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Implementation of a Computer-Vision System as a Supportive Diagnostic Tool for Parkinson's Disease

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by

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I dedicate this thesis to my family, who has always supported me and with their love, I have been able to achieve my dreams.

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Abstract

Parkinson's disease is the second most common neurodegenerative disorder, affecting nearly 1 million people in the US and it is predicted that the number will keep increasing. Parkinson's disease is difficult to diagnose due to its similarity with other diseases that share the parkinsonian symptoms and the subjectivity of its assessment, thus increasing the probabilities of misdiagnosis. Therefore, it is relevant to develop diagnostic tools that are quantitatively based and monitoring tools to improve the patient's quality of life. Computer-based assessment systems have shown to be successful in this field through diverse approaches that can be classified into two main categories: sensor-based and computer vision-based systems. In this thesis, the implementation of a computer vision system to detect Parkinson's disease is explored. As Parkinson's diseases has characteristic motor symptoms, and gait is mainly affected, a computer vision system is proposed to analyze the gait features to classify subjects with Parkinson's disease. Using Microsoft's Kinect sensor and Azure Kinect sensor, the position of body joints in a 3D space was obtained and angles between those were calculated. The standard deviation of 7 different angles over time was calculated for each and used as features in a support vector machine with the purpose of classifying Parkinson's disease patients versus controls. Moreover, challenges and future perspectives for the implementation of computer-vision systems as supportive diagnostic tools for Parkinson's disease are discussed.

Contents

Table of figures VI
Introduction 1
Chapter I: Background 4
Pathology and epidemiology of Parkinson's disease 4
Sensor-based assessments 8
Computer-based vision systems assessments 10
Gait analysis methods 11
Frontal versus sagittal 12
Kinect implementation 12
Chapter II: Materials and Methods 13
Chapter III: Results 18
Chapter IV: Discussion 23
Challenges 24
Future perspectives 25
References 26

Table of figures

Figure 1. 14
Figure 2. 14
Figure 3. 20
Figure 4. 21
Figure 5. 22

List of tables

Table 1. 6
Table 2. 15
Table 3. 16
Table 4. 16
Table 5. 18
Table 6. 18
Table 7. 18

Introduction

In the last decade, medicine has evolved exponentially; multiple treatments and diagnostic tools have been developed for many areas. However, the early diagnosis and treatment of neurodegenerative diseases has eluded this rapid evolution in medicine. The complexity and roots of these diseases play an important role in the difficulty to diagnose and treat them. One disease in particular, Parkinson's disease, has a vast impact on patients' quality of life. Parkinson's disease affects more than 10 million people worldwide, nearly 1 million people in the US, and it is expected that the number will keep growing (Marras *et al.* 2018). Parkinson's disease is a progressive parkinsonism due to the loss of dopaminergic neurons in the substantia nigra of the midbrain without an identifiable cause, and has bradykinesia, resting tremor, rigidity, postural reflex impairment, shuffling gait and imbalance as motor symptoms (Jellinger 1991; Jankovic and Tolosa 2015; Papadakis 2019). The treatment of Parkinson's disease in early stages with cabergoline, a dopamine receptor agonist, has shown a lower risk and delay of onset motor complications (Rinne *et al.* 1998). As the treatment of Parkinson's disease at early stages has shown a lower risk and delay of onset motor complications it is relevant to be able to recognize subtle motor problems as early as possible in the development of the disease. On the other hand, it is estimated that when motor symptoms appear, already 50% of all dopamine receptors have disappeared (Marsden 1990; Ross *et al.* 2004). Therefore, several premotor symptoms have been proposed for the early diagnosis of Parkinson's disease (Tolosa *et al.* 2007, 2009; Iranzo 2011; Lang 2011); however, the most studied premotor symptoms like olfactory loss, REM sleeping disorder, constipation and mood changes are not specific enough to

be used as stand-alone biomarkers to diagnose Parkinson's disease (Tinelli *et al.* 2016). As the non-motor motor symptoms are not specific enough to be used as stand-alone indicators of the development of Parkinson's disease, and concurrently a powerful revolution in computer science has taken place in the last decades, the implementation of computer systems as supportive diagnostic tools has become a growing research area.

Moreover, an important advantage of the computer-based systems compared to the traditional scales for Parkinson's disease diagnosis is their objectivity, as the analysis performed is quantitative contrasted to the qualitative assessment of traditional scales that could be confounded by observer bias. As beforementioned, while nonmotor symptoms are present in all patients, these symptoms are mainly used as supportive criteria for the diagnosis, as they are not definitive indicators of Parkinson's disease. Therefore, it is relevant to focus on the motor symptoms for the implementation of computer-based systems in the diagnosis and monitoring of Parkinson's disease.

In this research project, a computationally inexpensive pipeline and programs are developed in order to classify subjects as Parkinson's disease patients or controls. Microsoft Kinect Azure and Microsoft Kinect v2 are used to obtain the 3D position of the joints, and angles are calculated from those. Posteriorly, a support vector machine is implemented to classify Parkinson's patients versus controls using the standard deviation from the previously calculated angles as features. As one of the key motor symptoms of Parkinson's patients is a rigid gait, it would be expected that Parkinson's patients' angles would have a lower standard deviation compared to controls.

