A Review of the Assessment Methods of Voice Disorders in the Context of Parkinson's Disease

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***Abstract*—In recent years, a significant progress in the field of research dedicated to the treatment of disabilities has been witnessed. This is particularly true for neurological diseases, which generally influence the system that controls the execution of learned motor patterns. In addition to its importance for communication with the outside world and interaction with others, the voice is a reflection of our personality, moods and emotions. It is a way to provide information on health status, shape, intentions, age and even the social environment. It is also a working tool for many, but an important element of life for all. Patients with Parkinson's disease (PD) are numerous and they suffer from hypokinetic dysarthria, which is manifested in all aspects of speech production: respiration, phonation, articulation, nasalization and prosody. This paper provides a review of the methods of the assessment of speech disorders in the context of PD and also discusses the limitations.**

***Index Terms*—Parkinson's Disease; Voice Analysis; Speech Processing; Parkinson's Disease Assessment.**

I. INTRODUCTION

Parkinson's disease (PD) is one of many neurological disorders, including Alzheimer and epilepsy. These diseases cause negative physical and psychological effects in patients and their families. PD is generally seen in people aged over 60 years [1]. It is estimated that, world wide, nearly 10 million people suffer from this disease [2] [3]. The burden of PD is very expensive, and its costs may increase in future [4] [5]. At the moment, there is no efficient cure for it; therefore, patients require periodic monitoring and treatment. For PD patients, physical visits are very difficult. To this end, the development of easy to use self-monitoring and tele-monitoring is crucial to lower cost and facilitate treatment. Significant developments in information technology and telecommunication offer a good opportunity for tele-monitoring and tele-medicine [6] [7] to improve the quality of the diagnosis for such patients. In addition, this novel technology can improve outdated electronic health record maintenance systems in medical centres [8] [9] [10]. Now the question is how can these opportunities be exploited? Today, the major challenge for medicine is to correctly recognise PD in its early stages [11] [12] [13], in order to avoid the suffering of patients due to delayed treatment, since there is no cure at the moment [14]. Some studies have shown that PD causes vocal impairments in approximately 90% of patients [4] [15] [16] [17], and may indicate the early stages of the disease [18]. Since the speech processing is not a difficult task to manage, using vocal impairments to detect PD patients has caught the attention of many researchers [41] [19] [20]. PD represents a particular mode of dysfunction of the *Central Nervous System* (CNS) [21] [2] [22]. It is characterised by progressive nigrostriatal dopaminergic denervation, which leads to chronic dysfunction of the basal ganglia system [23] [22]. This system is essential to control the execution of learned motor plans [22]. Therefore, the impairment of the CNS causes partial or full loss in motor reflex, speech and other vital functions [21] [2]. The etiology of PD is currently unknown, although research into the causes behind the appearance of the disease is performed all over the world. Currently, there is a focus on several different diagnostic methods, such as DNA loci [24], deep brain stimulation [25], transcription phase [26], and gene therapy [27]. The symptoms of PD were described as "Shaking palsy" by Doctor James Parkinson [28]; this includes shaking in hands, arms, legs, face and jaw [29].

Speech production, particularly, highlights the concepts of automation (after learning and acquisition) and sequential or simultaneous organisation of motor plans [22]. It is a dynamic system whose behaviour at a given moment depends on its previous states [22]. The complex organisation of articulatory gestures of speech production is under control of the CNS, and especially the basal ganglia [22]. The impairments in normal production of vocal sounds known as dysphonia [30], lead to reduced loudness, breathiness, roughness, reduced energy in higher parts of the harmonic spectrum and overdone vocal tremor [4] [2] [31]. There are also other voice impairments caused by PD, such as hypophonia (reduced volume), dysarthria (problems in voice articulations) and monotone (reduced pitch range) [2]. Hypokinetic dysarthria is considered as an important characteristic of voice disorders observed in PD patients. The characteristics of this hypokinetic dysarthria are the reduction of articulatory movements and decreased prosodic modulation of speech, which is described as monotone [32]. According to [33], one of the treatment methods consists of injecting a small quantity of *botulinum toxin* into the larynx area. This treatment provides temporary rehabilitation for 3 to 4 months, and then the dysphonic symptoms return [8]. There were different rehabilitative methods aiming to increase the vocal intensity of PD patients, such as *Lee Silverman Voice Treatment* (LSVT) [34] [35] method, which increases vocal intensity by phonatory and respiratory efforts, and *Pitch Limiting Voice Treatment* (PLVT) [36] method, which increases vocal intensity and maintains lowest pitch.

