Glottal Flow Analysis in Parkinsonian Speech

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Abstract: Speech and vocal impairments are one of the earliest symptoms of Parkinson's disease (PD). Laryngoscope examinations have identified that patients with the disease show pathological behaviour of the vocal folds. The behaviour of the vocal folds is investigated by analysing the glottal flow waveform in Parkinsonian speech in this study. This study aims to determine the appropriate method for estimating the glottal source in PD speech and to identify glottal parameters that could be indicative of PD. An experiment was conducted to analyse a selection of glottal parameters (2 time-domain and 3 frequency-domain) measured from the glottal flow waveform estimated from speech recordings. A database of 52 healthy speakers and 44 speakers with Parkinson's disease was considered for this experiment. Two glottal estimation techniques are considered in the experiment: iterative and adaptive inverse filtering (IAIF) and quasi-closed phase (QCP) inverse filtering. The results showed that 2 of the 5 glottal parameters (1 time domain and 1 frequency domain) produced values indicating a difference between healthy and PD speech files in the database. The results also indicate that glottal estimates from the IAIF method resulted in parameters discriminating between healthy and PD higher than glottal estimates from the QCP method.

1 INTRODUCTION

Parkinson's disease (PD) is a chronic neurodegenerative disorder of the central nervous system generally observed in elderly people. It is the second most common neurodegenerative disease, after Alzheimer's, affecting an estimated 10 million people around the world, with these numbers expected to double in the next 10 years (Dorsey et al., 2007). Currently there is no cure for PD but early diagnosis and drug therapies can decrease the difficulties of the disorder and improve quality of life. This study aims to investigate the appropriate method for estimating the glottal flow in PD speech and identify glottal parameters that could be indicative of PD by analysing the behaviour of the glottal flow.

The cause of PD is attributed to the progressive loss of dopamine in the brain which is the chemical released by nerve cells to interact with other nerve cells. This interaction between nerve cells is responsible for controlling the motor and mental functions of a person, and the reduction in dopamine levels leads to PD symptoms. Typical motor symptoms observed in PD are muscular rigidity, resting tremor and slowness of movement. Along with these, many patients develop non-motor symptoms like sustained depression and memory loss. Individuals with PD experience different combinations of these symptoms at different severity levels. The muscles in the face, mouth and throat can be affected which results in problems with speech and swallowing. It is estimated that 89% of PD patients will suffer some form of vocal impairment (Logeman et al., 1978) and a vocal disorder may be one of the earliest symptoms of the disease (Harel et al, 2004). Speech related symptoms that have been reported to affect PD patients include harsh or breathy voice, reduced volume and vocal tremor. The most commonly used scale for the progression of PD is the Unified Parkinson's Disease Rating Scale (UPDRS). Employing the UPDRS is a complex and lengthy procedure which requires the subjective evaluation by a clinical expert. Analysing the speech signal in PD patients may provide a tool to help clinicians evaluate and diagnose the disease. This could provide a non-invasive method of indirectly examining the larynx which may help with further monitoring of the disease and could be performed remotely.

Previous studies of the larynx in PD patients have shown incidences of abnormalities of the vocal folds. These laryngeal dysfunctions have been observed through laryngoscope examinations where video

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frames of the vocal folds are obtained and analysed by a clinical expert. Hanson et al (1984) examined 32 PD patients and reported that 94% showed vocal fold bowing and 81% demonstrated varying degrees of asymmetry of the vocal folds. Smith et al (1995) reported that from videostroboscopic examinations of 22 patients, there was a 38% incidence of vocal-fold bowing and 67% incidence of incomplete glottal closure. Perez et al (1996) reported irregularities in the closure and vibration of the vocal folds with 50% of the patients demonstrating abnormal glottal closure and 47% demonstrating irregular vibration of the vocal folds with asymmetric behaviour. Yücetürk et al. (2002) examined 30 PD patients and reported that 70% had at least one of eight laryngeal dysfunctions with some of the patients featuring more than one. Tsuboi et al. (2015) reported that of 22 PD patients treated with subthalamic nucleus deep brain stimulation 77% showed an incidence of incomplete glottal closure and 50% showed signs of asymmetrical glottal movement.