The research question proposed is whether the standard deviation of the angles can be used as an effective feature for classifying the subjects.

Chapter I: Background

Pathology and epidemiology of Parkinson's disease

Parkinson's disease is the second most common neurodegenerative disorder (Reich and Savitt 2018) as it affects more than 10 million people worldwide and nearly 1 million people in the US (Marras *et al.* 2018). It is important to recognize the difference between parkinsonism and Parkinson's disease as they have different recommend treatments and disease courses. Parkinsonism refers to a clinical syndrome of bradykinesia, resting tremor, rigidity, postural reflex impairment, shuffling gait and imbalance, while Parkinson's disease refers to a type of progressive parkinsonism due to the loss of dopaminergic neurons in the substantia nigra of the midbrain without an identifiable cause (Jellinger 1991). The 3 most common disorders that lead to Parkinsonism are Parkinson's disease, Progressive Supranuclear Palsy (PSP) and Multiple System Atrophy (MSA). The most common cause of parkinsonism is Parkinson's disease; however, a differential diagnosis is required to differentiate between the multiple possible causes for parkinsonism (Reich and Savitt 2018).

The current medical procedure to assess Parkinson's disease is to perform a medical differential diagnosis, in which the medical practitioner uses several exclusion criteria to determine if the patient has Parkinson's disease (Papadakis 2019). Several characteristic symptoms of Parkinson's disease can be attributed to other disorders, such as rigidity and bradykinesia are found in Huntington disease patients, and myoclonic jerking in Creutzfeldt-Jakob disease patients (Papadakis 2019). However, the presence of symptoms not characteristic of Parkinson's disease is used as the exclusion criteria that indicate the possibility of another disorder to afflict the patient. For

example, Creutzfeldt-Jakob disease may present symptoms of parkinsonism, but the progression is rapid; as well as, Huntington disease could be mistaken for parkinsonism unless the family history and accompanying dementia are recognized (Papadakis 2019). The Movement Disorder Society (MDS) proposes clinical diagnostic criteria for Parkinson's disease, based on 4 main steps (Goldman and Postuma 2014). The first one is to establish the presence of parkinsonism through visual analysis to recognize bradykinesia and either rest tremor or rigidity. The second step is to establish the absence of absolute exclusion criteria to ensure that the parkinsonism is not caused by another disease. The third step is to identify supportive criteria that are characteristic of Parkinson's disease and not usually found in other unrelated courses of parkinsonism; the most important is a "clear and dramatic beneficial response to dopaminergic therapy" (Postuma *et al.* 2015). The fourth and last step is to search for red flags that might throw uncertainty on the diagnosis; for example, the rapid progression of gait impairment that would require the use of a wheelchair in the first 5 years of symptoms onset (Goldman and Postuma 2014). Once the medical practitioner has diagnosed Parkinson's disease, the next step is to assign a value in a standardized scale. The two main scales are the Hoehn Yahr and the Unified Parkinson's Disease Rating Scale (UPDRS) (Goetz *et al.* 2004). The original Hoehn Yahr scale is divided into 5 stages (Hoehn and Yahr 2011), while the UPDRS has rating scale out of 100. While the Hoehn Yahr has been criticized due to its focus mainly on the movement complications; the original version remains widely used nowadays due to its simplicity, and recommended by the MDS task force when clinical testing has not been performed (Goetz *et al.* 2004).

Table 1 presents the original Hoehn Yahr scale for rating the progression of Parkinson's disease; which was used in this research project.

Stages	Description
Stage 1	Unilateral involvement only.
Stage 2	Bilateral involvement without impairment of balance.
Stage 3	Mild to moderate bilateral involvement, some postural instability but physically independent.
Stage 4	Severe disability, still able to walk and to stand unassisted.
Stage 5	Confinement to bed or wheelchair unless aided

Table 1. Original Hoehn Yahr scale for Parkinson's disease progression rating scale.

However, in spite of the diagnostic criteria proposed by the MDS, it remains a challenge to have an accurate diagnosis for Parkinson's disease, as currently the misdiagnose rate is approximately 18% of the cases (Schrag *et al.* 2002; Wermuth *et al.* 2012). Moreover, in a systematic review of 20 studies from 1988 and 2014, it was found that during those 25 years, the overall validity of clinical diagnosis for Parkinson's disease did not improve significantly. Additionally, the accuracy of clinical diagnosis performed by movement disorders experts on an initial assessment was found to be at 79.6% (Rizzo *et al.* 2016).

The neuropathology of Parkinsonian disorders divides them into two main categories based on biochemical and structural abnormalities in tau protein and α-synuclein, which are two major proteins in the central nervous system (Jankovic and Tolosa 2015). Parkinson's disease has been traditionally classified as a synucleinopathy (affects α-synuclein); however, the discovery of common genetic variants in the tau gene (MAPT) in genome-wide association studies of idiopathic Parkinson's disease shows evidence

of a link between Parkinson's disease and tau protein (Jankovic and Tolosa 2015). Parkinson's disease neuropathology is characterized by degeneration of the nigrostriatal dopaminergic neurons in the substantia nigra (Jankovic and Tolosa 2015). At this point, synuclein pathology has spread to the midbrain to include basal forebrain and cortical structures (Jankovic and Tolosa 2015). The degeneration of the nigrostriatal dopaminergic neurons results in striatal dopamine-deficiency syndrome that, in turn, is responsible for the classical motor symptoms in Parkinson's disease (Jellinger 1991). Moreover, idiopathic Parkinson's disease is characterized by the presence of Lewis Bodies – which are abnormal protein aggregate that develop inside nerve cells (Michael-Titus *et al.* 2010) – in the nigrostriatal neurons and loss of neuromelanin pigmentation in the substantia nigra and locus ceruleus (Jankovic and Tolosa 2015).