To assess these symptoms, many vocal tests and approaches have been introduced [4] [30]. The most used approaches are *sustained phonations* [4] [30] [37] [38], where patients are asked to pronounce sustained vowels at a comfortable level, hold as long as possible [4] [30], and *running speech* [4] [30] [38], where patients are asked to speak standard sentences, which are constructed from representative linguistic units [4] [30]. Any one of these symptoms may give us enough information for detecting the severity of PD [4] [30]. The *running speech* tests are considered as more realistic in actual everyday usage, but it may contain many linguistic components and/or confounding effects of articulation [4] [30]. Long and sustained vowels represent the most stable vocal performances and allow a relatively simple acoustic analysis. Therefore, most studies used the first approach to detect dysphonia symptoms. There have been many studies of measurement of voice disorders in general [4] [39] [40] [41]. Moreover, other studies have focused on the analysis of voice disorders in the context of PD [20] [42] [43]. Generally, during standard tests, speech samples are recorded using a microphone and subsequently analysed using different measurement and algorithms implemented in some specific software like *Praat* [44], *Multi-dimensional Voice Program* MDVP [45], etc. Other measurements, such as complex nonlinear aperiodicity, aero acoustic, turbulent, non-Gaussian randomness of the sound may be used to increase the clinical efficacy of the PD diagnosis systems [39]. The main traditional measurements used to detect speech disorder include, the *fundamental frequency* F_0; *absolute sound pressure*, which indicates the relative loudness of speech; *jitter measurement*, which represents cycle to cycle variation in F_0; *shimmer measurement*, which represents cycle to cycle variation in speech amplitude; *harmonic to noise ratio*, which represents the degree of acoustic periodicity in speech signal; and, many others [4] [2] [30] [29] [46] [47] [8] [48]. By comparing PD patients with healthy people, studies have shown variations in all these measurements, which mean that these could be useful in assessing voice disorders in the context of PD [4] [49].

Vocal production is a nonlinear dynamic system, is it affected by the impairments of the vocal organs, muscles and nerves [4]. The changes in the system can be detected by *nonlinear time series analysis tools* [4] [50]. Voice recordings and measurements methods change according to the acoustic environment, physical conditions and characteristics of subject [4]. In order to have as much reliability as possible, all these measurement methods should be chosen to be highly robust in uncontrolled variations [4]. Measurements like absolute sound pressure level limit the reliability of these measures in telemedicine because they require costly calibration equipment, which is difficult to obtain [4].

II. The Characteristics of Voice

The speech sounds have as origins aerodynamic and acoustic phenomena. They are produced on an air flow coming from the lungs to the outside the human body. There are different mechanisms that allow the movement of a sufficient airflow in order to make audible the articulatory and phonatory actions (Figure 1) [51]. The most used mechanism by people for speaking is the use of the respiratory apparatus (diaphragm, lungs, and trachea) [52], it provides energy and the required airflow to generate the voice. The larynx is the first source of speech sounds; it is a phonatory organ (Figure 1). It controls the vocal folds (Figure 2 - A); it is like a regulator of the lungs air, releasing the airflow toward the *supra-glottis* part (Figure 1) [52]. The place of articulation extends from vocal folds to lips, including the following resonances and articulators cavities (Figure 1):

- The pharynx (or pharyngeal cavity) is a leading *musculo-membrane*; it is located between mouth and esophagus on one hand and between nasal cavity and larynx on the other hand [54].
- The nasal fossae (or nasal cavities) (Figure 1) are two cuneiform cavities separated by a vertical wall [54]. A nasal resonance is very characteristic (twang). The air passes through the nose when the velum (muscle extension of the osseous palate) is lowered.
- The mouth (or oral cavity) (Figure 1) is separated from the nasal fossae by a partition called the palate. The articulators are located in this cavity; some are fixed (passive), and others moving (active) [54].
- The labial cavity is a cavity that is created when projecting the lips forward (labial protrusion).
- Speech is a succession of two types of sound events; *voiced sounds* (vowels) which are characterised by the vibration of the vocal folds, and *unvoiced sounds,* which do not involve the vocal folds.

The voiced signal is a pseudo-periodic signal, having more or less important frequency areas. These maximum envelope frequency areas are called formants (F1, F2, F3 etc.) as can be seen in figure 2 - B. The spectrum (figure 2 - C) of the sound emitted by the vocal folds is modulated by the vocal tract and the position of the lips. The different modifications in these resonators, lead to the production of different sounds. The

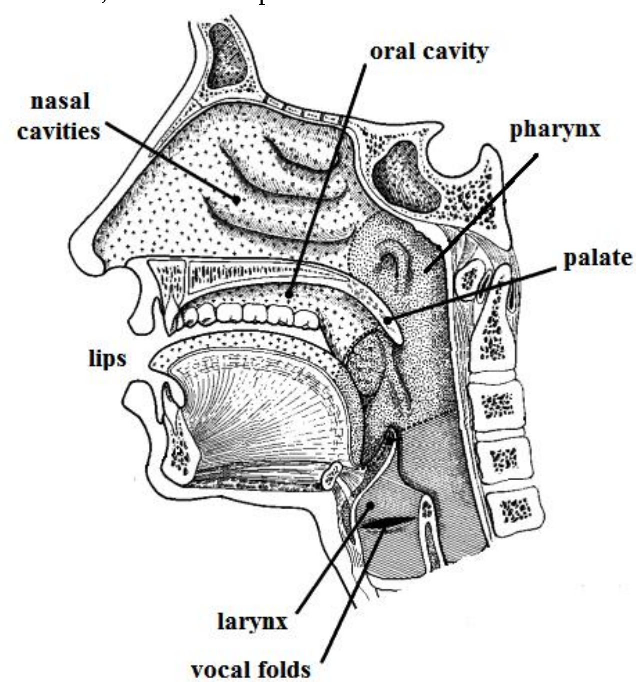

Figure 1: Vocal tracts. Modified from *Teston* [53]

