger tapping test is one of the popular tests being used to evaluate bradykinesia.

In motor assessment process, clinicians gather information on motor symptoms for treatment decisions. This is often done using standardized tools such as the Unified Parkinson's Disease Rating Scale (MDS UPDRS). These tools include tests that give a total score, reflecting the overall disability of the patients. For example, in the finger tapping test, where the patient is required to tap the index finger on the thumb as fast and as big as possible, the MDS-UPDRS scale gives scores based on the number of interruptions, slowing, or amplitude decrement observed during the test.

Currently, physiotherapists face challenges in documenting their observations during these tests manually. This process requires them to monitor each patient's performance, noting any interruptions, changes in rhythm, or other relevant details. However, this manual approach often proves to be insufficient and intensive, affecting the efficiency of patient assessment and potentially leading to inaccuracies in data recording. Therefore, it is crucial to develop rapid, affordable, and reliable methods to analyze and understand motor functions and their fluctuations. These methods are essential for assisting healthcare teams in effectively managing Parkinson's disease.

1.1 State of Art

The article [4] discussed the detection of bradykinesia, by analyzing hand movement frequency. The detection system utilized an accelerometer sensor embedded in a bracelet to measure movement frequencies. Data was collected from participants performing pronation-supination movements. [4].

The study by [5] introduced a method for detecting bradykinesia in PD patients using a deep learning-based system in conjunction with a wearable device. This device, equipped with inertial sensors, was connected to the patients' wrists and ankles. The authors implemented a deep learning model for the identification of bradykinesia, achieving an accuracy rate of 98.6% [5].

The study by [6] employed three sensors were attached to the patients' neck, symptomatic hand, and contralateral leg using straps to collect data for motor fluctuations analysis.A machine learning model was then employed to classify the activities based on the collected data. And the results demonstrated that the model could effectively detect resting tremors from physical activities.

The study [7] developed a model to assess the severity score of the finger tapping test. The researchers captured the data using computer webcams. Models were employed to detect and monitor hand movements, focusing on the finger-tapping angle between the thumb finger-tip and the index finger. Different metrics was measured, including finger tapping amplitude—determined by the maximum distance between the thumb and index finger—speed, acceleration, and wrist movement. These metrics were utilized to evaluate various aspects such as Aperiodicity (absence of repeating patterns), interruptions, freezing instances, longest freezing duration, and amplitude decrement. The model was then used machine learning to classify cases based on these features and assign scores according to the MDS UPDRS scale.

While the studies discussed above show promising results, there are certain limitations to consider. Firstly, the devices and wearable sensors used in the first three articles are expensive, which makes it impractical to provide them to every patient. Additionally, relying on body-attached sensors has its disadvantages. These sensors may not capture data from body parts not connected to them. Moreover, having sensors attached to multiple body parts can be uncomfortable for patients and may affect their willingness to use them consistently.

Furthermore, although using video for motor function assessment has produced positive outcomes, it may not be accepted by all patients. Some individuals may feel uncomfortable being recorded during assessments, raising concerns about privacy and personal comfort. These considerations highlight the need for the development of more affordable and patient-friendly monitoring solutions that prioritize accessibility and user comfort.

1.2 Aim

This method aims to offer hospitals a more reliable alternative to the current subjective assessment method for finger tapping test, which rely heavily on clinicians' memory and verbal descriptions of symptoms, lacking quantifiable data. By providing data-driven insights, doctors will have the tool to monitor the progression of the disease, evaluate medication effectiveness and make informed decisions based on objective facts rather than subjective impressions. We start by utilizing a simple and inexpensive sensor to collect data on finger tapping test which can be used routinely in hospital settings to evaluate motor symptoms. Subsequently, we analyze the gathered data to derive valuable insights into these motor symptoms. Finally, we deploy the model and evaluate its performance.

2

Theory

This chapter aims to provide a theoretical overview of various concepts related to Parkinson's disease. We'll explore both motor and non-motor symptoms associated with the condition and discuss how radar sensor technology works.

2.1 Parkinson Disease

Parkinson's disease (PD), which was identified by James Parkinson in 1817 for the first time, is the second most prevalent neurodegenerative disorder globally, after Alzheimer's disease [8]. This condition is characterized by a range of symptoms affecting motor and cognition functions. These symptoms arise due to the progressive loss of nerve cells in a specific region of the brain known as the substantia nigra. Dopaminergic (DA) neurons are specialized cells found in the substantia nigra. These neurons are essential for the synthesis and release of dopamine, a neurotransmitter that acts as a messenger in the brain, allowing different parts of the brain that regulate movement to communicate with one another [9]. The progressive loss of these DA neurons, especially after about 80% are destroyed, is demonstrated by the progressive development of typical symptoms of PD. Figure 2.1 illustrates the location of the substantia nigra within the brain and highlights the differences between the substantia nigra in healthy individuals and those with Parkinson's disease, due to the loss of DA neurons.

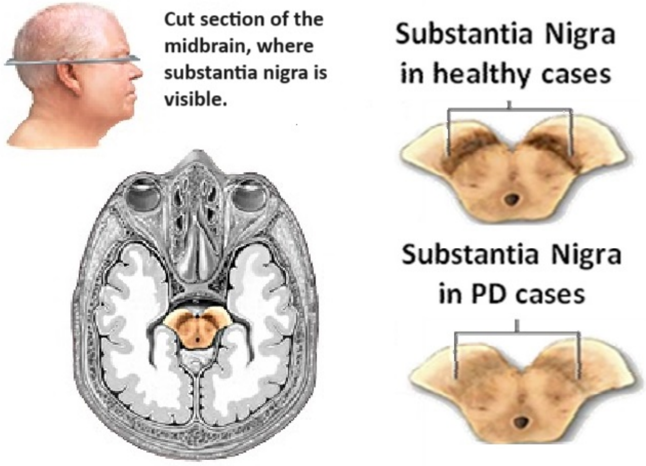

Figure 2.1: Substantia nigra in the human brain, in healthy individuals and PD patients [10]

The precise cause of Parkinson's disease remains unknown, but researchers have identified certain genetic mutations linked to the degeneration of DA neurons. Additionally, it is believed that exposure to environmental toxins or certain chemicals contribute to the development of PD. Parkinson's disease is more common as people get older, typically beginning at age 60 [11].

2.1.1 PD Symptoms

2.1.1.1 Non-Motor Symptoms

Non-motor symptoms are present in patients with PD. [13]. James Parkinson identified non-motor symptoms during the prodromal or pre-PD phase [15]. These symptoms include various categories as shown in figure 2.2, which can be explained as follows.

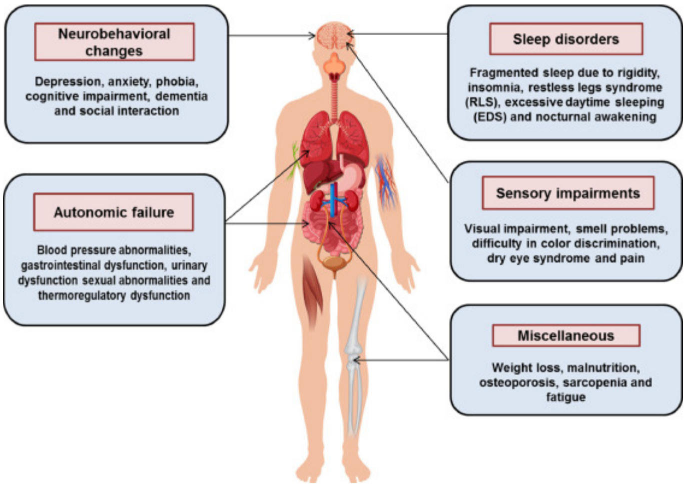

Figure 2.2: Non-Motor Symptoms Associated with PD [15]

- Neurobehavioral changes: people with PD often experience changes in behavior or mental health issues that aren't related to movement. These include depression, anxiety, phobia, inhibition in social interaction, cognitive impairment, and dementia [15].

- Autonomic failure: Autonomic failures involve issues like blood pressure abnormalities, gastrointestinal problems, sexual difficulties, thermoregulatory issues, and urinary problems [15].

- Sensory impairments: Sensory impairment often includes abnormalities in the sense of smell, visual problems such as reduced ability to distinguish colors, lower contrast sensitivity, and dry eye syndrome [15].

- Sleep disorders: Sleep disorders in PD may include difficulties in falling asleep or staying asleep, restless legs syndrome, vivid dreams, rapid eye movement sleep behavior disorder, and excessive daytime sleepiness (EDS) [16].

2.1.1.2 Motor Symptoms

Parkinson's disease is recognized as a progressive disorder affecting movement, with its primary symptoms being related to motor function. While there is growing knowledge of non-motor symptoms associated with PD, the diagnosis process has traditionally focused on identifying specific motor-related symptoms. A clinical diagnosis of PD typically requires the observation of two or more motor-related signs or symptoms. Below, we explain the most significant motor symptoms as illustrated in figure 2.3.

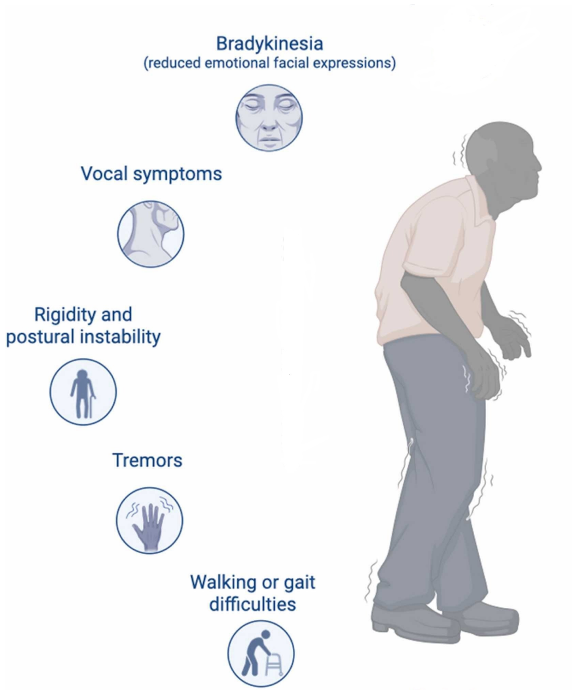

Figure 2.3: Motor Symptoms Associated with PD [17]

- Bradykinesia: Bradykinesia, marked by reduced movement speed, is a significant characteristic of PD. It is a key aspect of basal ganglia disorders, affecting the ability to plan, initiate, and carry out movements, as well as perform tasks concurrently or sequentially. Early indications often include sluggish performance in everyday tasks and delayed responses, particularly in activities requiring precise motor control, like fastening buttons or handling utensils. Evaluation typically entails monitoring patients as they execute quick, repetitive hand motions and heel taps, with attention paid not only to the slowness of movement but also to any decrease in movement amplitude [14].

- Tremor: Tremor is an involuntary, rhythmic shaking of a body part, such as the hand, caused by rapid muscle contractions and relaxations. There are two main types of tremor:
  1. Physiological tremor, which is normal and occurs in everyone, especially during periods of stress or anxiety.
  2. Pathological tremor, which arises from neurological conditions, and they

are further classified based on when they occur, such as rest tremor or action tremor.

In Parkinson's disease, tremor is often one of the initial symptoms, affecting approximately 70% of patients at the time of diagnosis. Rest tremor, characterized by the "pill-rolling" motion of the hands, is common and typically occurs when the body is relaxed. Action tremor, which happens during specific activities like holding objects or writing, is also prevalent, particularly in the hands. Tremor tends to worsen gradually over time, though the progression rate varies among individuals [18].

- Rigidity: Rigidity or stiffness is often described as a constant increase in muscle tightness, felt as steady resistance when moving a limb. In Parkinson's disease PD, two main types of rigidity are recognized and can occur together [20].

  1. Lead-pipe rigidity: It involves stiffness that remains consistent throughout the entire range of motion at any joint, both when extending and flexing. It tends to worsen as the disease progresses.
  2. Cogwheel rigidity: This involves muscle tightness that is regularly interrupted at a frequency of 4 to 6 Hz, and sometimes at 8 to 9 Hz. This type of rigidity often accompanies tremors and can be noticed clinically in the early stages of PD.

- Gait impairment: Gait, the manner of walking, is typically characterized by an upright posture, an even stride, and natural swinging of the arms. However, PD can affect this normal gait pattern. The characteristic Parkinsonian gait often includes diminished arm swing, less fluid movement, increased limb imbalance, slower pace, shorter steps, dragging feet, heightened reliance on both legs simultaneously, quicker step frequency, difficulty turning smoothly, challenges with initiating walking, freezing episodes, and decreased stability and posture control. These gait features usually worsen over time [21].

- Postural Instability: Postural instability refers to the difficulty in maintaining body balance in response to gravitational forces, whether at rest or in motion [22]. Achieving and preserving postural stability necessitates precise coordination between sensory and motor systems to perceive, adjust, and execute movements effectively [23].

- Vocal Symptoms: Vocal symptoms manifest across various aspects of speech, such as decreased voice volume, alterations in voice quality, limited articulatory movements, and reduced pitch and volume variation. Recent studies indicate that voice issues may be among the earliest signs of motor problems in PD. It's possible that the intricate motor control required for speech makes it vulnerable to dysfunction before other motor symptoms appear in the limbs [24].