While there is no specific cause for the degeneration of said dopaminergic neurons in the substantia nigra, there are several risk factors that have been directly associated with Parkinson's disease. These risk factors include increasing age, male gender, white race, drinking well water, a diet rich in animal fat, milk and iron, obesity, midlife constipation, rapid-eye-movement sleep disorder, physical and emotional stress, family history, rural residence, pesticides, farming, teaching and health care work, and exposure to metals like iron and manganese (Kasten *et al.* 2007). Furthermore, Parkinson's disease has been found to have 24 different associated genes (Fahn *et al.* 2011). These include SNCA, MAPT, Parkin, PINK1, LRRK2 and many other gene mutations. Pathology in patients can vary due to the different gene mutations and even within single families. Gene mutation can follow a mendelian inheritance as autosomal

dominant such as SNCA and LRRK2 or autosomal recessive such as Parkin, Pink1 and DJ-1 (Fahn *et al.* 2011; Jankovic and Tolosa 2015).

As before mentioned, Parkinson's disease affects more than 10 million people worldwide and nearly 1 million people in the US (Marras *et al.* 2018). Moreover, it has an estimated crude incidence that ranges from 5 to 20 cases per 100,000 population per year (Rosati *et al.* 1980; Rajput *et al.* 1984; Twelves *et al.* 2003). Incidence is defined as the number of new cases of a disease occurring in a specific population during a given period. As incidence is not affected by survival after diagnosis or by the migration of affected individuals, it is the best measure of disease frequency (Jankovic and Tolosa 2015). On the other hand, prevalence reflects both incidence and survival, as it is defined as the total number of individuals in a population who have the disease at a specific point in time. The estimated prevalence of Parkinson's disease in Europe is between 100 and 200 cases per 100,000 population (Kasten *et al.* 2007) and in North America 572 per 100,000 (Marras *et al.* 2018). Moreover, comparison of prevalence studies worldwide indicate that Parkinson's disease might be more common in the developed world (Kasten *et al.* 2007); however, due to the methodological differences, such as age distribution, the results might be confounded. Nevertheless, it is clear that the prevalence rises exponentially after the age of 50 (Kasten *et al.* 2007).

Sensor-based assessments

Since gait is a coordinated action between the nervous system and the musculoskeletal system, it makes gait a reliable indicator of neurodegenerative diseases (Ortells *et al.* 2018); therefore, the interest of implementing computer systems in the analysis of gait patterns to aid in the diagnosis of neurodegenerative diseases. An approach taken to

develop computer-based systems to aid in the diagnosis and monitoring of Parkinson's disease is the sensor-based assessment. Several systems have been developed with successful results, with different approaches between older and recent systems. Earlier versions involve more invasive wearable sensors strapped to upper or lower extremities (Keijsers *et al.* 2006; Bächlin *et al.* 2009; Pansera *et al.* 2009; Patel *et al.* 2009; Cancela *et al.* 2010). Contrastingly, more recent developments have diminished the invasiveness of the sensors and implemented a pair of sensors attached to the ankles or shoes (Moore *et al.* 2008; Barth *et al.* 2011; Raccagni *et al.* 2018). Moreover, some have focused on the detection of gait freezing, which is a common cause of falls in advanced Parkinson's, in order to monitor the patient and prevent falls that can later lead to lethal ailments, such as internal bleeding (Moore *et al.* 2008; Bächlin *et al.* 2009). Most of the sensor-based approaches use accelerometers, gyroscopes, EKG measurements or a combination of these in order to track and analyze a variety of movement-related features and find recognizable differences in the patterns (Keijsers *et al.* 2006; Rissanen *et al.* 2008; Bächlin *et al.* 2009; Pansera *et al.* 2009; Patel *et al.* 2009; Cancela *et al.* 2010; LeMoyne *et al.* 2010, 2010). The tracking of movement patterns other than gait has also shown promising results (Keijsers *et al.* 2006; Rissanen *et al.* 2008; LeMoyne *et al.* 2010; Eskofier *et al.* 2016). Furthermore, the implementation of deep learning algorithms – a subset of machine learning in artificial intelligence – in sensor-based movement assessment has shown improved results compared to machine learning algorithms previously used (Eskofier *et al.* 2016). It is important to highlight that while many of the systems cited are specialized in detecting or monitoring Parkinson's disease movement abnormalities, research has also been

performed to analyze the differences between gait patterns of other causes of parkinsonism that can be misidentified as Parkinson's disease (Raccagni *et al.* 2018), such as multiple system atrophy (MSA) and progressive supranuclear palsy (PSP). This is relevant as Parkinson's disease has been shown to be misdiagnosed in approximately 18% of the cases (Schrag *et al.* 2002; Wermuth *et al.* 2012).