Research is ongoing in the studies of diagnosing and monitoring PD with speech and is showing positive steps towards establishing an objective measurement of the disease (Little et al., 2009). Studies implementing advanced signal processing algorithms have shown that symptoms of PD can be predicted on the UPDRS scale remotely using non-invasive speech recordings (Tsanas et al., 2010). Speech impairments of PD patients were investigated by features such as jitter, shimmer and harmonic to noise ratio (Tsanas et al, 2012). Results obtained from these parameters showed accuracies of up to 98%. Sharma (2014) also reported jitter and shimmer showing different values, when tested on 14 PD and 7 healthy subjects. This study also reported the glottal pulse of the healthy subjects to be symmetric in nature when compared to the PD patients. The behaviour of the glottal flow in PD patients has been studied and parameters have been identified that discriminate from healthy speakers with accuracies of over 90% (Hanratty et al., 2016). Additionally, automatic detection of PD has been researched by analysing the non-linear behaviour of the vocal folds which affects the glottal flow signal with accuracies up to 78% (Belalcázar-Bolaños et al., 2016). Detection of early stages of Parkinson's disease using Mel-frequency cepstral coefficients was investigated by (Jeancolas et al., 2017), employing a detection framework similar to that used in speaker recognition and obtained results between 60% and 91%. It is difficult to compare results between studies as they have used different performance metrics on different test databases and recording protocols.

The aim of this study is to build on previous studies and contribute to the research of using speech files to aid in the diagnosis of PD. This will be achieved by analysing the behaviour of the glottal flow waveform in PD speech and identifying glottal parameters which are distinct to healthy speech. The glottal flow will be estimated from speech signals by different methods to identify which is the most applicable to extracting the glottal flow estimate in Parkinsonian speech.

The rest of this paper is organised as follows Section 1.1 describes the background on the glottal flow, glottal estimation techniques and glottal parameters. Section 2 describes the experimental procedure and details the data used in the experiment, Section 3 presents the results of the experiment, and Section 4 comprises the conclusions of the study.

1.1 Background

The glottal flow is the airflow that is generated from the lungs and then passed through the vocal folds, located in the larynx. The vocal folds vibrate which causes them to open and close periodically. This airflow is filtered by the vocal tract cavities to produce human speech (Quatieri, 2006). The glottal flow waveform is produced from this airflow and is depicted in Figure 1 (Drugman et al., 2012).

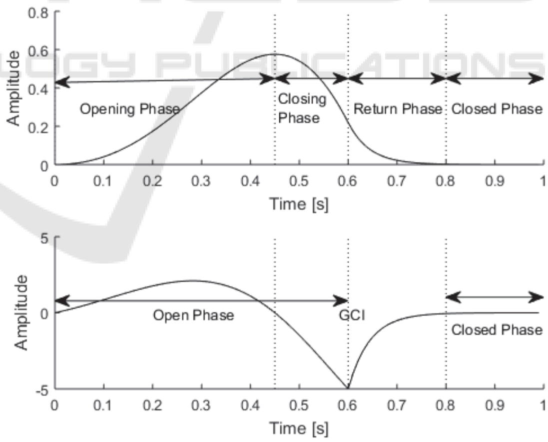

Figure 1: Glottal flow waveform (upper) and glottal flow derivative waveform (lower) with open phase and closed phase displayed.