2.1.2 PD Diagnosis

Diagnosing Parkinson's disease relies on a combination of factors, including the patient's medical history, reported symptoms, and results from motor function tests. There isn't a specific laboratory test or imaging technique that can definitively diagnose Parkinson's disease. However using the motor function assessment tests in conjunction with evidence from neuroimaging methods can help to diagnose PD more accurately. These imaging techniques help in detecting the degeneration of dopamine-producing neurons in the substantia nigra. Various neuroimaging techniques are employed in the diagnostic process, including Transcranial Sonography (TCS), Magnetic Resonance Imaging (MRI), Single Photon Emission Computed Tomography (SPECT), and Positron Emission Tomography (PET) [26].

2.1.2.1 Motor Function Assessment

Parkinson's disease is a progressive condition characterized by diverse symptoms, which can complicate the diagnostic process. In recent years, efforts have been made to refine the diagnosis of PD, leading to the development of the Unified Parkinson's Disease Rating Scale (MDS-UPDRS) by the International Parkinson and Movement Disorder Society (MDS). This comprehensive framework assesses both non-motor and motor symptoms, but we will focus on motor symptoms. According to the MDS-UPDRS criteria, a diagnosis of PD is indicated by the presence of bradykinesia and at least one other cardinal motor symptom, such as rigidity or resting tremor at 5 Hz [26].

Motor function assessment in PD involves a series of tests that evaluate various aspects of motor function. Here are the tests commonly used to evaluate each aspect:

- **Gait and Balance:** Tests such as the Timed Up and Go (TUG), the Chair Stand Test, the Free Walking Test, and the Pull Test provide valuable information about a patient's stability and ability to maintain an upright posture.

- **Rigidity:** Upper and lower extremity tests are used to evaluate rigidity.

- **Tremor:** Tests are designed to evaluate resting, action, and postural tremors.

- **Bradykinesia:** Commonly used tests include the Finger Tapping Test, the Fist Open-Close Test, the Pronation/Supination of the Hand Test, the Toe Tapping Test, and the Heel Tapping Test. These assessments measure the strength and coordination of the upper limbs.

These methods and scales provide a solution for evaluation and severity of symptoms which is important in assessing disease progression, and treatment response.

2.1.2.2 Finger Tapping

As discussed above, diagnostic criteria established by the International Parkinson and Movement Disorder Society (MDS) for PD necessitate the presence of 'parkinsonism,' characterized by bradykinesia alongside either rest tremor, rigidity, or both. Thus, bradykinesia is considered the defining feature of PD. Finger tapping test is one of the common methods to evaluate the existence and degree of bradykinesia in clinical settings [36].

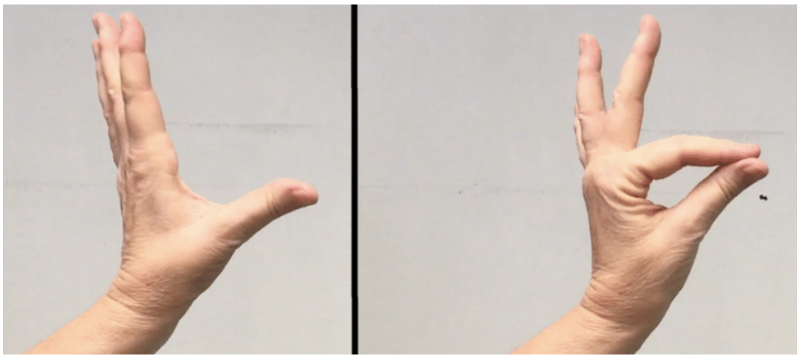

Figure 2.4: Finger tapping test [37]

In this method a clinician observes the patient repetitively tapping their index finger against their thumb as rapid and as big as possible as shown in figure 2.4. This finger tapping examination is integrated into the standardized clinical assessment tool MDS-UPDRS. Within this scale, three aspects of finger tapping bradykinesia; speed, amplitude, and rhythm; are evaluated and combined into a composite score ranging from 0 (normal performance) to 4 (severe) which can be seen in table 2.1 . The MDS-UPDRS finger tapping score displays the severity rather than the definitive presence of bradykinesia [36].

Table 2.1: Scoring Criteria for Finger Tapping Test

Score	**Level**	**Criteria**
0	Normal	No problems
1	Slight	(a) The regular rhythm is broken with one or two interruptions or hesitations of the tapping movement. (b) Slight slowing. (c) The amplitude decrements near the end of the 10 taps.
2	Mild	(a) 3 to 5 interruptions during tapping. (b) Mild slowing. (c) The amplitude decrements midway in the 10-tap sequence.
3	Moderate	(a) More than 5 interruptions during tapping or at least one longer arrest (freeze) in ongoing movement. (b) Moderate slowing. (c) The amplitude decrements starting after the 1st tap.
4	Severe	Cannot or can only barely perform the task because of slowing, interruptions, or decrements.

2.1.3 PD Treatment

Parkinson's disease treatment differs depending on the specific symptoms of each patient. However, the treatment focus is on reducing discomforts or disabilities, enhancing overall function and improving quality of life [28].

Levodopa is a common medication for PD patients which is a natural substance that enters the brain and converts into dopamine [28]. Studies have shown that initiating treatment with levodopa provides sustained mobility benefits and improved activities of daily living over several years compared to other medications [29]. However, this medication does not stop the progression of Parkinson's disease, and high doses of levodopa may result in uncontrollable movements [28].

Optimal treatment strategies for PD involve shared decision-making between patients and healthcare providers, considering the benefits and risks of each medication [28]. Over time, individuals with PD may require more frequent and higher doses of levodopa due to disease progression and changes in brain physiology based on motor function assessments [30]. Ultimately, having a reliable method for motor function assessment is critical, as it is essential for tailoring the treatment process effectively.

2.2 Frequency Modulated Continuous Wave Radar

The type of sensor which is utilized in this thesis is called Frequency Modulated Continuous Wave (FMCW) radar. The principle behind how FMCW radar works is that it continuously sends out sinusoidal signals, which are called chirps, with increasing frequency [32]. A synthesizer generates a chirp which is later sent out by an TX antenna/s and once the chirp hits an object, it reflects back to the radar and gets captured by an RX antenna/s. The signal which is used for further processing is called Intermediate Frequency (IF) signal which is a combination between the signal from the synthesizer and the signal from the RX antenna according to figure 2.6. The frequency of the IF signal is equal to the difference of the instantaneous frequencies of the two input signals according to figure 2.7. By studying the frequency and phase of the IF signal, valuable information can be extracted such as distance and velocity to the object. In order to understand how certain parameters can be extracted from the IF signal, the fundamental signal processing technique *Fourier Transform* needs to be considered.

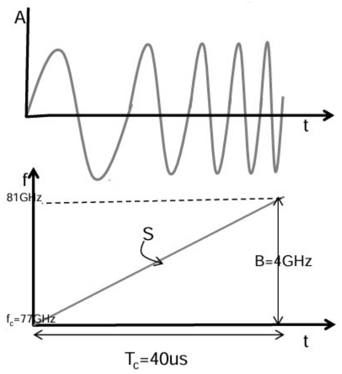

Figure 2.5: Chirp - a sinusoidal signal with increasing frequency over time [32]

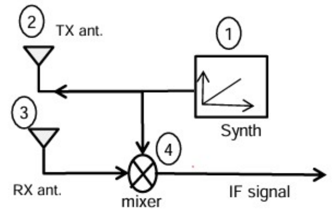

Figure 2.6: Steps for generating IF signal [32]

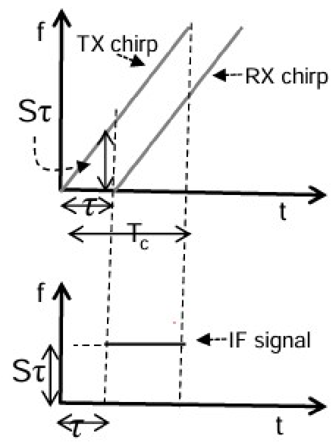

Figure 2.7: The IF signal for an object at a specific distance [32]

2.3 Fourier Transform

The Fourier Transform (FT) is a mathematical method that decomposes a signal into its constituent frequencies. The FT takes a function of continuous/discrete time and transforms it into a function of frequency, revealing the frequency content of the original signal as in figure 2.8. The reason why the FT has a significant importance regarding FMCW radar, is because it enables identification of the frequency of the IF signal.

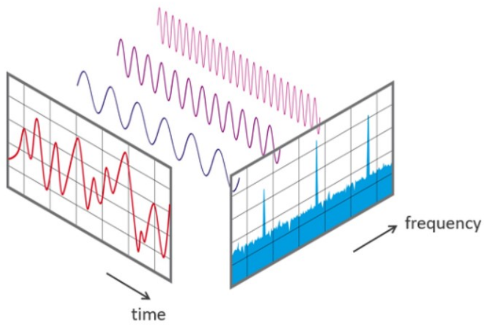

Figure 2.8: Frequency components in a signal [34]

2.3.1 Discrete Fourier Transform

When applying the FT operation, one needs to consider whether it's supposed to be in the continuous or discrete time domain. The FT in continuous time domain is usually used for theoretical analysis while FT in the discrete domain (DFT) is used in more practical applications where signal processing is utilized.

As mentioned before, the FT reveal the frequency components in a given signal and the DFT operation does it according to 2.1. The output from the DFT $X[k]$ is complex valued with a certain magnitude $|X[k]|$, which represents the level of presence of the frequency bin k in the signal $x[n]$, and a phase $\angle X[k]$ which represents the phase shift of the signal $x[n]$ at the given frequency bin k [35]. The frequency bin k is equivalent with the frequency $f_k = n\frac{k}{N}$ and one can see that the DFT divides the frequency spectrum into N evenly spaced frequencies where N is the number of samples of the signal $x[n]$. Lastly, the Fast Fourier Transform (FFT) is commonly used in practise instead of DFT because, in short terms, it's a more efficient operation of DFT but the principle and outcome is the same.

$$X[k] = \sum_{n=0}^{N-1} x[n]\, e^{-i2\pi n\frac{k}{N}} \tag{2.1}$$

2.3.2 Short Time Fourier Transform

Another version of the DFT, which is fundamental in this thesis, is the Short Time Fourier Transform (STFT). The STFT computes the DFT of the signal but not at once since it divides the signal into shorter time windows. The result of this is that one can study how the frequency in the signal changes over time as in figure 2.9. This will be of significant importance in order to analyze the change of frequency over time in the finger tapping test later on.

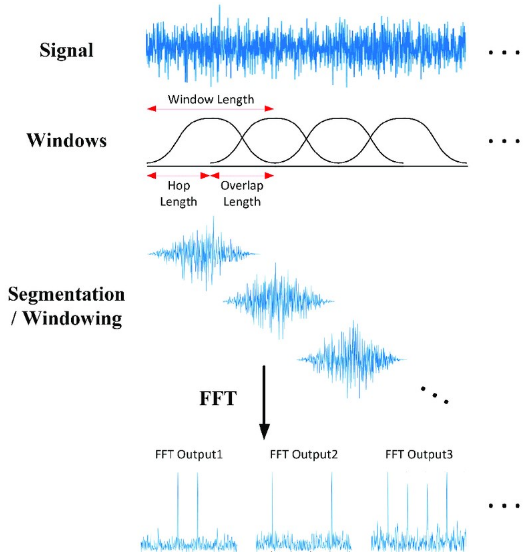

Figure 2.9: The Short Time Fourier Transform [31]

2.4 FMCW Radar Theory

Once the data has been collected from the radar, there are some common data processing procedures which will be applied in order to capture some desired patterns.

2.4.1 Generating Range Profile

As mentioned in the beginning regarding FMCW radar, the frequency and phase of the IF signal gives valuable information about the object in front of the radar. The frequency of the IF signal represents a specific distance between the radar and the object according to equation 2.2 where c is the speed of light, S is the slope of each chirp and f_{IF} is the frequency of the IF signal. Therefore, by applying FFT on a certain IF signal gives the frequency of the IF signal which in turn gives the distance between the radar and the object.

$$d = \frac{c f_{\mathrm{IF}}}{2S} \tag{2.2}$$

In figure 2.10 one can study how a range profile is being generated where the left side represents how many chirps that are transmitted from the radar with a certain frame interval T_c between each chirp. Each transmitted chirp reflects onto the object and generates a certain IF signal (study figure 2.7) which corresponds to a row in the matrix in figure 2.10. Each box in a specific row corresponds to a sample of the IF signal and when the FFT is applied to the IF signal, it's applied to the whole sequence of samples in a specific row. By applying FFT to the sequence of samples (columns) in each frame (row), one will generate a range profile matrix. The range profile matrix is complex valued where in each frame, the column/frequency bin, which contains the complex value with the greatest magnitude, corresponds to the frequency of the IF signal. In this way, the distance between the radar and the object can be extracted in each frame.