Computer-based vision systems assessments

Computer vision systems can gain high-level understanding from digital images and videos. The implementation of computer vision systems to track gait patterns is a field that has grown significantly in the last decade as gait is unique for every person and the visual assessment can be automated with a computer. In addition, computer vision analysis is a non-invasive, non-intrusive measurement since the subject does not need to behave in a certain way (Lee *et al.* 2014). Moreover, cameras and video processing software have improved enough to track and analyze biomechanical data. For these reasons, the implementation of computer vision systems as a diagnostic and treatment supportive tool has gained interest in the scientific and medical community. Some systems tend to need specialized environments and computationally expensive processes (Green *et al.* 2000; Lee *et al.* 2008; Cho *et al.* 2009), while less sophisticated vision devices, such as Microsoft Kinect, have shown accurate measurements on a variety of gait parameters (Rocha *et al.* 2015; Xu *et al.* 2015) and some other devices have used computationally inexpensive calculations (Khan *et al.* 2013).

Most computer-based vision assessments use consumer standard cameras to record the movements of Parkinson's disease patients. The main differences appear in the image analysis methods and algorithm to determine if the subject has Parkinson's

disease. Dr. Kahn and his team in Motion Cue Analysis for Parkinsonian Gait Recognition (Khan *et al.* 2013) provide a clear vision-based algorithm for parkinsonian gait recognition. First, a recording of the subject is made, then a background subtraction is applied to differentiate the pixels from the subject and the background. Posteriorly, a noise-filtering technique is applied and then the silhouette is isolated. Afterward, a skeleton is made by applying a model fitting to distinguish the head, torso and leg segments. Finally, motion cues are extracted and compared to an imaginary perfect gait to determine if the subject presents normal or parkinsonian gait.

Gait analysis methods

Different analysis techniques are used for the gait parameters. The most prevalent are Linear discriminant Analysis (LDA) (Green *et al.* 2000; Cho *et al.* 2009) and Support-Vector Machine (SVM) (Bauckhage *et al.* 2009; Khan *et al.* 2013). Linear discriminant analysis is a method commonly used in machine learning for the classification of one or more groups in a sample by using features related to the groups. Support Vector Machine works similarly to LDA with the main difference that the SVM focuses on the points that are difficult to classify giving more weight to those. Meanwhile LDA assumes that data is normally distributed. SVM finds a hyperplane that divides the sample into groups by optimizing the distance between the data points that are close to the boundary. Both approaches are less computationally expensive compared to neural networks and other deep learning techniques. Moreover, a more recent approach used a cloud platform-based web service to perform a classification between normal and abnormal gait (Nieto-Hidalgo *et al.* 2018). A cloud platform is convenient as it

eliminates the need for on-site data processing, and it optimizes the need for computational resources.

Frontal versus sagittal

Another relevant difference within the published research is the use of frontal versus sagittal image analysis. In frontal analysis, the patient walks straight to and away from the camera, while in sagittal analysis the subject walks on a straight line perpendicular to the vision field of the camera. Frontal analysis is advantageous due to the reduction of space for the patient to walk. However, as shown by Nieto-Hidalgo and his team, the sagittal approach proved to be more accurate (Nieto-Hidalgo *et al.* 2018).

Kinect implementation

In previous research, Microsoft's Kinect has been implemented for Parkinson's disease detection. Rocha and her team were able to develop a system based on Kinect v2 for Parkinson's Disease Assessment (Rocha *et al.* 2015). The data evaluated showed that 96% of gait parameters were statistically significant to make a distinction between controls and Parkinson's subjects. Therefore, they concluded that the gait analysis provided by Kinect v2 was valuable as a supportive method for assessing Parkinson's disease in a clinical setting. It is important to recognize the advantages provided by the implementation of the Kinect, which are the computational inexpensive processing and the reduction of the constraints in the environment while reducing noise in the image processing at the same time.

Chapter II: Materials and Methods

The subject's gait was recorded using a Microsoft Kinect v2 and Microsoft Kinect Azure while the subject walked unaided over an unobstructed 10 meters walkway. The Kinects were placed perpendicular to the subject's path (sagittal view or side view). Recordings by the beforementioned devices were limited to joint tracking and calculation between the angles of the specific joints. Two programs were developed, as each one of the sensors uses a different language. The program used for Microsoft's Kinect for Xbox One was a modified version provided by Guillermo Hernandez from a previous project; while the program used for Microsoft Azure Kinect was a modified version of Microsoft's Azure Kinect Samples, specifically a modified version of the simple_sample project (Microsoft 2019). The 3D position of the body joints was provided by the sensors and in the same programs, the angles between the joints were calculated and recorded over time. The joints tracked by Kinect Azure and Kinect v2 are shown in figures 1 and 2 respectively. The angles of the joints were calculated using the following formula, where a, b, c are the 3D vectors of the corresponding joints for the angles.

$$A = a - b$$

$$B = c - b$$

$$180 - \operatorname{acos}\left(\frac{A}{|A|} * \frac{B}{|B|}\right) * \frac{180}{\pi}$$