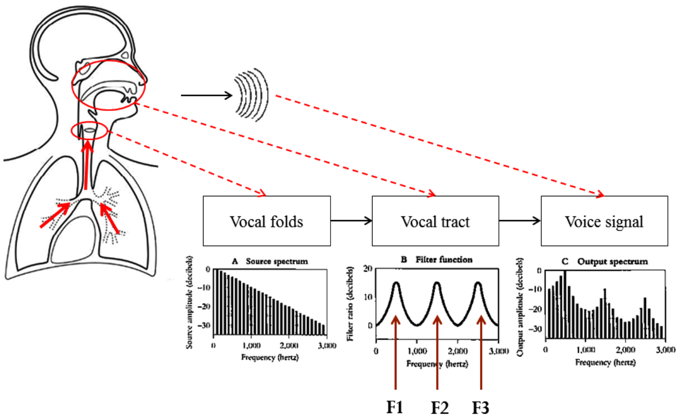

Figure 2: Representation of the speech production system from the Lungs to the outside of human body and the role of each part of this system. A- Vocal folds are the source spectrum of the vocal signal. B- Vocal tract (pharyngeal, nasal, labial cavities and lips) filter the signal provided from the vocal folds. C- Vocal signal is the convolution product between the vocal folds signal and vocal tract filters.

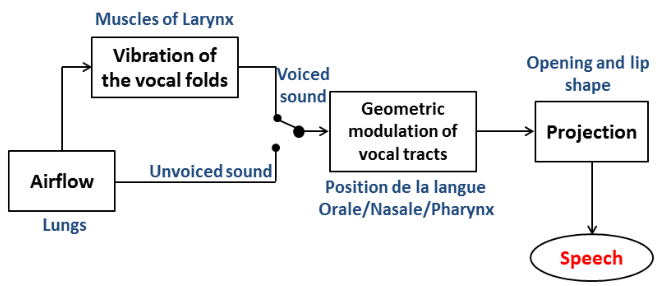

Figure 3: Speech production model

model of speech production is represented in Figure 3. As can be seen, the vibrations of the vocal folds in the larynx generate a complex periodic signal (voiced sound), which is constituted of a fundamental frequency F_0. The multiples of F_0 are called harmonics. The representation of the amplitude of these frequency components is called the acoustic spectrum. The representation of the evolution of the spectra as a function of time (time-frequency analysis) is called a spectrogram.

The variations of F_0 define the melody of the voice; it depends on pulmonary pressure and especially on the larynx neuromotor control. The intensity of the voice depends on the pulmonary pressure. The formant frequency ($F1$, $F2$ and $F3$) depends on the distance between the highest point of the tongue and the roof of the oral cavity, the distance between this point and the larynx, and the rounding and the projection of the lips.

Each language has its own phonetic system that manages the existence of sounds in languages depending on two factors: *Physiological constraints* imposed by the vocal apparatus, and *Phonetic system* of the language or the way of using speech articulators.

It is often forgotten that the vocal apparatus is not biologically destined in priority for speech production activities; its main function is to ensure respiration and nutrition. Indeed, the lungs are the respiratory apparatus, the larynx has a role of control of respiratory functions and at level of supra-glottis structures are operating the mastication and the deglutition of food [52].

III. Assessments of Parkinson's Disease in Literature

There are two different assessments of voice disorders in the literature consisting on distinguishing PD patients from healthy people, and predicting the severity of PD.

A. *The assessment of voice disorders for detecting PD patients*

In 2009, Max Little et al. [4] presented an assessment of voice disorder in order to discriminate healthy people from patients with PD by detecting dysphonia. In their work, they used pitch period entropy, which is a robust measure against noisy environment and healthy voice frequency. The database used in their work comprises 23 patients with PD and eight healthy people. After examining all possible combinations, they selected four of ten measurements, which lead to a correct classification accuracy of 91.4% using a kernel Support Vector Machine (SVM). There are many novel methods for the assessments of dysphonia in the context of PD. However, according to Little et al. [4], there is no efficient method, which may characterise this dysphonia in the presence of certain other factors such as subject gender and variable acoustic environments. To overcome this problem, Little et al. [4] introduced a new method to measure dysphonia called Pitch Period Entropy (PPE). It is a robust measure sensitive to changes in speech in the context of PD [4]. Relying only on statistical significance is insufficient to determine which measurement or set of measurements is useful to asses dysphonia in the context of PD. Using methods of statistical learning theory, such as Support Vector Machines (SVM) and Linear Discriminate Analysis (LDA) [55] are preferred since they can directly select the best measurement that discriminates patients with PD from healthy people. Also, it is possible with such classification methods to combine measures to improve discrimination. Theoretical considerations show that the classification accuracy decreases when a large feature size is used [55]. Therefore, it is important to use a minimum number of measurements, which contain an optimal amount of information for more reliable classification [55]. However, this is not guaranteed to produce an optimal feature set [56]. As a compromise, Little et al. [4] removed redundant measures, and then tested all possible combinations with an SVM classifier.