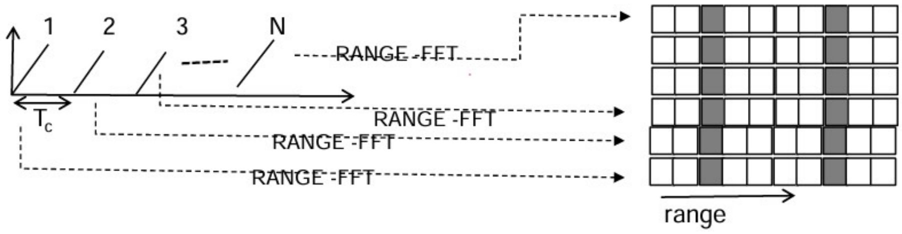

Figure 2.10: Range profile matrix [32]

2.4.2 Detection of Small Movements with Varying Frequencies

In this thesis, there will be of a significant importance to detect small changes in movements because of the finger tapping test that will be implemented later on. Small changes in movements can sometimes be hard to recognize by the human eye, especially to categorize the movement change. However, detecting changes of frequency with radar is much easier and this is where STFT is utilized. If the change of movement is approximately performed at the same distance to the radar, which will be the case in this thesis, then STFT can be applied to the frequency bins (columns) that corresponds to the distance for all frames (rows). The result of this would be to see how the doppler frequency of the movement changes over time. Also, one will later see that a conversion from doppler frequency to velocity is preferred and in order to do that the following formula is used in 2.3 where c is the speed of light, f_{Doppler} is the doppler frequency and f_{Start} is the start frequency of the chirps.

$$v = \frac{\lambda\omega}{4\pi T_c} = \left\{ \begin{matrix} \lambda = c/f_{\text{Start}} \\ \omega = 2\pi f_{\text{Doppler}} \end{matrix} \right\} = \frac{cf_{\text{Doppler}}}{2f_{\text{Start}}} \tag{2.3}$$

3

Methodology

3.1 Radar Settings

The sensor utilized in this study is a FMCW radar sensor operating at frequency of 77 GHz, manufactured by Texas Instruments. This radar sensor generates the chirp signal, covering a maximum frequency range of 4 GHz. The Analog to Digital Converters (ADCs) sample the IF signal. These sampled signals are then transmitted to a computer via User Datagram Protocol (UDP) packets through an Ethernet cable connection.
The data transmission process is further supported by an additional evaluation board, the DCA1000, which works in conjunction with an FPGA board.The specifications of the radar sensor system are detailed in Table 3.1. Figure 3.1 illustrates the radar sensor, highlighting the positions of the antenna and the data capture board (DCA1000).

Table 3.1: Radar Sensor Specifications

System Configuration	Value	Unit
Start Frequency	77	GHz
Max Bandwidth	4	GHz
Max ADC Sampling	10	Msps

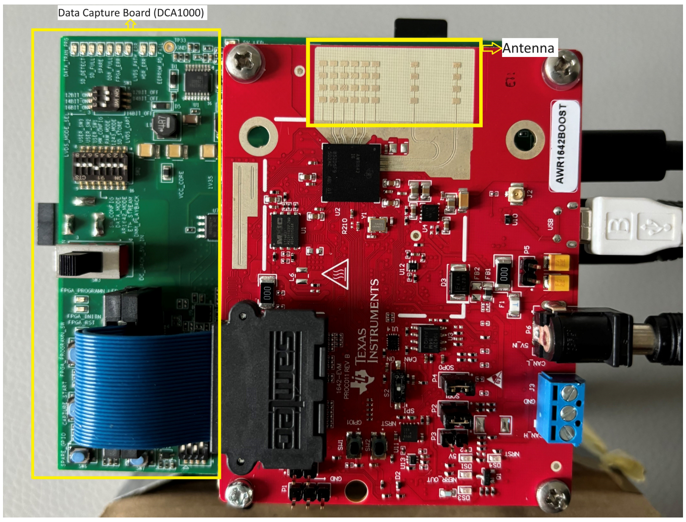

Figure 3.1: FMCW Radar Sensor

The performance of the FMCW radar is affected by the configurations of its chirp parameters, which can be adjusted based on the application. Communication between the radar sensor and the data capture board is through a Graphical User Interface (GUI), known as mmWave Studio provided by Texas Instrument. By using GUI users can configure and tune the chirp parameters, such as the total number of frames transmitted by the radar, Bandwidth, and other parameters. The specific configurations utilized for data acquisition are outlined in Table 3.2.

Table 3.2: Chirp Parameters

Parameter	**Value**	**Unit**
Start Frequency	77	GHz
Bandwidth	3.6	GHz
ADC Sampling	6250	ksps
ADC Samples	256	-
Chirp Slope	80	MHz/µs
Total Frames	40000	-
Chirps per Frame	1	-

3.2 Data Collection

Following the configuration of the radar sensor, data collection was conducted within a laboratory setting from participants. Each participant was positioned approximately 50 cm away from the radar sensor, with their hand situated at a distance of about 10-15 cm. Participants performed finger tapping tests in front of the sensor within the designated transmission time frame. To ensure comprehensive data collection for model development, various scenarios were considered, resulting in the first dataset being collected. These scenarios are detailed below:

- Case 1: Participants performed the finger tapping test under normal conditions without any interruptions.
- Case 2: Participants simulated the finger tapping test with 1 or 2 interruptions.
- Case 3: Participants simulated the finger tapping test with 3 to 5 interruptions.
- Case 4: Participants simulated the finger tapping test with more than 5 interruptions and freezing.
- Case 5: Participants simulated the finger tapping test with a slight decrease in frequency.
- Case 6: Participants simulated the finger tapping test with a mild decrease in frequency.
- Case 7: Participants simulated the finger tapping test with a moderate decrease in frequency.
- Case 8: Participants performed the test with a slight decrease in amplitude.
- Case 9: Participants performed the test with a decrease in amplitude midway through the 10 taps.
- Case 10: Participants performed the test with a decrease in amplitude starting after the first tap.
- Case 11: Participants simulated the finger tapping test as if unable to perform the task.

After developing the model, two additional data collection sessions took place to validate and evaluate its performance. One session was conducted with physiotherapists, and the other with the students involved in this thesis. During these sessions, more data including all the aforementioned cases was collected.

3.3 Finger Tapping Quantification Algorithm

Once the raw radar data from the finger tapping assessment has been collected, it needs to be converted before the algorithm can process the data. After the conversion, the data will be sent as an input to the Finger Tapping Quantification Algorithm (FTQA) in order to evaluate the motor performance. The structure of the work chain and the FTQA can be studied in figure 3.2 and 3.3. In order to obtain a fundamental understanding of the FTQA, two cases will be considered during the analysis of the algorithm. One of the cases will include true interruptions and the other one will include slight decrease in frequency.

Figure 3.2: Overview of the work chain from data collection to output parameters

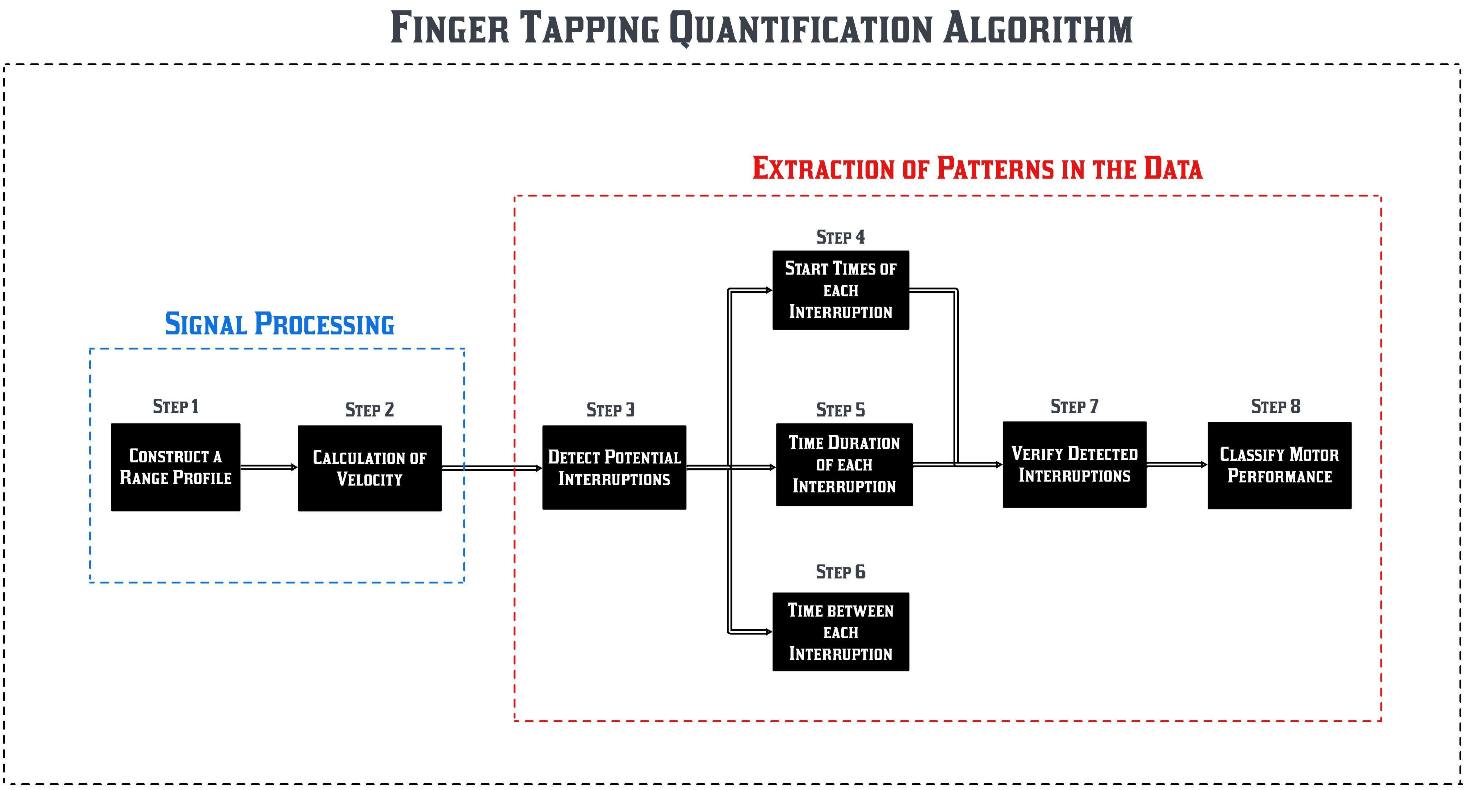

Figure 3.3: Data processing algorithm for finger tapping assessment

3.3.1 Signal Processing

The first two steps are highly connected to what was covered in the last part of the theory 2.4.1, 2.4.2, which is to generate a range profile and then utilize STFT. Since the distance to the radar was approximately calculated before the measurements, the desired range/frequency bins could be determined. Once the range profile has been generated, STFT is applied onto the desired range/frequency bins in order to analyze how the doppler frequency changes over time for the given collected data.

Two figures which are created in the second step is the doppler velocity and binary image of a certain finger tapping test. The doppler velocity is the velocity detected by the radar with noise while the binary image extracts the doppler velocity in clearer way, both with and without noise. The binary image is created by studying the values in the doppler velocity and comparing them with a certain threshold. If the value is underneath the threshold then that pixel will be set to zero and in the other case one if the value is above the threshold. For two finger tapping tests, one with five interruptions and one with slight decrease in frequency, the corresponding doppler velocity and binary image can be studied in figure 3.4-3.7.