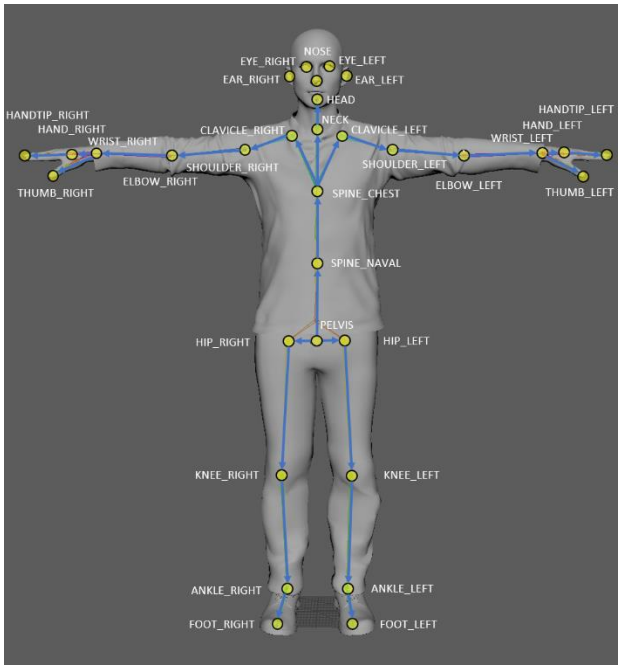

Figure 1. Body joints tracked by Kinect Azure. Retrieved from: (Microsoft 2019b)

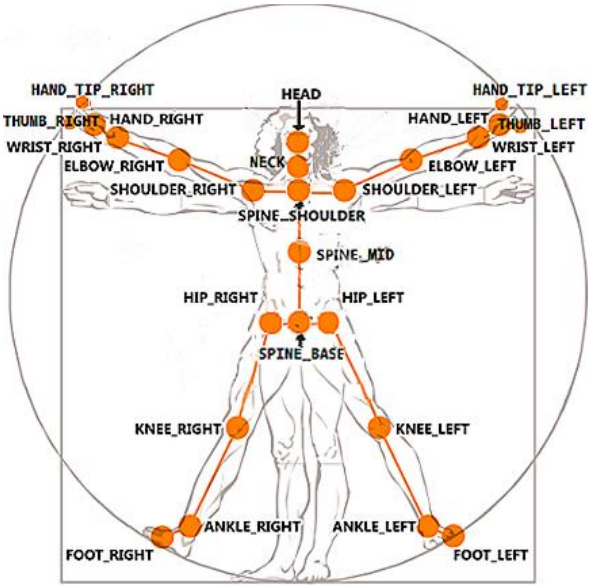

Figure 2. Retrieved from:(Microsoft 2018)

In this research project, seven different angles were calculated, as shown in table 1.

Angle name	Joints
Right knee angle	Right ankle, Right knee, Right hip
Inner torso angle	Pelvis, Spine Navel, Spine chest
Wide torso angle	Neck, Spine navel, Pelvis
Right elbow angle	Right shoulder, Right elbow, Right wrist
Neck angle	Head, Neck, Spine chest
Stride angle	Pelvis, Right ankle, Left Ankle
Right arm swing angle	Right shoulder, pelvis, right wrist

Table 2. Angles and their corresponding joints used in the calculations

Parkinson's patients were recruited from Clinica Parkinson Puebla, which is a Parkinson's clinic in Puebla, Mexico. Subjects recruited were older than 18 years old (male or female) with a Parkinson's disease diagnosis by a neurologist. 12 previously diagnosed Parkinson's patients accepted to participate in the research. These patients were diagnosed by the head neurologist of the Clinica Parkinson Puebla, Dr. Enriquez-Coronel. Parkinson's patients ranged in the Hoehn Yahr scale from levels 2 to 4. All patients were under treatment; however, none have gone under deep brain stimulation surgery (DBS). Deep brain stimulation is a common treatment for Parkinson's disease patients as it shows improvement of all cardinal motor symptoms with sustained long-term benefits, and significant improvement of quality of life when compared with best medical treatment (Groiss *et al.* 2009). Therefore, patients with DBS would show reduced symptoms; thus, being impractical for this experiment. Ages ranged from 52 to 83 years old. Moreover, 13 controls were recruited from the University of Mississippi student, faculty and staff population. Ages ranged from 21 to 55 years old.

	Parkinson's Patients		Controls	
	Male	**Female**	**Male**	**Female**
Participants	2	10	8	5
Age range	52-76	62-83	23-55	21-24

Table 3. Distribution of patients and controls by gender and age range for each group.

Hoehn Yahr Scale	Male	Female
1	-	-
2	-	3
3	2	5
4	-	2
5	Not able to walk unless aided	

Table 4. Distribution of Parkinson's patients for the Hoehn Yahr scale. Patients on level 5 were not included as those patients cannot walk unless aided.

1-3 measurements were taken for each Parkinson patient depending on gait difficulties of the subject; additionally, 3 measurements for each control were taken to ensure that at least one measurement was available for analysis, as sensors failed often to record the data resulting in empty files.

A linear support vector machine (SVM) was implemented in R for the classification of Parkinson's patients versus controls. The angles provided by the first two programs were read into the R program, and the standard deviation for each angle per subject was calculated. The mean and median of the standard deviations for the angles of Parkinson's patients and controls were calculated and compared to see which angles had a larger difference and thus expected to be better classifiers. Afterward, the

standard deviations of each angle per patient were fed to the SVM as features for classification.