The database used by Little et al. [4] contains 195 sustained vowel phonations from a set of 31 people. There were 23 patients with PD and eight healthy people. For PD patients, the time since diagnosis ranged from 0 to 28 years, and the age of patients ranged from 46 to 85 years (mean 65.8, standard deviation 9.8). Each participant gave an average of six records ranging from 0 to 36 seconds in length. This study has paved the way for many researches to improve the accuracy of PD diagnosis. This is achievable due to the availability of the database used by little Max on the UCI machine learning repository website [57].

Shahbaba et al. [58] introduced a new nonlinear model for classification using Dirichlet process mixtures for PD detection. They compared the results with, multinomial logit models, decision trees and SVM, the best obtained classification accuracy was 87.7%. To seek effective diagnosis of PD Resul das [59] compared four independent classification schemes. Various evaluations methods were employed to calculate the performance score of Neural Networks, DMneural, and Regression and Decision Tree [59] using SAS based software [60]. This software makes the data mining procedure simpler, from data access to model valuation, and supports all essential tasks within a single, integrated solution and offers the flexibility for efficient collaborations [60]. In his study, Resul das [59] described efficient approaches to distinguish between affected and healthy people. A maximum discriminative accuracy of 92.9% was achieved using neural networks. Furthermore, he compared his results with the results of a previous study [61].

To provide medical decision boundaries for PD detection, and create learning feature functions on the basis of ordinary feature data (features of voice), Guo et al. [62] combined genetic programming and the expectation maximisation algorithm (GP-EM), the best classification accuracy of 93.1% was obtained. With the aim of developing remote diagnosis of PD, Sakar et al. [63] selected a minimal subset of dysphonia features with maximal common relevance to discriminate PD patients from healthy people. In addition, to maximise the generalisation of their predictions, they built a predictive model with minimal tendency in order to perform well with unseen test examples. In their study, they applied a joint information measure with a permutation test for assessing the statistical significance of the relations between the dysphonia features and the discriminative results. Furthermore, they classified these features according to the Maximum Relevance Minimum Redundancy (mRMR) criterion. For classification, they used SVM to build and test a model with a leave-one-individual-out cross-validation scheme, instead of using conventional bootstrapping or leave-one-out validation methods. They also evaluated the success of the model according to its accuracy, sensitivity, and specificity. A maximum classification accuracy of 92.75% was achieved using the validation method subset of mRMR-4. In order to design high performance computer-aided diagnosis systems, Ozcift et al. [64] constructed rotation forest (RF) ensemble classifiers of 30 machine learning algorithms to evaluate and detect patients with PD, the best achieved classification accuracy was 87.13%. AStröm et al. [65] aimed to predict PD by using a parallel feed-forward neural network structure. The maximum obtained classification accuracy was 91.20% using nine networks. Spadoto et al. [66] applied evolutionary-based techniques in order to find the subset of features, which maximise the accuracy of the Optimum-Path Forest classifier (OFP). The best classification accuracy obtained was 84.01% using Gravitational Search Algorithm (GSA-OPF) technique with eight features. Li et al. [67] proposed a fuzzy-based non-linear transformation method along with SVM classifier to improve PD diagnosis, the best classification accuracy achieved was 93.47%. In the same context, Mandal et al. [8] presented different reliable methods, such as *Bayesian network* [68] [69], *Sparse Multinomial Logistic Regression* (SMLR) [70], SVM, Boosting methods [71], *Artificial Neural Networks* (ANNs) [72] [73] and other machine learning models. Furthermore they used *Rotation Forest* (RF) [74] [75] consisting of logistic regression [76]. Haar wavelets were used [77] [78] as projection filter. They also presented new computational methods of machine learning ensembles. This includes rotation forest (RF) [74] [75] used as a projection filter integrated with the logistic regression classifier to enhance the accuracy of logistic regression. The RF method was used by Oscift [79]; the maximum accuracy achieved was 96.93% [79]. The best obtained result was 100% using SMLR classifier [8].