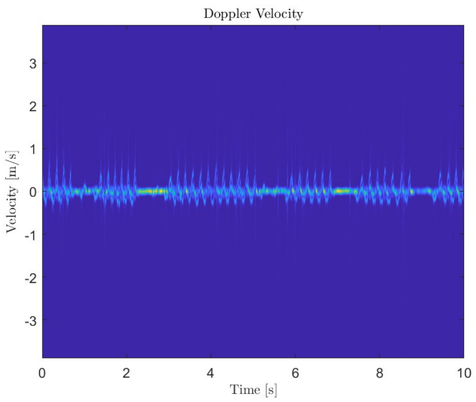

Figure 3.4: The doppler velocity with five interruptions

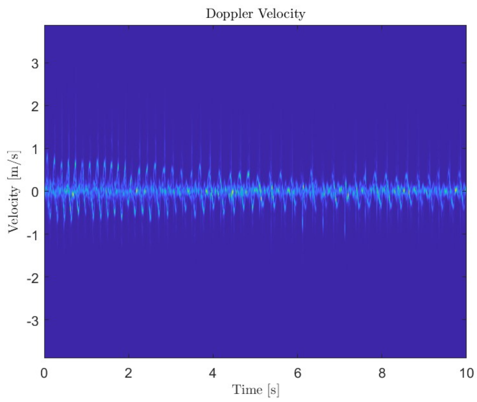

Figure 3.5: The doppler velocity with slight decrease in frequency

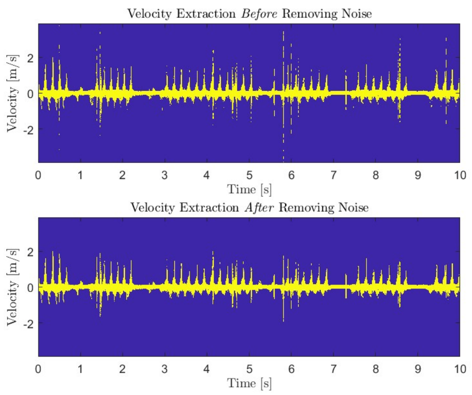

Figure 3.6: The binary image with five interruptions

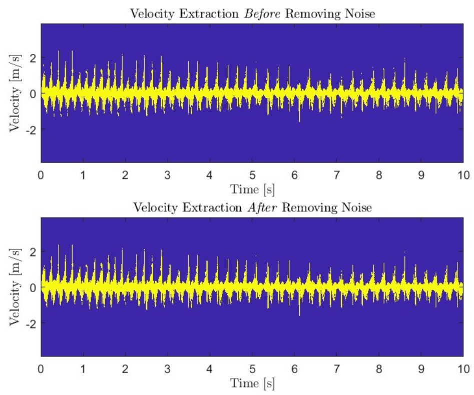

Figure 3.7: The binary image with slight decrease in frequency

Continuing, the extracted velocity without noise is processed even further by extracting the maximum velocity peak in each time instant. Note that it's only the velocities that have a positive sign that will be extracted because otherwise, the unique pattern for interruptions won't be present. The velocity peaks for the two finger tapping tests with five interruptions and slight decrease in frequency, can be studied in figure 3.8, 3.9. One may notice that when interruptions occurs, the velocity peak immediately drops significant and this is the pattern that makes the interruptions detectable by the FTQA. If the velocity peak drops below the velocity threshold for sufficiently long time, it will be detected as an interruption by the algorithm. The velocity threshold is dynamically determined by taking a portion of the mean value of the ten highest velocity peaks obtained in the measurement. The last figure which is created in this step is the moving average of the velocity peaks and the moving average really simplifies the visualization of the interruptions present in a finger tapping test. The moving average velocity for the two finger tapping tests with five interruptions and slight decrease in frequency can be studied in figure 3.10, 3.11.

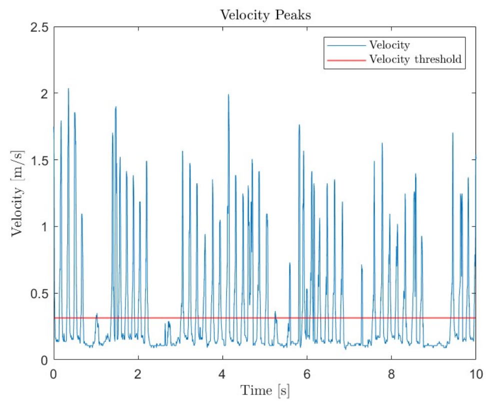

Figure 3.8: The velocity peaks with five interruptions

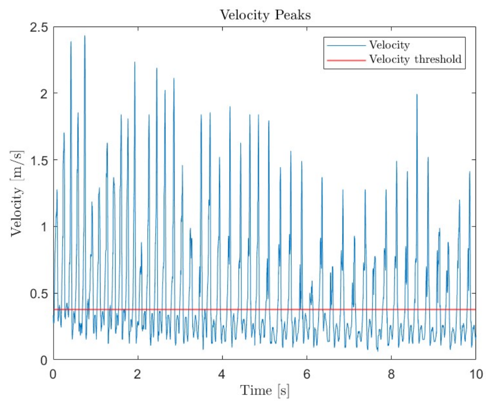

Figure 3.9: The velocity peaks with slight decrease in frequency

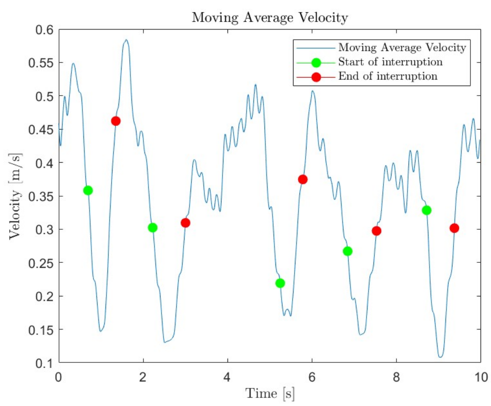

Figure 3.10: The moving average velocity with five interruptions

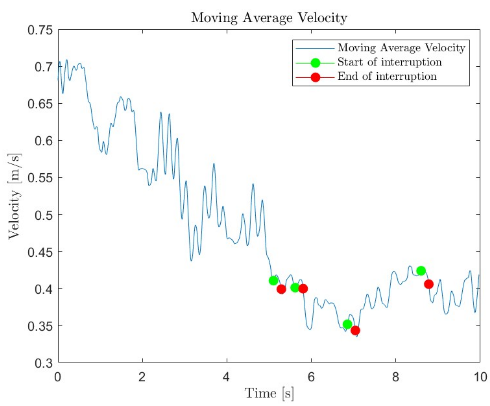

Figure 3.11: The moving average velocity with slight decrease in frequency

3.3.2 Extraction of Patterns in the Data

The third step in the FTQA is to detect where possible interruptions occur and keep track of how many that occurred. The information from the previous step, regarding the velocity peaks in figure 3.8 and 3.9, will be used in order to detect the possible interruptions. This is done by continuously checking the velocity peak (blue graph) and if the value goes below the velocity threshold for 0.175 seconds, then it's considered as an interruption. An important output from this step is represented as an array, containing zeroes and ones, which is called Predicted Interruption Pulse Graph (PIPG). The zeroes indicates an interruption and the ones indicates non-interruption. The PIPG contains valuable information about how many interruptions that occurred, where each interruption occurs, the time duration of each interruption and the time between each interruption.

Sometimes the velocity peak will exceed the velocity threshold in the middle of an ongoing interruption due to the sensitivity of the radar. This is not desirable since this would mean that more interruptions will be detected since real interruptions will be divided into several ones. However, the third step has a built-in feature that prevents this behaviour by checking the time duration of all non-interruptions in the PIPG. If the time duration of a certain non-interruption goes beneath a predefined time threshold, namely 0.0775 seconds, the location of the non-interruption in PIPG is set to zero which means that it's considered as an interruption.

Step four, five and six is all about extracting the interesting time properties, that were mentioned above, of the predicted interruptions. The calculated time properties are the time instances where each interruption start, the time duration of each interruption and lastly the time between each interruption. This is easily done given the information in the PIPG.

In the seventh step, the predicted interruptions will be verified which means that it will be determined whether these predicted interruptions was caused by real interruptions or by frequency/amplitude decrements. In some cases there might be significant frequency/amplitude decrements such that the velocity peaks as in figure 3.9 goes below the velocity threshold for sufficiently long time and therefore interpreted as interruptions. This is something which the seventh step will prevent and therefore distinguish between what is real interruptions and interruptions caused by either frequency or amplitude decrements. The core idea behind distinguishing between them is to study the moving average velocity in figure 3.10 and 3.11. When true interruptions are present then the slope of the moving average velocity, from where the interruption begins/ends to the lowest velocity obtained inside the time duration of the interruption, is significantly larger than the slope of interruptions caused by frequency/amplitude decrements.

The main output from this step is to create the True Interruption Pulse Graph (TIPG) and visualize it along with the PIPG. For these two cases with five interruptions and slight decrease in frequency, the two IPGs can be studied in figure 3.12, 3.13. As one can see for the case with five interruptions in figure 3.12, the TIPG is just a copy of the PIPG because the interruptions detected are in fact real. However for the case with slight decrease in frequency, the TIPG maintained a constant value even though the PIPG detected two interruptions. The reason for that is because the predicted interruptions was not caused by real interruptions, they were caused by frequency decrement. This is something which will also appear in the result section 4.1, both with variations of frequency slowing and amplitude decrements 4.1.

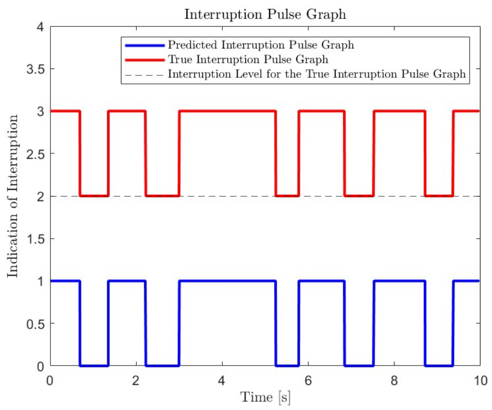

Figure 3.12: Interruption Pulse Graph with five interruptions

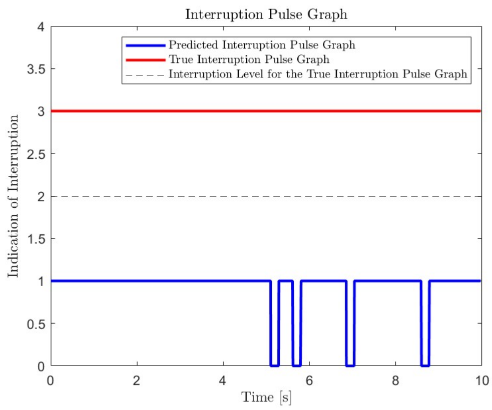

Figure 3.13: Interruption Pulse Graph with slight decrease in frequency

The final step in the FTQA is to categorize the motor performance by stating a score $\in [-2, 4]$ based on the information that has been extracted in previous steps. In figure 3.14 there is a flowchart that describes how the decisions are made in the classification step. The black boxes are statements which are evaluated and the green boxes are the outputs. One can confirm that the classification has two major decisions trees, one where true interruptions are present and one where it's not. When true interruptions are present, the first statement which is evaluated is if one of the interruptions is a freeze or not. Since the time duration of each interruption is given, this can easily be evaluated where a freeze is defined as an interruption that exceeds 0.9 seconds. The rest of the statements in the first decision tree is all about the number of interruptions detected.

In the second tree, the motor performance is either -2:*Frequency Slowing*, -1:*Amplitude Decrement*, 0:*Normal* or 4:*Severe*. When the score is -2 then that means that the motor test included frequency slowing and -1 for amplitude decrements but the level of frequency or amplitude decrements could not be determined. Frequency and amplitude decrement are distinguished by counting the number of velocity peaks during the test ($\approx$ number of finger taps) and then comparing the average number of peaks in the first three seconds of the test with the last three seconds. If the average number of peaks decreases by more than one at the end of the test, it is classified as a frequency decrement. The idea behind this method is that when frequency slowing is present, then the number of finger taps should decrease. However, when amplitude decrement is present then the number of finger taps should remain the same as a normal case. One can study how the peaks are highlighted in the cases where either frequency or amplitude decrement are present in the following result sections 4.1.5, 4.1.6, 4.1.8, 4.1.9. The normal case is detected by checking if the minimum moving average velocity is greater than 0.3 [m/s] or if the difference between the mean value of the moving average velocity in the beginning and end is less than 0.1 [m/s]. The reason for that is because in most cases when interruptions or frequency/amplitude decrement are present, the velocity drops down to values below 0.3 [m/s] and there are significant changes between the velocities in the beginning and the end of the measurement.

In order to detect the worst case, 4-*Severe*, a variable that defines how large portion of the whole measurement time for which the velocity peaks was beneath the velocity threshold, is utilized. This means that it can be both true interruptions and interruptions caused by frequency/amplitude decrements. The variable is then evaluated in order to see if it's higher or lower than a predefined threshold which is set to 0.6. This means that if 60% or greater of the whole measurement sequence consisted of either true interruptions or interruptions caused by frequency or amplitude decrement, then this would be considered as 4-*Severe*.