Chapter III: Results

As the Kinect V2 sensor had problems to record the data often resulting in empty files, the data obtained from the Kinect V2 sensor was not used in this analysis. All the following results are based on the Azure Kinect sensor recordings.

In order to have a better understanding of what features could work best for the SVM the medians and means of each angle for all Parkinson's patients and controls where calculated, as it can be seen in table 5.

Angle	Right knee angle	Inner torso angle	Wide torso angle	Right elbow angle	Neck angle	Stride angle	Right arm swing angle
Median SD of PD	11.60	1.928	2.333	12.59	1.920	9.370	6.539
Median SD of controls	17.68	1.816	2.341	11.77	1.929	12.42	6.577
Mean SD of PD	17.75	1.874	2.535	13.84	1.881	13.30	7.253
Mean SD of controls	11.39	2.012	2.506	14.08	1.749	11.62	7.484

Table 5. Medians and means of standard deviation per angle for Parkinson's patients (PD) and controls.

Posteriorly, the difference for the median and mean of the standard deviation between Parkinson's patients and controls is shown in tables 6 and 7 respectively.

Angle	Right knee angle	Inner torso angle	Wide torso angle	Right elbow angle	Neck angle	Stride angle	Right arm swing angle
Median SD	6.079	0.1126	0.0076	0.8146	0.0086	3.0555	0.0377

Table 6. The difference of median standard deviation between PD patients and controls per angle.

Angle	Right knee angle	Inner torso angle	Wide torso angle	Right elbow angle	Neck angle	Stride angle	Right arm swing angle
Mean SD	6.360	0.1383	0.0294	0.2310	0.1319	1.682	0.2304

Table 7. The difference of mean standard deviation between PD patients and controls per angle.

As seen in the tables, the right knee angle showed the highest difference for both mean and median. While the stride angle also showed a high difference in the median, the difference was much lower in the mean. This could probably happen due to median being less susceptible to outliers compared to the mean. Furthermore, the right elbow angle showed a lower difference in the median compared to the previous two angles; however, it showed to be a better classifier than the stride angle. The support vector machine (SVM) showed better results at classifying the subjects when the standard deviation from the right knee angle and the right elbow angle were used as shown in figure 3. When the right knee angle and right elbow angle standard deviations were used as features for the SVM, it was able to classify the Parkinson's patients with an 86% accuracy. Moreover, the SVM was fitted with the right knee angle and stride angle, as the stride angle showed a high difference in the median standard deviation between Parkinson's patients and controls. The SVM classification plot is shown in figure 4. However, the accuracy for the SVM fitted with right knee angle and stride angle standard deviations was lower, achieving an 83.7%, as seen in figure 5. The accuracy of the SVM was calculated using the following equation.

$$\frac{True\ Positive + True\ Negative}{True\ Positive + True\ Negative + False\ Positive + False\ Negative}$$

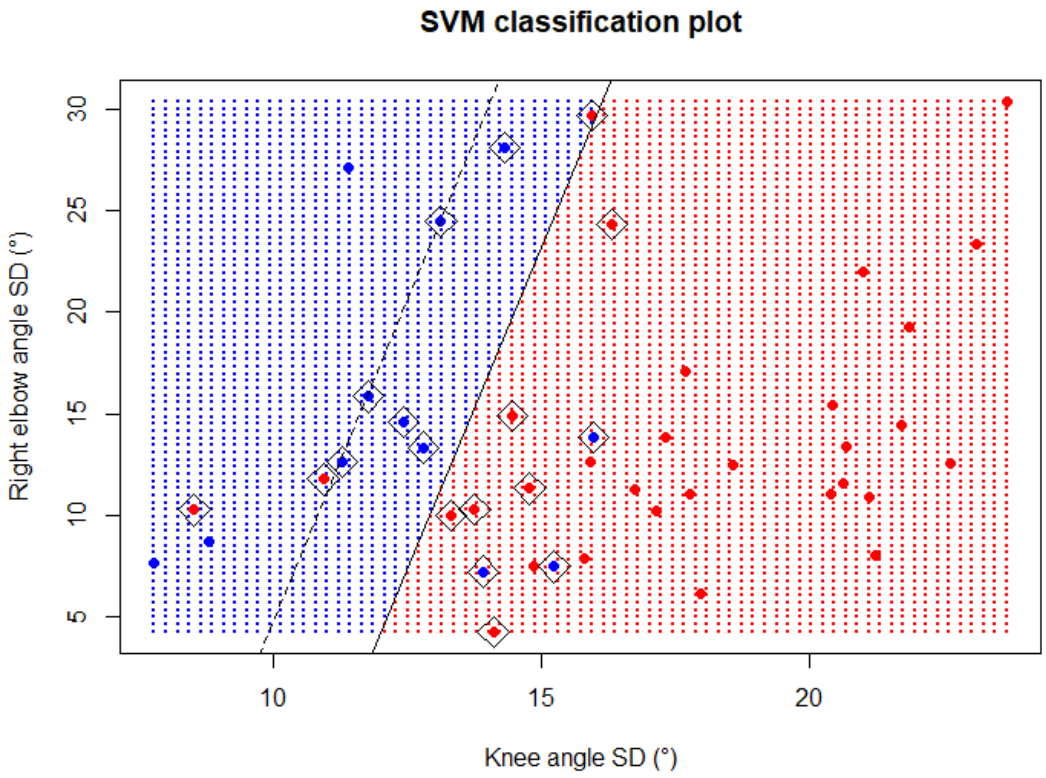

Figure 3. SVM classification plot for right knee angle standard deviation and right elbow angle standard deviation. Blue points represent the Parkinson's patients, red points represent controls. Points in a square represent support points. The solid black line represents the decision boundary. Dashed lines represent the upper and lower margin of the decision boundary.