In a similar vein, Wan-li Zuo et al. [48] presented an efficient diagnosis system based on particle swarm optimisation (PSO) and reinforced by fuzzy KNN. The PSO technique was first developed by Eberhart and Kennedy [80] with the aim of treating each individual as a particle in d-dimensional space, where the position and the velocity of the particle are represented. This system, called PSO-FKNN, was first developed for predicting successfully bankruptcy [81] [82]. However, in their study, this system was used to explore the maximising classification performance for discriminating PD patients from healthy people [48]. Both continuous and binary versions of PSO were used to optimise parameters and select features at the same time. First, the FKNN classifier was adaptively specified by the continuous PSO algorithm. Subsequently, a binary PSO approach was used to identify the most discriminant subset of features for prediction. A mean accuracy achieved was 97.47% by using 10-fold CV method [48]. In order to develop an efficient diagnosis for detecting PD, Hui-Ling Chen et al. [29] used time fussy KNN (FKNN) [83] with 10-fold cross validation method which outperformed SVM classifier, showing a mean classification accuracy of 96.07%. Recently, Hariharan et al. [84] used a hybrid intelligent system, the maximum classification accuracy obtained was 100% using feature pre-processing, feature reduction/ selection, and classification with least-square SVM, probabilistic neural network and general regression neural network.

In order to develop predictive tele-diagnosis and tele-monitoring systems for detecting voice disorders in PD, Betul et al. [2] used multiple vocal tests per subject, including sustained vowel phonation and running speech [2]. After applying different machine learning tools on the database, they found that the most discriminative information is carried by sustained vowels. On other hand, they used a central tendency and dispersion metrics in order to improve and generalise the predictive model instead of using each voice sample independently [2]. They also compared the success of alternative cross-validation methods for PD diagnosis [2]. Extracted features were fed into SVM and KNN classifiers for PD diagnosis by using a Leave-One-Subject-Out (LOSO) cross-validation scheme and summarized Leave-One-Out. They also evaluated the success of the models according to their accuracy, sensitivity, specificity and Matthews correlation coefficient scores [2]. In their work, they were able to discriminate PD patients from healthy people using multiple types of voice recording with a best classification accuracy of 85%.

The database used by Betul et al. [2] consisted of 20 patients with PD (6 women, 14 men) and 20 healthy people (10 women, 10 men). For PD patients, the time since diagnosis ranged from 0 to 6 years. The age of PD patients ranged from

43 to 77 (mean: 64.86, standard deviation: 8.97) and the age of the healthy subjects ranged from 45 to 83 (mean: 62.55, standard deviation: 10.79). Another database was used in their study as an independent test set to validate the results obtained from the multiple sound recordings database.

In order to discriminate PD patients from healthy people, Jaafari [30] presented a combinational feature extraction method using voice samples. The extracted features used in this study contained seven nonlinear features and 13 Mel frequency cepstral coefficients (MFCC). In addition to nonlinear phonetic features, such as pitch period entropy (PPE), recurrent period density entropy (RPDE), noise-to-harmonic ratio (NHR), detrended fluctuation analysis (DFA) and fractal dimension (FD), Jaafari [30] introduced two new methods to measure dysphonia: EDC-PIS (energy distribution coefficient of peak index series) and EDS-MPS (energy distribution coefficient of peak magnitude series). These two measurements are said to be robust to several uncontrollable confounding effects such as noisy environment [30]. MFCC have been widely used in speech processing tasks such as speech recognition and speaker identification. The 20 extracted features were fed into a Multi-layer perception (MLP) neural network classifier with one hidden layer. The best obtained discrimination accuracy was 97.5%. The database used by Jaafari [30] consists of 200 voice samples from a group of 25 PD patients (5 women, 20 men) with different severity levels and 10 healthy people (2 women, 8 men). The age of PD patients ranged from 49 to 70 (mean 58.64) and that of the healthy subjects from 39 to 63 (mean 50.7).

In [85], different methods to discriminate PD patients from healthy subject were used. A number of cepstral coefficients between from 1 to 20 Mel Frequency Cepstral Coefficients (MFCC) were extracted from a set of 34 people (17 PD patients and 17 healthy people). The frames of the MFCC were compressed using Vector Quantification (VQ) with is six codebook sizes (1, 2, 4, 8, 16 and 32). For classification, LOSO validation scheme was used along with SVM. The maximum classification accuracy achieved was 100%, and the mean classification accuracy was 82%. In the same context, in another work [86], the same work used in [85] was replicated except that instead of using MFCC, Perceptual Linear Prediction (PLP) technique was used. The maximum classification accuracy achieved was 91.17% and the best average result obtained was 75.79%. As a related work, in [87] the frames of the PLP was compressed by calculation their average value in order to extract the voiceprint of each subject, the best classification accuracy achieved was 82.35%. In other work [88], a database, which contains 14 PD patients (7 women, 7 men) and 6 healthy people (2 women, 4 men) was used. And then, from these samples, the best acoustic features were extracted according to the pathological thresholds defined by the MDVP. Subsequently, a hybridisation metrics was used along with SVM and KNN for classification. The best discriminative accuracy achieved was 95% using only four acoustic features and SVM.