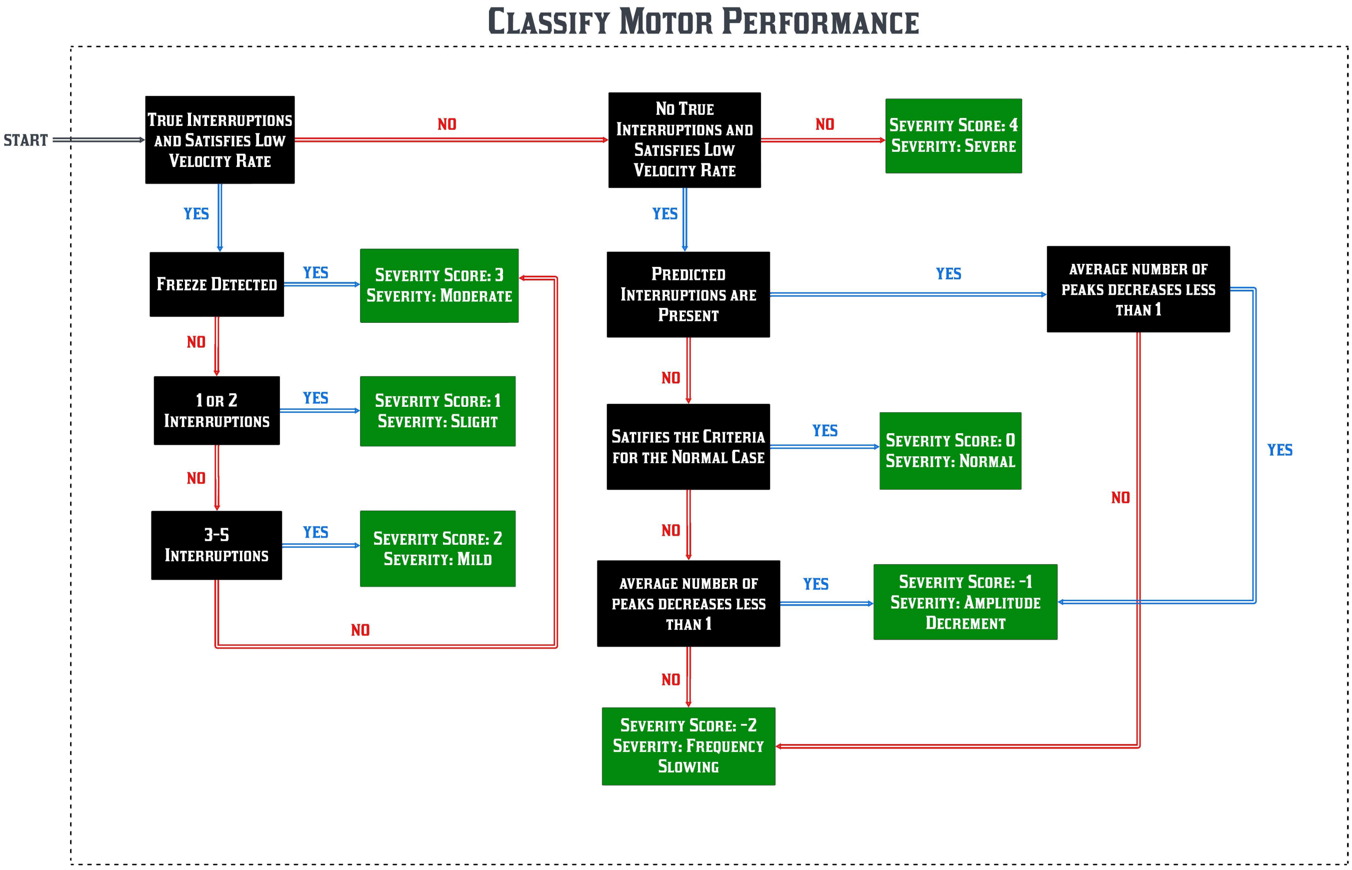

Figure 3.14: A flowchart over how the motor classification function works

3.4 Validation of the Accuracy of the FTQA

To validate the accuracy of the FTQA, two separate tests were conducted. The first test was carried out by the students involved in this thesis. Data were collected and various scenarios were simulated to represent different cases mentioned in 2.1.2.2. The data was then examined by the FTQA to classify the motor performance. Recordings of the motor performance were done in order to analyze the test afterwards such that a ground truth of the motor performance can be made. The second series of tests was performed by physiotherapists since they have very good experience regarding how certain cases tend to behave. Validation for this test was structured such that one physiotherapist simulated several cases, and another physiotherapist evaluated and classified severity scores. Then, the FTQA also tried to classify the motor performance in order to make a comparison. The model's performance was then compared with the physiotherapists' evaluations to determine its accuracy. Recordings of the motor performance were also made here in order to analyze the test afterwards and state a ground truth.

These two validations will reveal how robust the FTQA is since the algorithm will be exposed to many different cases because of the variety of the examined data. The accuracy of the algorithm can be studied in section 4.2.

4

Results

4.1 Outputs from the FTQA in Different Cases

In the previous section 3.3 one could see an example of what the output from the FTQA would be for two certain finger tapping tests in order to understand how it works. However, there are a lot of different cases that needs to be considered in order to get a fundamental understanding of how the FTQA works and this will be presented in this section. A final notice is that the different cases which will be presented, have been mimicked by the students of this thesis. Therefore, some of the cases may be hard to mimic precisely and especially the ones with different levels of decrement.

4.1.1 Normal Motor Performance without any Issues

The first case is the least complex one since it doesn't involve any interruptions, slowing or amplitude decrements. Therefore, the motor performance will be classified as *Normal* by the FTQA which is supported by the figures 4.1-4.4 below.

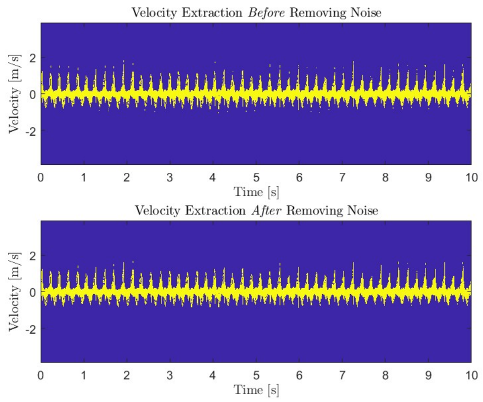

Figure 4.1: The velocity of a normal motor performance

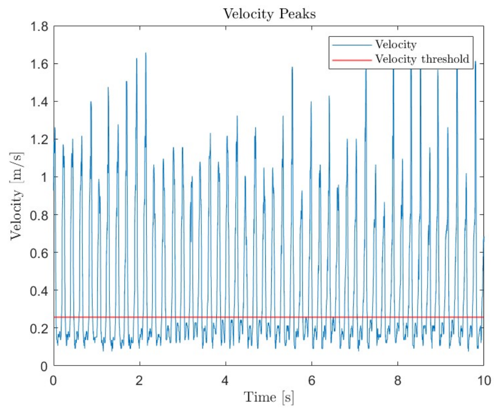

Figure 4.2: The velocity peaks of a normal motor performance

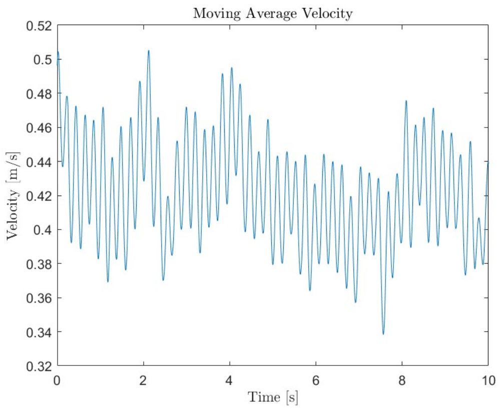

Figure 4.3: Moving average velocity of a normal motor performance

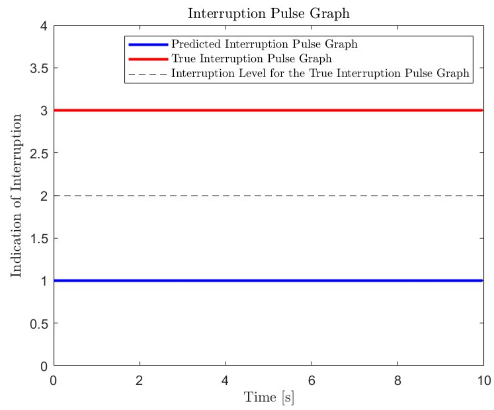

Figure 4.4: Interruption Pulse Graph of a normal motor performance

4.1.2 Two Interruptions

The next case involves interruptions in the motor performance and in this specific case, two interruptions are present which is supported by the accompanying figures in 4.5-4.8. Since there are two interruptions present, the correct motor performance score is *Slight* and this is also what the FTQA predicts.

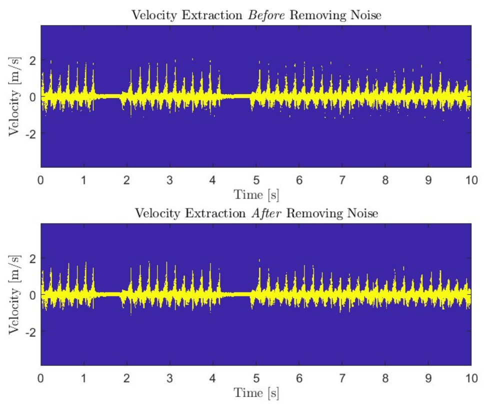

Figure 4.5: The velocity of a test which contains two interruptions

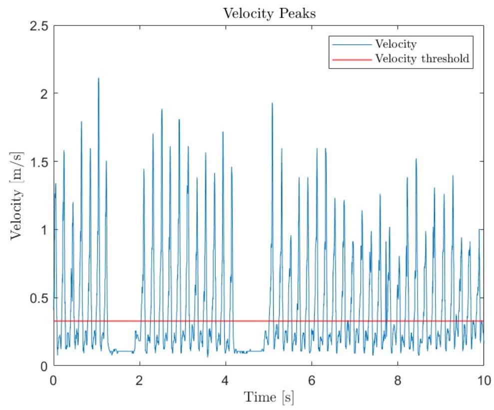

Figure 4.6: The velocity peaks of a test which contains two interruptions

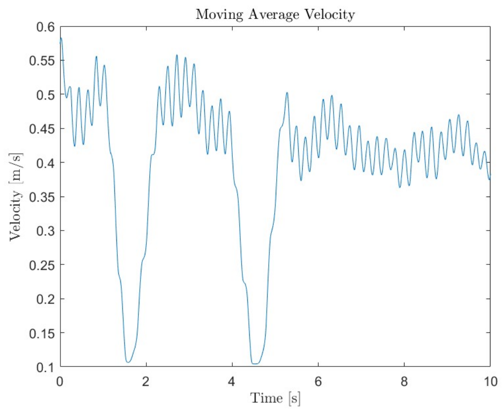

Figure 4.7: Moving average velocity of a test which contains two interruptions

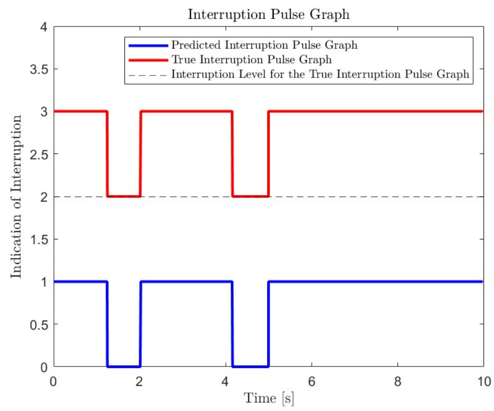

Figure 4.8: Interruption Pulse Graph containing two interruptions

4.1.3 Four Interruptions

This case will also consider interruptions but this time four interruptions will be present and this can be confirmed by studying the figures 4.9-4.12. Since there are four interruptions present, the correct motor performance score is *Mild* and this is also the outcome from the FTQA.

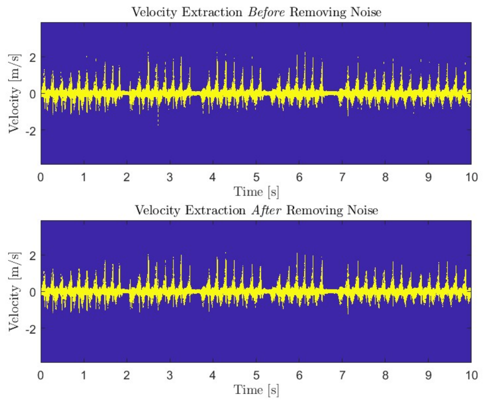

Figure 4.9: Velocity of a test which contains four interruptions

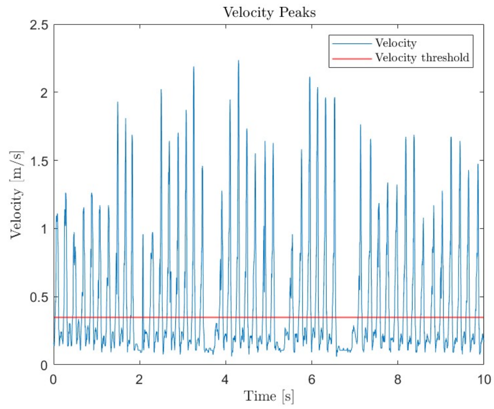

Figure 4.10: Velocity peaks of a test which contains four interruptions

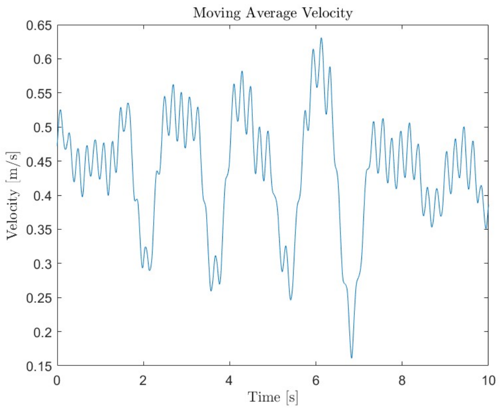

Figure 4.11: Moving average velocity of a test which contains four interruptions

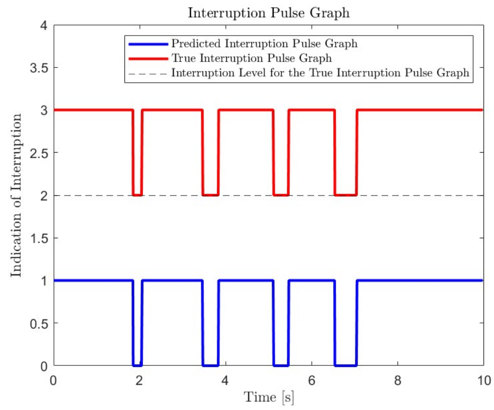

Figure 4.12: Interruption Pulse Graph containing four interruptions

4.1.4 Five Interruptions Including One Freezing

This case includes five interruptions but the most important factor is that one of these interruptions is considered as a freeze. An interruption is defined as a freeze if the duration of the interruption exceeds approximately 0.9 seconds. The correct motor performance output will be *Moderate* since there is a freeze present and this also aligns with output from the FTQA. The output figures can be studied in 4.13-4.16.