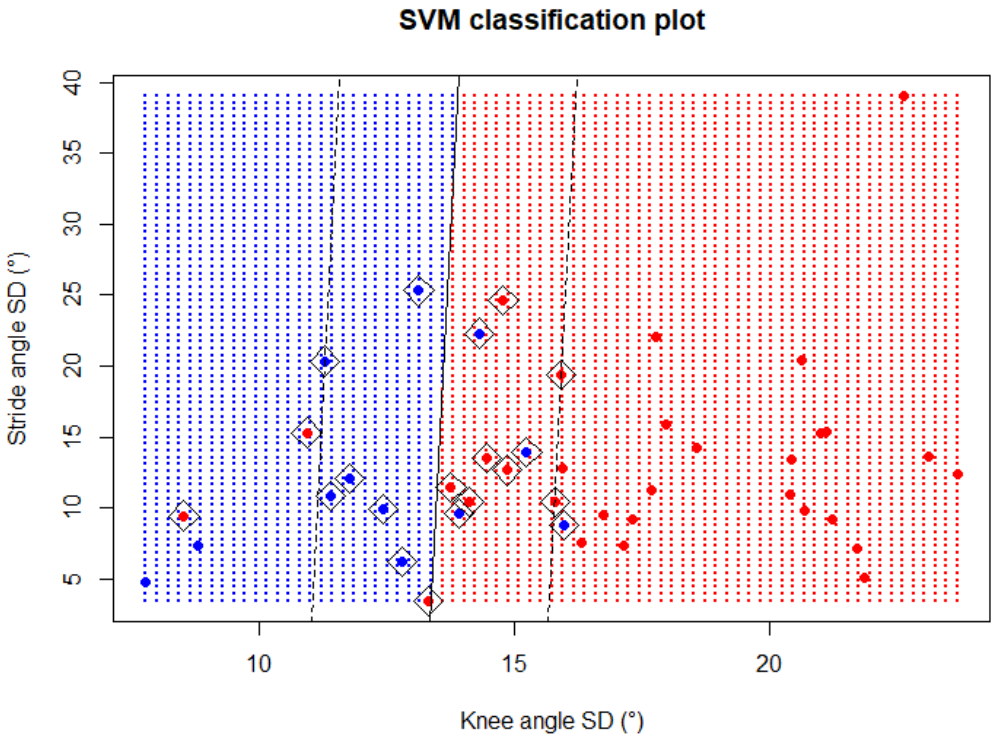

Figure 4. SVM classification plot for right knee angle standard deviation and stride angle standard deviation. Blue points represent the Parkinson's patients, red points represent controls. Points in a square represent support points. The solid black line represents the decision boundary. Dashed lines represent the upper and lower margin of the decision boundary.

Furthermore, to see if an improvement in accuracy could be achieved, the same SVM was fitted with recordings from Parkinson's disease patients that were diagnosed with a level equal or greater than 3 in the Hoehn Yahr scale. As can be seen in figure 6, the accuracy of the SVM to classify the data increased to 90%, by just misclassifying 1 out of 9 Parkinson's patients and the previous 3 controls.