B. *The assessment of voice disorders for detecting the severity of PD*

The assessment of voice disorders in PD may be useful in other applications in addition to distinguishing PD patients from healthy people. Recent studies have shown that there is a strong relation between speech degradation and PD progression [89]. The progression of the disease is monitored using different empirical tests and physical examinations, which are mapped using one of the famous clinical metrics, known as the "*Unified Parkinson's Disease Rating Scale*" (UPDRS) [46]. Recently, there have been many reports of approaches in the aim of mapping map PD dysphonias to UPDRS scores [30] [46] [89] [90].

To improve the applications of automated assessment of PD symptom progression from voice signals Tsanas et al. [46] used Praat [44] to compute classical dysphonia measures. such as *Jitter*, *Shimmer* and *harmonics to noise ratio*. They also used *MDVP* [45] prefix to associate measures, which are equivalent to the results of the *Kaypentax MDPV*. Also, they suggested that in addition to these measures, log-transformed classical measures, which convey superior clinical information and are selected by an automatic feature selection algorithm, are more appropriate for UPDRS prediction. In order to reduce the number of features used and enhance the quality of log-transformed classical measures, Tsanas et al. [46] used *Least Absolute Shrinkage and Selection Operator* regression, which searches for all possible combinations to minimise prediction error. The database used in this study, consists of 42 patients (14 women, 28 men) with idiopathic PD diagnosis, who had a mean age of 64.4 years (standard deviation: 9.24). The motor-UPDRS average was 20.84 ± 8.82 points and the total UPDRS average was 28.44 ± 11.52 points [46].

Recently, Tsanas et al. [31] investigated the potential of using sustained phonation of the vowel /a/ to automatically duplicate a speech expert's assessment of the voices of PD patients. The results of the assessment may be acceptable (a clinician would allow persisting during the rehabilitation treatment) or unacceptable (a clinician would not allow persisting during the rehabilitation treatment) [31]. Tsanas et al. [31] extracted and mapped the most informative feature subset in order to reduce from 309 to ten most informative dysphonia measures. The maximum performance achieved was 90% using an SVM classifier. The database used in this research had 14 PD patients (6 women, 8 men). The age of the patients ranged from 51 to 69 years (mean: 61.9, standard deviation 6.5). Each patient produced nine phonations, 25% of these phonations were repeated in order to *qualify intra-rater ratability*, which gave a total of 156 voice samples.

IV. ASSESSMENTS METHODS IN LITERATURE

A. *Subjective methods*

Perceptual assessments of speech disorder are made by listening to patient when talking, and then focusing on simple aspects of his vocal production, such as pitch, intensity, rhythm and the intelligibility of his speech. [91]. Many perceptual methods have been proposed for assessing the quality of the voice [92] [93] [94]. Among all these methods, the GRBAS scale [93] appears to be the most widely used [32] [53]. Dysarthria in PD can be assessed with a speech assessment grid, which was proposed by the multidimensional rating scale for PD called [95] [96] [97]. In fact, the UPDRS scale is not necessary for diagnosis, but it is useful for monitoring the disease. It describes five stages of increasing severity of the speech [32]:

- 0 = normal speech
- 1 = slight decrease of intonation and volume
- 2 = monotone speech, blurred but understandable, clearly disturbed
- 3 = marked disturbance of speech difficult to understand
- 4 = speech unintelligible

Beyond the UPDRS, neurologists have been involved in multidisciplinary approaches that aim to carefully assess the anomalies of the various interferences in the function of the speech production system (respiration, phonation, resonance and articulation), without ignoring the cognitive and psychological dimensions of speech communication [91]. For this reason, they have adopted more objective methods.

B. Objective methods

a. Aerodynamic methods

The aerodynamic is fundamental in the speech production. It is the origin of all sound events. In fact, the pulmonary air column is the source of the speech signal, which is modulated by various constrictions of the vocal tract [91]. The aerodynamic parameters are formed by air flows at the mouth (oral) and nostrils (nasal), and intraoral and subglottic pressures [91]. Rousselot *(1895)* [98] made the first attempt of the objectification of aerodynamic measures and codification. Knowledge of variations in these parameters based on pronounced phonemic segments provides information about the movements of the articulator's vocal tract organs [99] [100] [91].

b. Time-frequency acoustic measurements

In this section, the present acoustic assessment is given. They are the most used measurements for detecting voice disorder in the context of PD. Acoustical measurements are correlated with many dysfunctions of the voice; for example: hoarseness is correlated with stability of the laryngeal vibrator; breath with *harmonic to noise ratio*; asthenia with *intensity;* and, voice forcing with a higher F_0. The instability of vibration of the glottis is the main cause of dysphonia. Therefore, the measurement of these fluctuations is essential for assessing dysphonia. These measurements are performed on the frequency or on the amplitude of the laryngeal signal from the melody and the intensity of the voice. The indicators of instability can be defined according to the duration of these fluctuations.