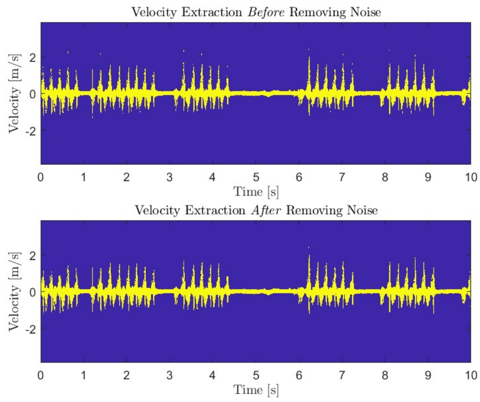

Figure 4.13: Velocity of a test which contains five interruptions with one freeze

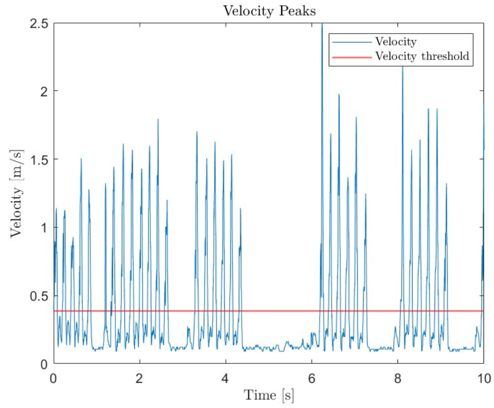

Figure 4.14: Velocity peaks of a test which contains five interruptions with one freeze

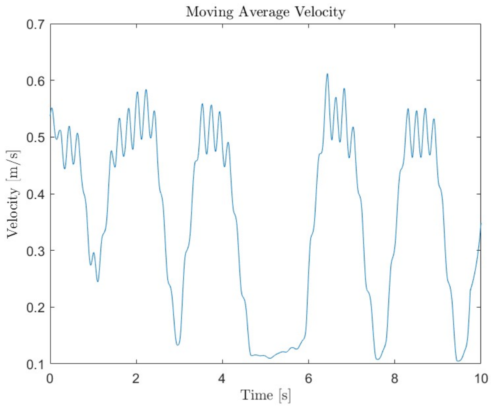

Figure 4.15: Moving average velocity of a test which contains five interruptions with one freeze

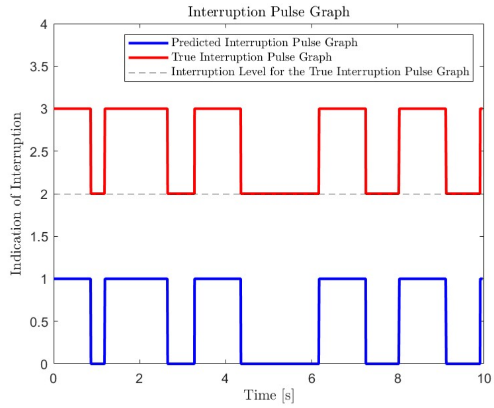

Figure 4.16: Interruption Pulse Graph of a motor performance with five interruptions that includes a freeze

4.1.5 Slight Slowing

In this case, slight slowing has been tried to be mimicked after approximately 4.5 seconds in the test. Slight slowing should be classified as the score *Slight* but according to the FTQA, it classifies it as *Frequency decrement* because it is not able to score the level of frequency decrement. The different figures can be studied in 4.17-4.20.

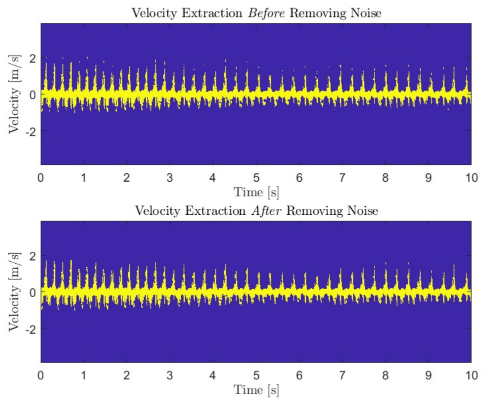

Figure 4.17: Velocity of a test which contains slight slowing

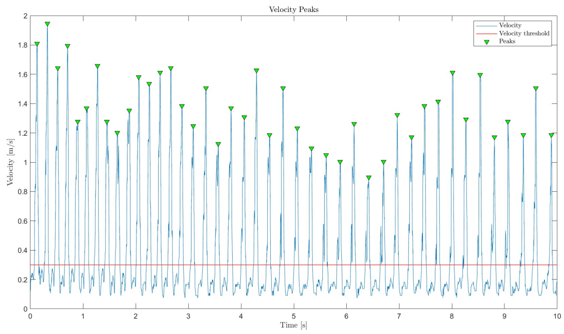

Figure 4.18: Velocity peaks of a test which contains slight slowing

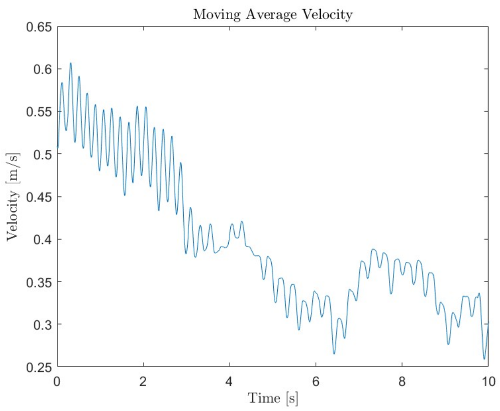

Figure 4.19: Moving average velocity of a test which contains slight slowing

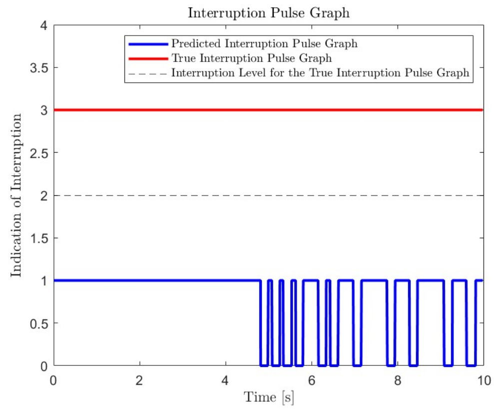

Figure 4.20: Interruption Pulse Graph of a motor performance with slight slowing

4.1.6 Mild Slowing

Mild slowing was tried to be mimicked in this case and the predicted motor performance score by the FTQA is *Frequency decrement*. The output figures from the FTQA can be studied further in 4.21-4.24.

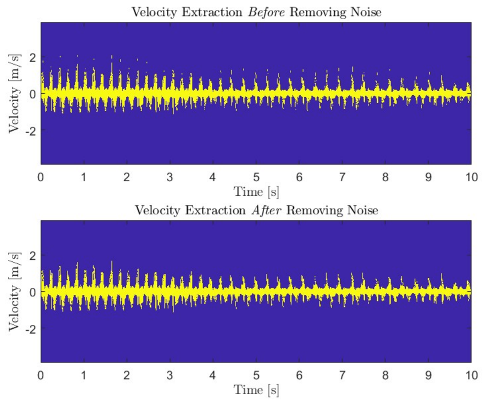

Figure 4.21: Velocity of a test which contains mild slowing

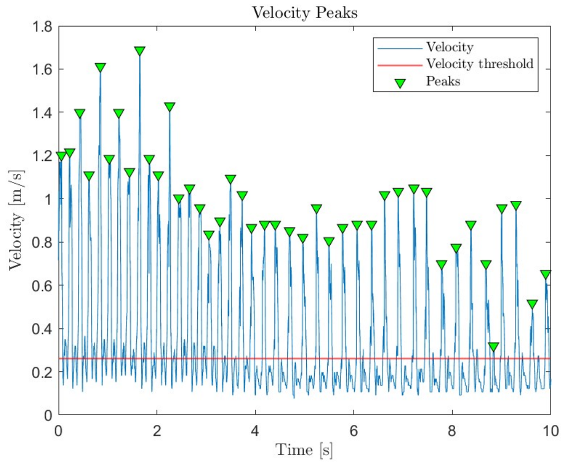

Figure 4.22: Velocity peaks of a test which contains mild slowing

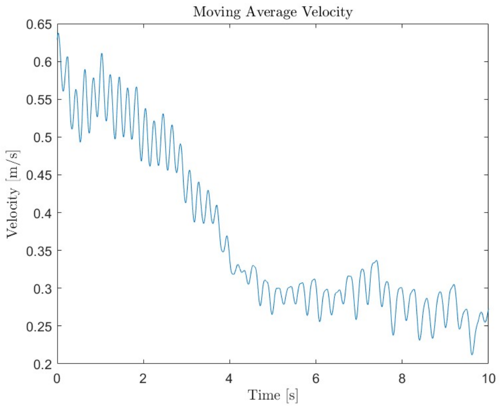

Figure 4.23: Moving average velocity of a test which contains mild slowing

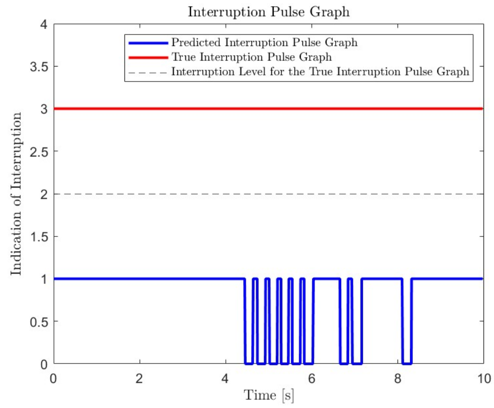

Figure 4.24: Interruption Pulse Graph of a motor performance with mild slowing

4.1.7 Moderate Slowing

The last level of slowing was performed in this test which is moderate slowing. The output from FTQA is *Frequency decrement* as expected but could not state the severity score *Moderate*. Accompanying figures can be analyzed in 4.25-4.28.

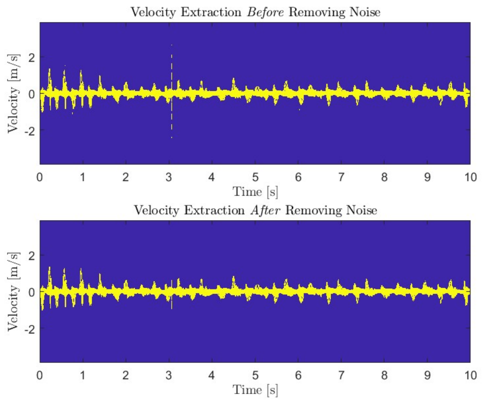

Figure 4.25: Velocity of a test which contains moderate slowing

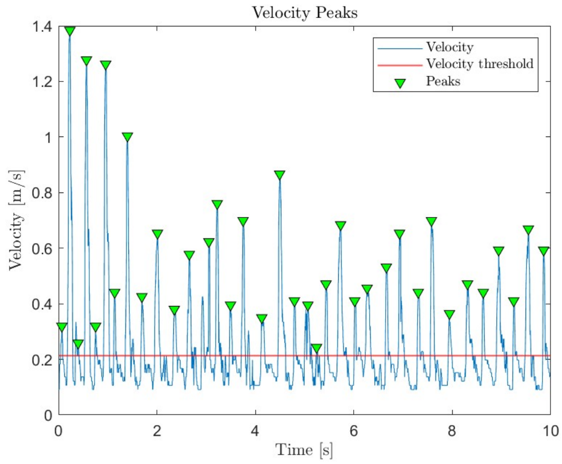

Figure 4.26: Velocity peaks of a test which contains moderate slowing

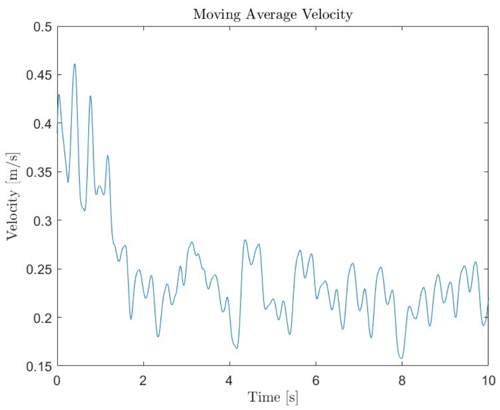

Figure 4.27: Moving average velocity of a test which contains moderate slowing

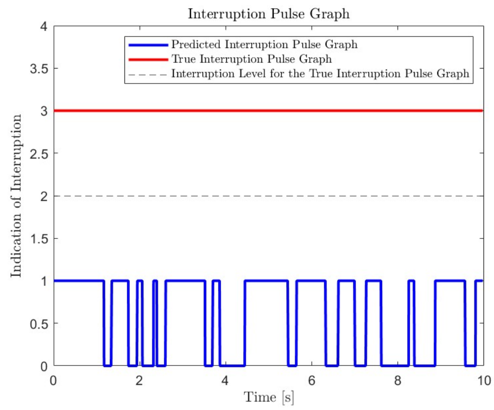

Figure 4.28: Interruption Pulse Graph of a motor performance with moderate slowing

4.1.8 Amplitude Decrements Near the Middle of the Test

The third parameter which will be investigated is the decrease of amplitude and in this case the amplitude was decreased close to the middle of the test. The correct motor performance score would be *Mild* in this case but the predicted motor performance score by the FTQA was *Amplitude Decrement*. One can further study the different figures in 4.29-4.32.