Each period of the glottal flow waveform can be separated into three main parts, the open phase, the return phase and the closed phase. During the open phase, the air pressure gradually increases until it comes to an abrupt stop when the glottis closes, which is called the glottal closure instant (GCI; Drugman and Dutoit, 2009). In healthy speech, during the closed phase, there is no air flow through the vocal folds and the amplitude of the signal has returned to zero. The open phase of the glottal flow waveform is divided into two phases, the opening phase and the closing phase. The opening phase refers to the timespan up to the maximum positive amplitude of the glottal pulse, while the closing phase is the period after this until the GCI. After the open phase, there is a period where the waveform returns to the initial state, this is called the return phase (Drugman et al., 2012). The glottal flow can be represented as a glottal flow derivative waveform, as shown in Figure 1, as it reflects some characteristics that are not represented in the glottal flow waveform (Plumpe et al., 1999).

1.1.1 Estimating the Glottal Source

A speech signal can be represented as being made up of two main components, the glottal flow (source) and the vocal tract (filter) (Fant, 1971). Glottal inverse filtering (GIF) is a technique used to estimate the glottal flow waveform from a speech signal. The idea of GIF is to estimate a model for the vocal tract filter from a recorded speech signal and then filter the recorded signal through the inverse of this model to cancel the effects, resulting in an estimate of the glottal flow signal (Alku, 2011). Modern GIF methods can be categorised as (1) closed-phase methods (2) iterative methods and (3) spectral decomposition methods. Closed-phase methods use the closed-phase of the glottal flow signal as there is said to be less interaction from the vocal tract and it provides a more accurate model of the vocal tract, resulting in more accurate glottal estimates (Wong et al., 1979). Iterative methods utilise the whole pitch period to remove the influence of the glottal waveform and estimate the vocal tract. This vocal tract estimate is then used by inverse filtering to provide an estimate of the glottal flow (Alku, 1992). Spectral decomposition methods involve estimating the glottal flow by separating the speech by maximum and minimum phase components (Alku, 2011). All methods except iterative methods require accurate identification of glottal closure instants (GCI) and glottal opening instants (GOI; Drugman and Dutoit, 2009). Most studies when evaluating GIF methods will use synthetic speech because the glottal flow signal cannot be measured directly from the human larynx (Airaksinen, 2014). A recent study (Chien et al., 2017) has shown that closed-phase and iterative methods perform well and show stability on different voice qualities of sustained synthetic vowels, while spectral decomposition methods provided a less stable performance on the tested database. Breathy voice quality is one of the reported speech disorders of Parkinson's disease and this paper reported that

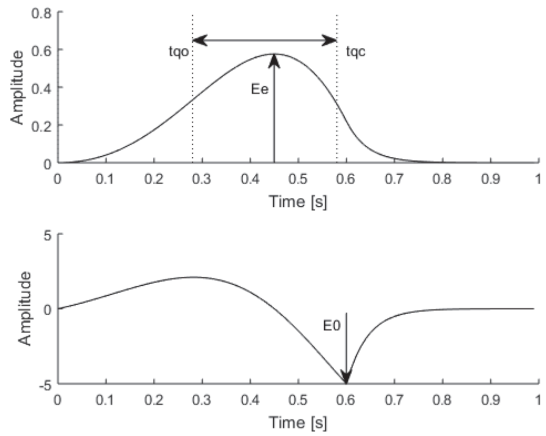

Figure 2: Glottal flow pulse (top) and glottal flow derivative pulse (bottom) with measurements for quasi-open quotient (QOQ) and normalised amplitude quotient (NAQ).

closed-phase and iterative methods display robustness on this voice quality across a number of synthetic vowels.

1.1.2 Glottal Flow Parameters

Many parametrisations of the glottal flow exist but not all are suitable for Parkinsonian speech. Parkinsonian speech is known to show harsh and breathy characteristics among other pathologies. This indicates that the glottal parameters must be robust to noise for effective measurement. This section gives an overview of the glottal parameters selected to be considered in this study.

The time-domain parameters, Quasi-open quotient (QOQ) and normalised amplitude quotient (NAQ), were selected as they are known to be robust measurements of the glottal waveform in adverse conditions. Previous studies have reported that they show potential for separating PD and healthy speech (Hanratty et al., 2016).