i. Jitter measurements

Short-term fluctuations (duration of the order of one glottal cycle) especially characterise morphological damage the vocal cords. These fluctuations are jitter, for the fundamental frequency (F0), and shimmer, for the amplitude (intensity). There are different representations of jitter. *Jitter (absolute)* represents the cycle-to-cycle variation of F_0. It is computed as the average absolute difference between consecutive periods [101] [102]. *Jitter (relative)* is defined as the average absolute difference between consecutive periods, divided by the average period of the signal [101] [102]. *Jitter (RAP)* represents the *Relative Average Perturbation*, computed as the average absolute difference between a period and the average of it and its two neighbours, divided by the average period of the signal [101] [102]. Finally, *Jitter (PPQ5)* represents the *five-point Period Perturbation Quotient*, defined as the average absolute difference between a period and the average of it and its four closest neighbours, divided by the average period of the signal [101] [102]. The measurement of jitter poses many problems because there is no unique mathematical definition of jitter [31], and its value depends on the measurement technique of the fundamental frequency [53]. In the same sample, the value of jitter varies when using different measurement software.

ii. Shimmer measurements

Shimmer measurements have also almost the same problems as *jitter measurements*. There are also several definitions of shimmer. *Shimmer (dB)* represents the variability of the peak-to-peak amplitude in decibels, computed as the average absolute base 10 logarithm of the difference between the amplitudes of consecutive periods, multiplied by 20 [101] [102]. *Shimmer (relative)* is expressed as the average absolute difference between the amplitudes of consecutive periods, divided by the average amplitude of the signal, expressed as a percentage [101] [102]. Lastly *shimmer (APQ11)* represents the *11-point Amplitude Perturbation Quotient*, defined as the average absolute difference between the amplitude of a period, and the average of the amplitudes of it, and its ten closest neighbours, divided by the average amplitude of the signal [101].

iii. Harmonicity

The instability of the glottal signal appears as noise, which is superimposed on it. Therefore, it can be assessed using the ratio of the harmonic energy in the spectrum of the signal and the noise energy. There are several methods to measure the aperiodic part of the speech signal. There are two main techniques, although their results are not only based on the stability of the glottal signal. *Harmonic Noise Ratio (HNR)* is the *relative energy of the harmonic / noise energy* expressed in (dB). This method was first proposed by Yumoto et al. [103]. The other technique is Normalised Noise (NNE) proposed by Kasuya et al. [104]. *HNR* and *NNE* measurement do not always give an accurate assessment of the noise of the blowing voice if there is not a stable vibration frequency. To overcome this problem, Qi et al. [105] proposed a measurement method of the HNR. which minimises the effects of vibrational instability *(jitter)* [53].

iv.Phonetogram

The main idea of Phonetogram is to represent in a Cartesian plane the dynamic range of the human voice, in terms of both fundamental frequency (x-axis) and intensity or loudness (y-axis) [53]. This representation is very useful to identify the boundaries of vocal function. The length of this graph presents the dynamic frequency (Hz), and the thickness of the graph presents dynamic intensity (dB) [53].

Figure 4 (*top*) shows the Phonetogram of a normal person aged 58 years. As can be seen, the tonal dynamics of this

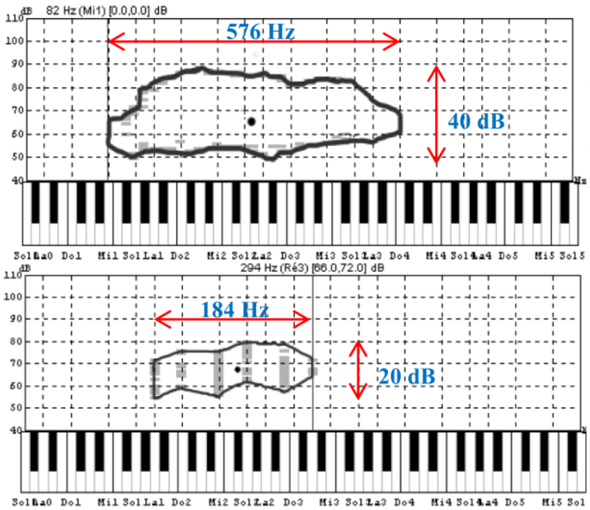

Figure 4: Phonetogram of a normal person *top* and a PD patient *bottom*, Modified from *Teston* [53]

person ranged from 82 to 523 Hz, almost three octaves (576 Hz), and the dynamic range of the intensity is 40 dB. This example has good tonal dynamics but it lacks some dynamic intensity. The centre of gravity is on the point (220 Hz, 56 dB) [53].

Figure 4 (*bottom*) shows the Phonetogram of a PD patient.