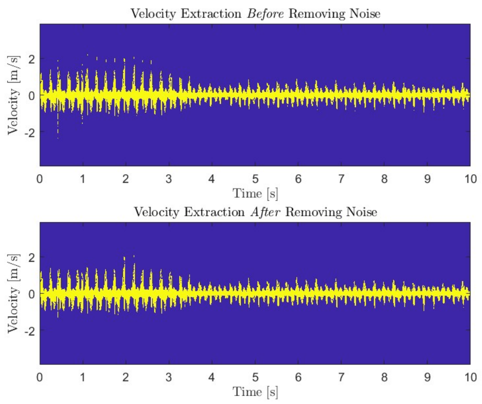

Figure 4.29: Velocity of a test which contains amplitude decrement in the middle of the test

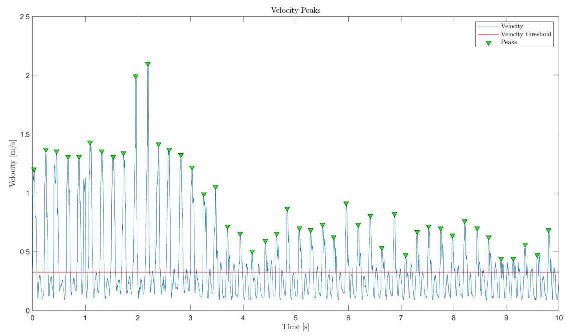

Figure 4.30: Velocity peaks of a test which contains amplitude decrements in the middle of the test

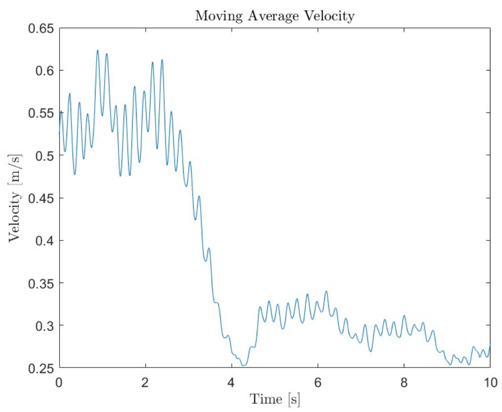

Figure 4.31: Moving average velocity of a test which contains amplitude decrements in the middle of the test

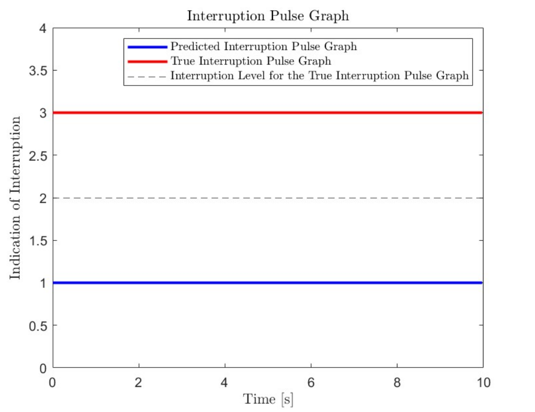

Figure 4.32: Interruption Pulse Graph of a motor performance with amplitude decrement in the middle of the test

4.1.9 Amplitude Decrements Near the Beginning of the Test

In this case the amplitude decrement started early in the test which can be supported by figures 4.33-4.35. The output predicted by the FTQA was *Amplitude Decrements* even though *Moderate* should be the correct severity.

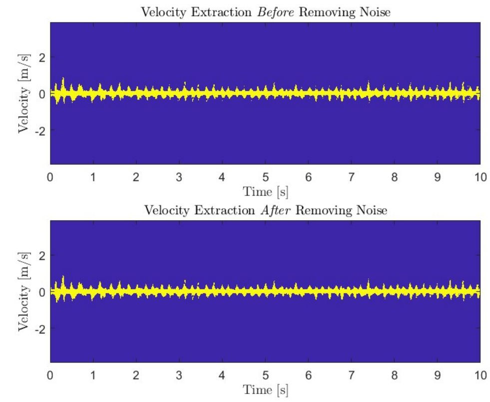

Figure 4.33: Velocity of a test which contains amplitude decrement in the beginning of the test

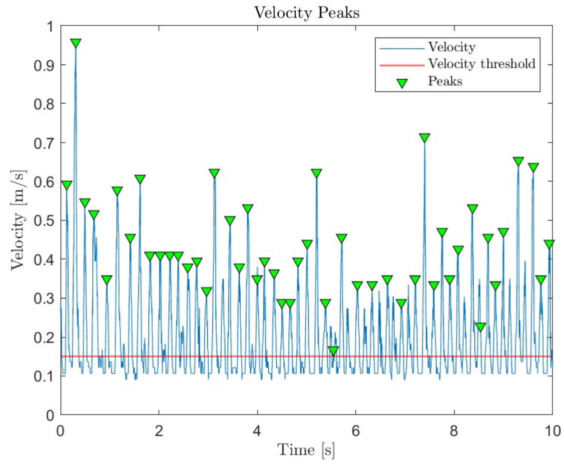

Figure 4.34: Velocity peaks of a test which contains amplitude decrements in the beginning of the test

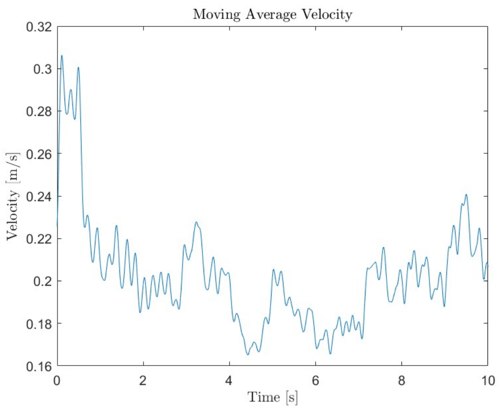

Figure 4.35: Moving average velocity of a test with amplitude decrement in the beginning of the test

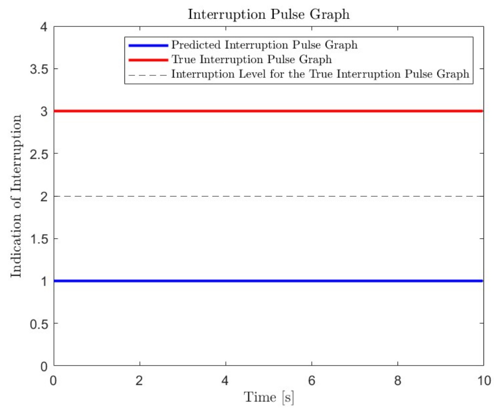

Figure 4.36: Interruption Pulse Graph of a motor performance with amplitude decrement in the beginning of the test

4.1.10 Severe

The last case contained major issues in the motor performance such as very long freezes and is therefore classified as *Severe*. According to the FTQA, the predicted motor performance is also in fact *Severe* and the accompanying figure can be further studied in 4.37-4.40.

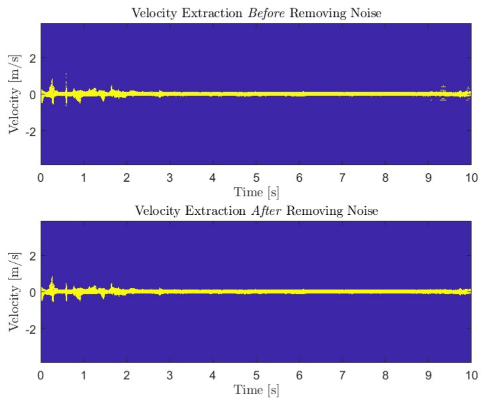

Figure 4.37: Velocity of a test which is supposed to mimic the severe case

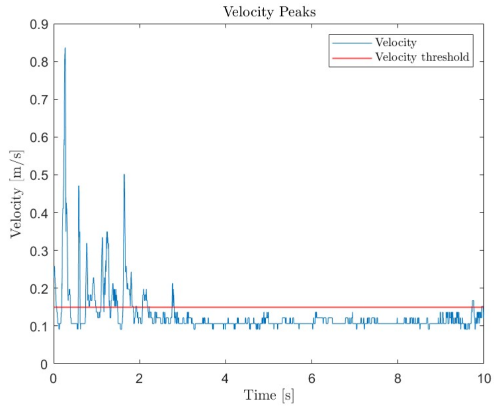

Figure 4.38: Velocity peaks of a test which is supposed to mimic the severe case

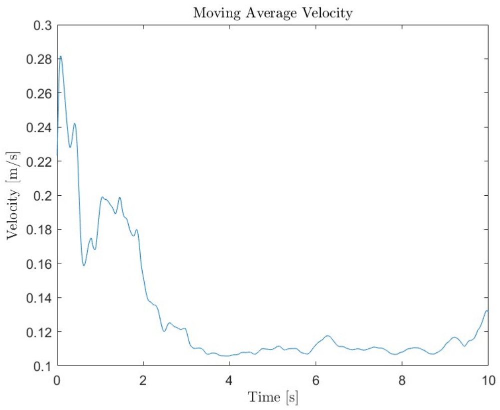

Figure 4.39: Moving average velocity of a test which is supposed to mimic the severe case

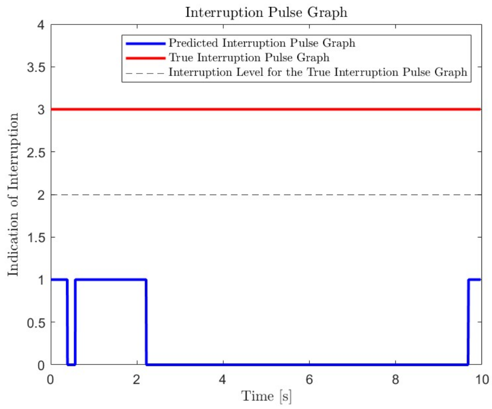

Figure 4.40: Interruption Pulse Graph of a severe motor performance

4.2 Accuracy of the FTQA

Table 4.1 presents the results from the initial series of tests conducted. Each row corresponds to an individual test, and the columns provide information about each test and its outcomes.
Description column provides a brief overview of what each test involved. It includes specific conditions or scenarios of the test. N_{PI} column indicates the number of interruptions predicted by the model in the first stage of testing. These predictions are based on the model's preliminary analysis. N_{CI} lists the number of interruptions that were confirmed after further verification. Severity and score columns show the output of the model for these parameters. The final column, contains True/False value indicating whether the model's predictions and the severity in reality were in agreement.

Table 4.1: Validation Results of the Test Conducted by Students

Test	**Description**	**Model Output**				
		N_{PI}	N_{CI}	**Severity**	**Score**	**Outcome**
1	7 interruptions	6	6	Moderate	3	True
2	2 interruptions	2	2	Slight	1	True
3	2 interruptions + freeze	2	2	Moderate	3	True
4	4 interruptions	4	4	Mild	2	True
5	0 interruptions	0	0	Normal	0	True
6	1 interruption	1	1	Slight	1	True
7	2 interruptions	3	3	Mild	2	False
8	5 interruptions	5	5	Mild	2	True
9	5 interruptions	5	5	Mild	2	True
10	Freq. Dec. Beg.	4	0	Freq. Dec.	-2	True
11	Freq. Dec. Mid.	10	0	Freq. Dec.	-2	True
12	Amp. Dec. Mid.	1	0	Amp. Dec.	-1	True
13	Amp. Dec. Mid.	3	0	Amp. Dec.	-1	True
14	Amp. Dec. Mid.	2	0	Amp. Dec.	-1	True
15	Amp. Dec. End	3	0	Amp. Dec.	-1	True
16	Freq. Dec. End	4	0	Freq. Dec.	-2	True
17	Severe	6	0	Freq. Dec.	-2	False
18	3 interruptions	3	3	Mild	2	True
19	5 interruptions + freeze	5	5	Moderate	3	True
20	Normal	0	0	Normal	0	True
21	Normal	0	0	Normal	0	True
22	3 interruptions	3	3	Mild	2	True
23	4 interruptions	4	4	Mild	2	True
24	4 interruptions + freeze	4	4	Moderate	3	True
25	7 interruptions	7	7	Moderate	3	True
26	2 interruptions	2	2	Slight	1	True
27	5 interruptions	5	5	Mild	2	True
28	5 interruptions	5	5	Mild	2	True

Continued on next page

Table 4.1 – continued from previous page

Test	Description	Model Output				
		$N_{\mathbf{PI}}$	$N_{\mathbf{CI}}$	**Severity**	**Score**	**Outcome**
29	7 interruption	7	7	Moderate	3	True
30	4 interruptions + freeze	4	4	Moderate	3	True
31	Normal	0	0	Normal	0	True
32	2 interruptions	2	2	Slight	1	True
33	2 interruptions	2	2	Slight	1	True
34	Freq. Dec. Beg.	11	0	Freq.Dec.	-2	True
35	Amp. Dec. Mid.	0	0	Amp. Dec.	-1	True
36	4 interruptions	4	4	Mild	2	True
37	4 interruptions	4	4	Mild	2	True
38	Freq. Dec. Mid.	9	0	Freq. Dec.	-2	True
39	Amp. Dec. Mid.	0	0	Amp. Dec.	-1	True
40	9 interruptions	7	0	Freq. Dec.	-2	False
41	5 interruptions + freeze	5	5	Moderate	3	True
42	Freq. Dec. End	12	0	Freq. Dec.	-2	True
43	Amp. Dec. End	0	0	Amp. Dec.	-1	True
44	Severe	2	0	Severe	4	True
Accuracy: 93.18%						

Table 4.2 illustrates the results of the physiotherapists' tests, where the second physiotherapist's evaluations are detailed in the "Description" column.