Quasi-open Quotient (QOQ): This parameter measures the duration of the open phase from when the amplitude of the glottal pulse crosses the 50% marker line at the point, t_{qc} until it falls below it again at t_{qo} as shown in Figure 2. The marker t_{qc} is defined as the point at which the amplitude of the glottal pulse reaches 50% of its maximum value and t_{qo} marks the point at which the glottal pulse goes below 50% of the maximum value. The timing distance between these two points is referred to as the quasi-open phase. This duration is subsequently normalised with respect to the pitch period, T_0. It was designed as a more robust version of the open quotient (OQ) (Airas, 2008; Kane,

2012) and mitigates the issue of noise corrupting the measurement of the instant of glottal opening. The formula for QOQ is displayed in Equation 1 (Hacki, 1989).

$$\mathrm{QOQ} = \frac{t_{qc} - t_{qo}}{T_0} \quad (1)$$

Normalised Amplitude Quotient (NAQ): This parameter is measured from the peak amplitude of the glottal flow, E_e, and maximum negative amplitude of the glottal flow derivative, E_0, as shown in Figure 2. This is then normalised with respect to the pitch period, T_0, as shown in Equation 2 (Alku et al., 2002). This is selected as a glottal parameter as it representative of the glottal pulse and glottal derivative pulse. It is robust to variations in recording conditions as it is normalised with respect to amplitude.

$$\mathrm{NAQ} = \frac{E_e}{E_0 T_0} \quad (2)$$

Frequency-domain parameters, H1-H2, harmonic richness factor (HRF) and parabolic spectral parameter (PSP), were selected for this study. Measurements in the glottal source spectrum give an alternative approach to the time-domain parameters and they are known to distinguish between voice qualities (Alku, 2011). Two of these glottal parameters, H1-H2 and HRF, have been tested in combination with time-domain parameters on Parkinsonian and healthy speech (Belalcázar-Bolaños et al., 2016). Discrimination between healthy speech and Parkinsonian speech was made using a Support Vector Machine (SVM) and produced accuracies of up to 78%. These parameters were selected to determine their individual performance in detecting PD.

H1-H2: This is a measure of the change in amplitudes of the first two harmonics, H1 and H2, of the differentiated glottal source spectrum (Fant, 1995). This measurement has been used as a glottal parameter as it is reported that changes in the open-quotient of the glottal cycle produce a corresponding change in H1-H2 (Doval et al., 2006). This has been used to detect different phonation types by analysing the measurement.

Harmonic Richness Factor (HRF): This spectral parameter is a measurement computed by the sum of the amplitudes of the harmonics above the fundamental harmonic. This is then normalised with respect to the first harmonic, H_1, and is shown in Equation 3 (Childers and Lee, 1991). This parameter represents the spectral tilt of the glottal flow and has been used to identify different phonation types.

$$\mathrm{HRF} = \frac{\sum_{i \geq 2} H_i}{H_1} \quad (3)$$

Parabolic Spectral Parameter (PSP): This is a measure to model frequency domain characteristics within the glottal signal. It is computed by fitting a parabola to the lower frequencies in the glottal source spectrum (Alku et al., 1997). This parameter was introduced as a robust measurement of the spectral decay in the glottal signal to detect phonation type.

2 EXPERIMENTAL PROCEDURE

The objective of this experiment was to identify the appropriate method for estimating the glottal source in Parkinsonian speech. This was completed by analysing the glottal signal from PD and healthy speech recordings using different estimation techniques and identifying parameters that behave different. These parameters would then be tested to quantify if a separation exists between PD and heathy speech.

The performance of the parameters was quantified using receiver operating characteristic (ROC) curves and the area under the ROC curve (AUC) (Fawcett, 2006). The ROC curve and AUC value quantify the performance of the glottal parameters in their task to separate between PD and healthy speech. The AUC value can range from 0 and 1 and it can be interpreted as the probability of making the correct decision on classifying a particular file correctly. An AUC value of 0.5 indicates no separation.