The tonal dynamics of this patient ranged from 110 Hz to 294 Hz, which is much less than two octaves, and the dynamic range of the intensity is almost 20 dB [53]. The centre of gravity is on the point (196 Hz, 57 dB) [53].

v. Maximal Phonation Time (MPT)

The main idea of using the MPT technique is to have information about the capacity of vocal organs as well as the performance of vocal source [53]. It consists of measuring the time of the phonation of the sustained vowel / a / [53].

vi.Intensity

Voice disorders and the reduction of subglottic pressure is an obvious factor of the reduction of the intensity. The variation of the intensity values in function of the time are computed by the root-mean-square value of the acoustic speech signal for every window of 10 milliseconds and presented in the form of an intensity curve [32]. The average value of the intensity is about 70 dB at 30 cm from the mouth in a normal conversation, 85 dB in raised voice and 105 dB in shouting voice [32]. Concerning the estimation of the intensity of the voice, *Praat* software remains a reliable and powerful tool, which shows in every moment the value of the intensity, maximum and minimum, average value and its allure.

c. Cepstral domain measurements

The application of the Mel frequency cepstral coefficient for the assessment of speech disorder in PD was first proposed by Fraile et al. [106]. It has been demonstrated that using the MFCC technique reduces noisy information; as a result, dimensionality is also reduced and the task of pattern classifications becomes easier [107] [108].

In related works Kapoor et al. [109] and Benba et al. [85] used MFCC along with vector quantification to discriminate PD patients from healthy people.

MFCC has been traditionally used in speech recognition systems. It uses high dimensional features extracted from frequency domain. The use of this technique for voice analysis systems was first supported by experiential proofs rather than theoretical analysis [30]. The choice of the MFCC is supported by two additional empirical reasons. The first one is that the computation of the MFCC does not require pitch detection, which has been demonstrated that it is fairly robust to several kinds of voice distortion [30] [110]. The second reason is that the analysis in the cepstral domain for this application is justified by the presence of noise information in the cepstrum [30] [111] and also that MFCC technique compresses this information on the first cepstral coefficient, consequently dimensionality is reduced and the task of pattern classifiers become easier [107] [108] [112]. There is another technique which has been also used in speaker identification, called *Perceptual Linear Prediction* (PLP) and was first proposed by Hermansky (1990) [113]. This technique is similar to the conventional Linear Prediction (LP) except that it models the psychophysical properties of human hearing to estimate the auditory spectrum [113]. This was done by using three main concepts (critical-band resolution curves, the equal-loudness curve, and the intensity-loudness power-law) [113]. The advantage of PLP over conventional LP is that it keeps only the relevant information of the speech in order to improve speech recognition accuracy [113].

V. Critiques and Limitations

Voice disorders may be due to a physical problem, such as vocal nodules or polyps, which are almost like a callous on the vocal cord; paralysis of the vocal cords because of strokes or after some surgeries; or, contact ulcers on the vocal cords. These disorders may also be caused by misuse of the vocal instrument, such as using the voice at too high or low a pitch; using the voice too softly or too loudly; or, with insufficient breath support, often because of postural problems. Some dysphonia manifests as a cross between misuse and something physiological. [59].

Dysphonia in the context of neurological disorders may be caused, according to Teston [53], by multiple factors such as *hypotonia* (low muscle tone which may involve reduction in muscle strength), which causes reduced level of voice and F_0 [114]; *hypertonia* (anomalous increase of muscle tone of symptomatic muscles), which causes breaks and difficulties in the speech signal [115]; *tremor*, which causes a trembling voice [116] and instability of the F_0 during sustained phonations [117]; *Spasmodic dysphonia* (laryngeal dystonia), which causes abrupt changes in the pitch, breaks, unintelligibility and trembling voice; or, *laryngeal paralysis*, where the vocal cord remains more or less open position after a bad *neuromotor* control [53]; as a result, the voice become monotonous, blown and husky with significant air leak which cause breathlessness at the end of a sentence and discontinuities in voice [53].

The other source of dysphonia is anatomical changes in the glottis. This is due to the appearance of nodules, polyps or cysts (benign lesions of the vocal cords), which are usually caused by permanent or brutal vocal forcing. As a result, the voice becomes deeper, hoarse, and breathy [53].

These anatomical changes may be also caused by laryngitis (inflammations of all the vocal cords) and amplified by vocal forcing. As a result, the voice becomes deeper, with difficulties in high-pitches, slightly hoarse and stamped; it may even disappear completely (voice off) [53].

Finally, major anatomical changes of the glottis are caused by surgical trauma following a removal of a *cordal cancer*. As a result, the voice is severely degraded, deeper, low in intensity, but intelligible in a noise-free location. The stamp is very harsh, grainy, and blown in connection with the glottal leakage [53].

VI. CONCLUSION

This review contains a presentation of the state of the art concerning the assessments of speech disorders in the context of PD in order to distinguish PD patients from healthy people and to detect the severity of the disease. It also contains a presentation of the aspect of speech production, a discussion of the most used measurements to detect dysphonia in time, frequency and cepstral domains. A discussion of the limitations of these assessments is also included. Finally, it is concluded that there is no efficient diagnosis at the moment because all studies in literature distinguished only PD from healthy people, considering that there are big differences between them. However, the challenge is to be able to distinguish PD from other neurological and vocal disorders.

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