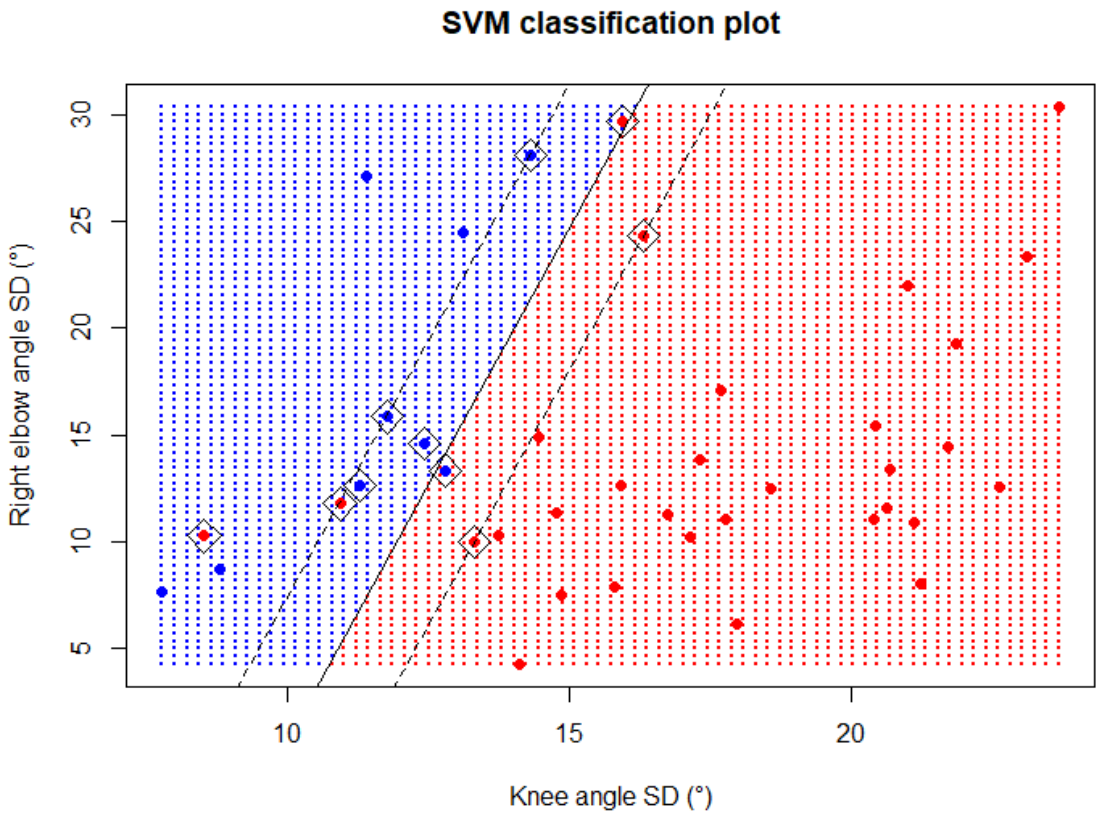

Figure 5. SVM classification plot for right knee angle standard deviation and right elbow angle standard deviation with recordings only from patients that had a Hoehn Yahr level of ≥3. Blue points represent the Parkinson's patients, red points represent controls. Points in a square represent support points. The solid black line represents the decision boundary. Dashed lines represent the upper and lower margin of the decision boundary.

Chapter IV: Discussion

As Parkinson's disease is the second most common neurodegenerative disorder (Reich and Savitt 2018) and it has no identifiable cause, it is a public health concern to find more effective methods to diagnose and monitor the disease. As presented in this thesis, several different approaches have been taken in order to develop systems that can aid doctors in their diagnosis and monitor the disease progression. While in more recent developments the size of the sensors has been reduced and the placement has been in less uncomfortable areas, the sensor-based assessments remain invasive. Computer vision systems show a significant advantage over the sensor-based assessment, as these are not invasive and have similar effectiveness in detecting parkinsonian gait patterns. Moreover, computer-vision systems can be computationally expensive, which can limit their implementation in the clinics, thus the importance of developing systems that are less computationally expensive.

It is interesting that only 3 of the 7 angles measured were significant for the SVM classification, and that it was mainly the right knee angle feature that allowed the SVM to classify the subjects. While in this thesis the patient population was small, the accuracy for classifying the subjects was slightly higher (86% vs ~82%) than the current subjective assessment, which currently has a ~18% misdiagnose rate (Schrag *et al.* 2002; Wermuth *et al.* 2012). Furthermore, it is important to notice that when Parkinson's patients' recordings were limited to patients with level 3 or higher, the accuracy of the SVM classification increased to 90%.

Challenges

Despite the promising results from this system, there are some challenges for the implementation in a clinic setting. Some patients might feel uncomfortable with a camera recording them during their visit to the doctor. Furthermore, a key challenge is that most of the systems analyzed in current literature and the one implemented in this thesis are efficient at detecting the parkinsonian gait; however, less research has been performed in order to differentiate between the diverse causes of parkinsonian gait, as it can not only be caused by idiopathic Parkinson's disease but atypical parkinsonism disorders such as MSA and PSP. Moreover, even Parkinson's disease has been found to have 24 different associated genes (Fahn *et al.* 2011); therefore, further research is needed to have a better understanding of the disease; which consequently will allow having better diagnostics and treatments.

A larger and more diverse sample for Parkinson's disease patients and controls would be desired to increase and test the accuracy of the SVM classification system; however, it is difficult to recruit Parkinson's disease patients that can walk unaided and show enough symptoms to have a Parkinson's disease diagnosis.

At the same time, a relevant challenge is that, as before mentioned, the misdiagnose rate is ~18%; thus; putting in doubt the validity of the data used to perform the analysis. In all the literature analyzed in this thesis; it is assumed that the patients have been correctly diagnosed, and, as in this research project, patients are recruited from highly experienced neurologists that should have very low misdiagnose rates.

Future perspectives

These challenges should be encouraging to the scientific and medical community to continue developing systems that aid medical practitioners in their diagnosis and understanding of the disease course, as well as improve life quality for patients. Further research needs to be performed to develop more accurate and precise systems. A more complete assessment could include a combination of approaches for the diagnosis of Parkinson's disease, including genetic profiles and non-motor symptoms. This type of future assessment could be very helpful in the analysis of the disease's course and decrease the misdiagnose rate. Furthermore, the implementation of computationally inexpensive computer vision systems, such as the one presented in this thesis, in the clinical setting could be incredibly helpful as a supportive tool in the diagnosis of Parkinson's disease by adding a quantitative component to the diagnosis as well as, with a very large sample, be able to classify the Parkinson's disease progress into the 5 main stages of the Hoehn Yahr scale. Moreover, future research could develop systems that detect subtle movements imperceptible to some medical practitioners; this could lead to opportune treatments to delay the onset of motor symptoms.

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