2.1 Data

The data used in the experiment was taken from three components to create one database, containing healthy and Parkinsonian speech files.

2.1.1 Parkinsonian Speech

The Parkinson's disease speech recordings consisted of a combination of two databases from different sources.

The first database was recorded in a quiet environment with a Zoom H2n recorder at St. Mary's Hospital in Dublin, Ireland as reported in (Hanratty et al., 2016). The signals were sampled at 44.1 kHz per channel with a 16 bit resolution. The database contains 22 Parkinson's disease patients who were asked to make a sustained sound of the vowel 'a' for as long as possible, therefore the signals are of varying durations.

The second Parkinson's disease speech database was recorded by a Trust MC-1500 microphone placed 10 cm from the speaker's lips as reported in (Sakar et al., 2013). The signals were sampled at 44.1 kHz per channel with a 16 bit resolution. The database contains 28 Parkinson's disease patients with an age range from 39 – 79 and who are suffering with the disease for 0 – 13 years. The patients recorded sustained vowels 'a' and 'o' three times with varying durations. For this study, the 'a' sounds were taken from this database to correspond with the recordings taken from the previous database.

2.1.2 Healthy Speech

The healthy speech database was obtained from (Childers, 1999). This database was recorded in a professional single-wall sound room with an Electro-Voice RE-10 cardioid microphone. The microphone was placed 15 cm from the speaker's lips and the signals were sampled at 10 kHz per channel with a 16-bit resolution. The database contains 52 subjects (25 male and 27 female) with a normal larynx and an age range from 20 – 80 years old. All subjects recorded 28 tasks which included 12 sustained different vowel sounds with a duration of approximated 2 seconds. This database also included full words and spoken sentences from the speakers. For this study, the sustained vowel 'aa' was taken from this database to be consistent with the Parkinsonian database.

2.1.3 Glottal Estimation from Database

For this experiment all speech recordings with a sustained vowel 'a' were investigated. As all speech recordings were of various durations, a window of 500ms of continuous voiced speech was extracted from the centre section of each recording. This also ensured there was no transient effects included for the glottal analysis. 5 of the 22 speech files from the source (Hanratty et al., 2016) were excluded as they did not meet the protocol for requirements of 500 ms of continuous speech. The recorded sustained vowel 'o' from the source (Sakar et al., 2013) were excluded as the 'a' recordings were only considered for this experiment. The overall database included 52 healthy speech files and 44 Parkinsonian speech files of a sustained 'a' sound from each speaker for a duration of 500ms.

For this experiment, the GIF methods chosen were closed phase methods and iterative methods as they have shown to be robust in extracting the glottal source in varying phonations. Spectral decomposition methods were not selected as they consider the closed phase of the glottal signal to be zero (Alku, 2011) and this would not be appropriate for Parkinsonian speech knowing the vocal fold disorders attributed to the disease. The closed phase technique chosen was quasi-closed phase (QCP) inverse filtering (Airaksinen et al., 2014) and the iterative method chosen was iterative and adaptive inverse filtering (IAIF) (Alku, 1992). The QCP method needs identification of GCIs and GOIs and these were computed by the SEDREAMS algorithm (Drugman and Dutoit., 2009). The glottal signal was estimated from each speech recording by both methods. Algorithms for these methods were implemented from the sources (Degottex et al., 2014; Alku et al., 2017).

For each glottal estimate from all speakers, the selected five glottal parameters were measured on every pitch period across the 500ms window. The median value of the parameter was computed to represent the value for the parameter on each file. The median value was selected to remove any outliers and to represent a true single value of one parameter from the glottal signal. This single value for each of the five glottal parameters was used to create ROC curves to show the performance of distinguishing between healthy and Parkinsonian speech. A value for the AUC and the SE was computed to illustrate the performance of the parameters. Glottal parameters were extracted twice, using the IAIF and QCP methods to indicate if one is producing a better performance.