Table 4.2: Validation Results of the Test Conducted by physiotherapists

Test	**Description**	**Model Output**				
		$N_{\mathbf{PI}}$	$N_{\mathbf{CI}}$	**Severity**	**Score**	**Outcome**
1	2 / 5 interruption	3	0	Freq. Dec.	-2	False
2	3 / 7 interruptions	7	7	Moderate	3	True
3	Score 1	4	0	Freq. Dec.	-2	False
4	Score 1	1	1	Slight	1	True
5	Score 3	10	10	Moderate	3	True
6	Score 3-4	11	0	Amp. Dec.	-1	False
7	Score 2	4	4	Mild	2	True
8	Score 4	4	0	Severe	4	True
9	1 / 1 interruption	0	0	Amp. Dec.	-1	False
10	0 / Normal	0	0	Amp. Dec.	-1	False
11	2 / 3 interruption	3	3	Mild	2	True
12	3 / 6 interruption	4	4	Mild	2	False
13	2 / 4 interruption	1	1	Slight	1	False
14	3 / 2 interruption + freeze	1	1	Slight	1	False
15	Score 4	4	0	Severe	4	True
16	0 / Normal	0	0	Normal	0	True
17	2 / 3 interruption	3	3	Mild	2	True
18	1 / 1 interruption	1	1	Slight	1	True
19	2 / Freq. Dec. End	10	0	Amp. Dec	-1	False
20	2 / Amp. Dec. End	0	0	Amp. Dec	-1	True
21	3/ Freq. Dec. Mid.	3	0	Severe	4	False
22	1 / Freq. Dec. End	9	0	Amp. Dec.	-1	False
23	1 / Amp. decrement	2	0	Amp. Dec.	-1	True
24	3 / Amp. + Freq. Dec.	2	0	Amp. Dec.	-1	True
25	3 / Amp. Dec. End	0	0	Amp. Dec.	-1	True
26	4 / Amp. Dec. Beg.	10	0	Amp. Dec.	-1	True
27	2 / Amp. + Freq. Dec	1	0	Amp. Dec	-1	True
28	3 / Amp. + Freq. Dec	14	0	Amp. Dec	-1	True
Accuracy: 60.71%						

5

Discussion

In this section, we discuss the challenges encountered and the outcomes achieved through the various stages of our methodological approach. Furthermore, we provide practical recommendations and suggestions for future research endeavors.

5.1 Results

As can be seen in table 4.1, the model achieved an accuracy of 93.18%, which is promising. However, the model is currently unable to analyze combination cases involving both interruptions and amplitude or frequency decrements. Therefore, all tests were conducted to focus on either interruption cases or frequency and amplitude decrements only.

As illustrated in table 4.2 the model achieved an accuracy of 60.71% for the test conducted by physiotherapists. This accuracy is lower than that observed in 4.1. The significant difference is due to the data collection method. Since the radar sensor is highly sensitive to movements, and distance, any change in distance or large body movements can significantly affect the data. Consequently, this impacts model's ability to predict the output accurately.

To illustrate, consider one of the incorrect predictions from this test. For instance, in test 10 from table 4.2, which was classified as normal by the physiotherapists but as a decrement by the model, the velocity plots (figures 5.1 and 5.2) show a decrease in velocity during the test period. Additionally, if we look at the moving average plot of the velocity, figure 5.3, it is evident that the moving average is much lower towards the end of the test compared to the beginning. This decrease was significant enough to be classified as a decrement. This trend is not typical for a normal classification and is usually observed in cases of frequency or amplitude decrement. This discrepancy can be attributed to movements or changes in the distance between the hand and the radar sensor during data collection, leading to a reduction in the magnitude of the collected data.

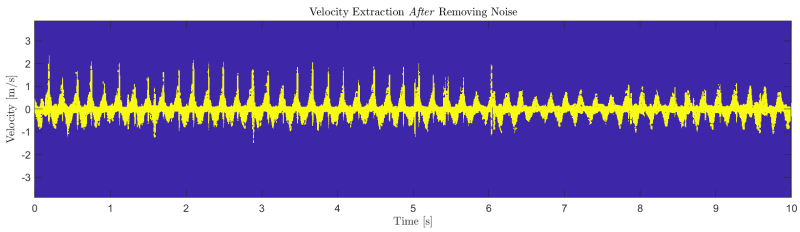

Figure 5.1: Velocity plot- Test 10

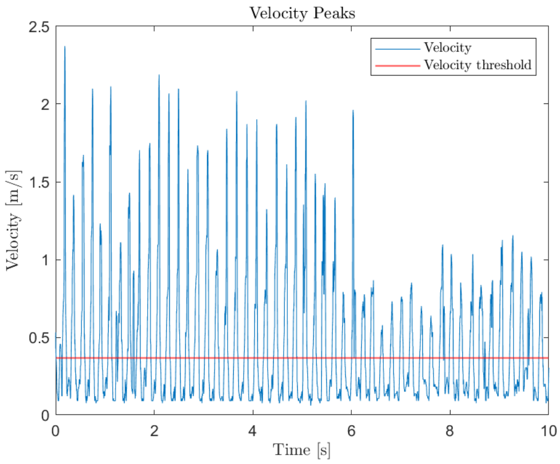

Figure 5.2: Velocity Variation- Test 10

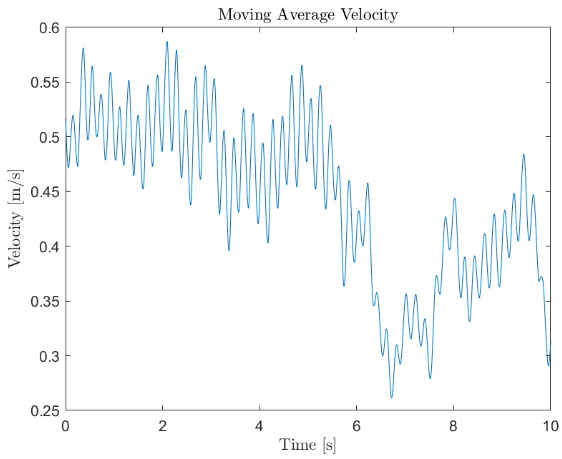

Figure 5.3: Moving average - Test 10

5.2 Data Collection

During the data collection phase, we encountered several significant challenges that influenced the applicability of our model. The first challenge was the way in which the data was collected. We conducted the data collection ourselves, which introduced a level of standardization and control but also deviated from the variability present in real-world scenarios involving Parkinson's disease patients. As a result, the data collected may not fully capture the complexities and variations observed in clinical settings, thus limiting the generalizability of our findings. While we attempted to address this limitation by consulting with physiotherapists and sharing our testing protocols, it remains an important consideration in interpreting the results.

Another challenge was the limitations of the sensor utilized in our study. The sensors employed had a threshold for detecting movements, leading to an inability to capture and measure finger movements with very small amplitudes accurately. This constraint can potentially affect the accuracy of the measurements.

As discussed in the discussion of results, we encountered challenges related to the positioning and movement of participants during the finger tapping test. Maintaining a consistent distance between the hands and the sensor was essential for obtaining reliable data. However, variations in hand positioning and movements could introduce variability in the recorded measurements, impacting the consistency and validity of the results. This is something which will be an issue in the future if measurements are being performed on real patients since hand tremor is very common for Parkinson's disease.

Despite these challenges, we endeavored to address them to the best of our ability, implementing strategies to mitigate their impact on the study outcomes. However, it is crucial to acknowledge these limitations when interpreting the findings.

5.3 Model Development and Evaluation

Throughout the development of our model, several challenges arose that required consideration and resolution. One significant challenge was about the definition and identification of interruptions in the finger tapping tests. Initially, we lacked a standardized and clearly defined definition of what considered as an interruption. To address this issue, we started a careful process of data analysis, aiming to establish specific thresholds based on our collected data. However, defining these thresholds proved to be a complex and time-consuming task, as there is no universally accepted definition for the duration of an interruption. The similar issue was encountered when determining the velocity peak threshold. Firstly there was a search for a constant velocity peak threshold but after many empirical tests, the most suitable threshold was determined to be dynamic where it depended on the given data. Consequently, determining suitable threshold values required extensive trial and error, consuming significant amount of time and effort.

Another notable challenge emerged when the model exhibited instances of incorrectly identifying interruptions, particularly in cases involving frequency and amplitude decrements. This issue is due to the limitations of the threshold values set for both amplitude and frequency. To mitigate this challenge, we implemented an additional validation process to validate potential interruptions and verify their validity. This extra validation step enabled us to distinguish between genuine interruptions in the dataset and frequency or amplitude decrement.

Continuing, there was also a significant challenge to distinguish frequency slowing and amplitude decrement from each other because of the large variability in these two parameters. The patterns for frequency and amplitude decrement was not always unique in the sense that you could easily separate them apart, in comparison to interruptions that follows a more deterministic behaviour and thus easier to detect. Eventually, they could be separated from each other with fairly good accuracy. Moreover, concerning frequency and amplitude decrements, the model cannot determine when these decrements commence during the data collection process. While the plots indicate the onset of decrements, distinguishing whether they initiate at the beginning, middle, or end of the collected data remains a challenge for the model. Nonetheless, visual inspection of the plots can provide insights into the timing of decrements, particularly if they occur prominently towards the midway through the data sequence.

Furthermore, our method's output score is only derived from one parameter: the number of interruptions. This contrasts with the comprehensive scoring system presented in table 2.1, which considers all three parameters. However, the absence of defined weights for each parameter and the lack of clear guidance on how to combine them into a single score lead to challenges for implementation. As a result, we were unable to integrate this aspect into our methodology, limiting the assessment of finger tapping performance.

5.4 Ethics

The ethical aspect in this thesis has a significant part since it will involve interactions with patients if this method would be applied. Before motor function assessment of patients can be done, ethical processes are required such that evaluations of the integrity of the patients can be considered if this method would be applied in practise. However, in this thesis the privacy of the patients is highly protected because of the sensor setup that the method utilizes. The method is only using a radar sensor which means that no pictures/films from cameras will trespassing the privacy of the patients. This is one of the most significant advantages with this method since this would mean that the time it takes to deploy this method in practise, is significantly decreased because of the preserved privacy of the patients.

5.5 Future work

Looking ahead, there's a great opportunity to make our model even better by using machine learning techniques. This means we could create a more precise and reliable tool for analyzing finger tapping tests. However, it's important to understand that achieving this improvement requires a lot more data to train the model effectively since machine learning algorithms rely heavily on data. To develop a strong model, we need a large and varied dataset that covers a wide range of tapping patterns, interruptions, and motor variations. Additionally, using machine learning allows us to explore more advanced analytical methods and algorithms. By using complex machine learning techniques we can gain deeper insights into tapping behavior and uncover patterns that traditional methods might miss. Moreover, machine learning enables us to continually refine and enhance the model over time. As we gather more data and the model learns from new observations, its accuracy and predictive power will improve, making it a more valuable tool for clinical assessment.

Additionally, we used a single antenna in the radar sensor to collect data. Future research could explore the use of multiple antennas to enhance the sensitivity and accuracy of the sensor. By utilizing additional antennas, it may be possible to reduce the sensor's sensitivity to movements and distance changes, thereby improving data quality and reliability. One may also consider to utilize even more frequency bins in order to capture the patterns in the data when distance changes, between the radar and the hand, are significantly present.

6
Conclusion

In conclusion, this thesis has provided an investigation of the finger tapping test as a mean to assess motor function and develop a scoring model for such evaluations. The developed model exhibits capabilities in detecting interruptions and providing accurate scores for individual cases, while also identifying frequency and amplitude decrements with an accuracy rate of 93.18%.

Despite the success achieved, several challenges and limitations were encountered throughout this research. Issues related to data collection with sensors, sensor sensitivity. However, these challenges have served to reveal key areas for improvement and future research. It is noteworthy that radar sensors offer a suitable method for data collection, ensuring patient privacy by only capturing movement data without recording any visual content. Yet, potential enhancements to these sensors in the future could lead to even better data quality.

Moreover, the findings in this thesis paved the way for further research in motor function assessment. By improving sensor technology, utilizing machine learning algorithm, and addressing current limitations, we can work towards creating a fully automated model for assessing motor function. Such a model has the potential to help healthcare teams by providing measurable data for their evaluations.

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