3 RESULTS

The performance of the separation of healthy and PD speech for each parameter for the IAIF method is shown in Figure 3. This is presented as individual ROC curves for each parameter in different colours, where the dashed line represents the value 0.5. It can be seen from the curves that three of the tested glottal parameters produce a good performance; QOQ, PSP and H1-H2. The parameter QOQ shows the highest performance for separating healthy and PD speech for the IAIF method.

The performance of the separation of healthy and PD speech for each parameter for the QCP method is shown in Figure 4. This is presented as individual ROC curves for each parameter in different colours, where the dashed line represents the value 0.5. It can be seen from the graph that the performance of all the glottal parameters is slightly above the 0.5 line with no single parameter showing an excellent performance of separating PD and healthy speech.

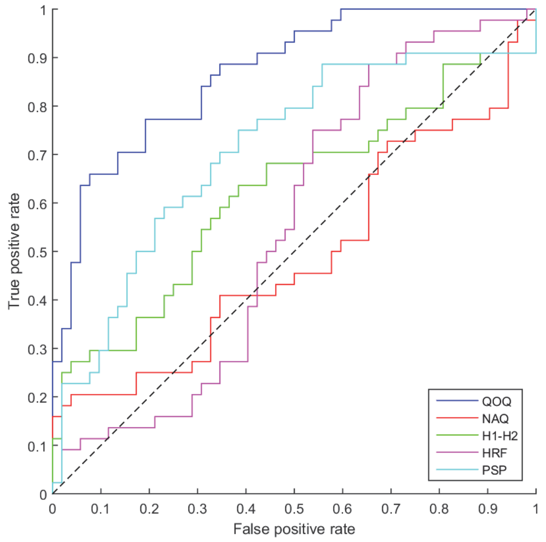

Figure 3: ROC curves for glottal parameters tested by IAIF method.

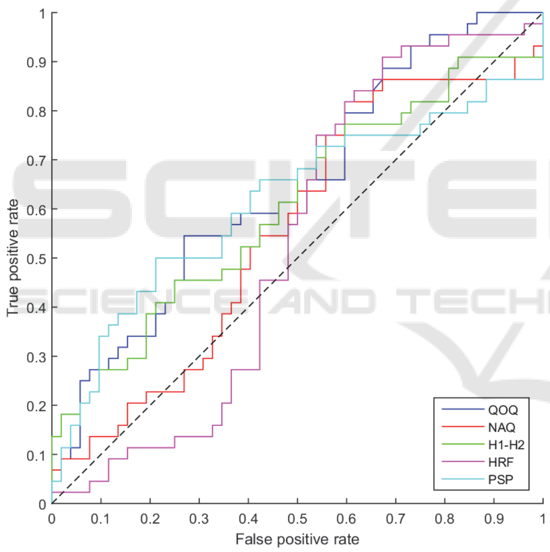

Figure 4: ROC curves for glottal parameters tested by QCP method.

The ROC curves for the glottal parameters are shown in Figure 3 and Figure 4. For further analysis of the performance, the AUC was computed for each parameter for both estimation techniques. The obtained values from this experiment are presented in Table 1. The results are presented in terms of AUC and SE, with each individual glottal parameter result from the two glottal estimation techniques, IAIF and QCP.

Table 1: Results obtained for glottal parameters tested.

Glottal Parameter	IAIF		QCP	
	AUC	SE	AUC	SE
QOQ	0.857	0.040	0.631	0.057
NAQ	0.467	0.059	0.547	0.059
H1H2	0.613	0.058	0.593	0.058
HRF	0.533	0.059	0.520	0.059
PSP	0.708	0.053	0.619	0.058

According to the results obtained from the IAIF estimation algorithm the glottal parameter, QOQ, computed an AUC value of over 0.857 which indicates this parameter was different in healthy and PD speech. PSP was found to have an AUC value exceeding 0.71 which again indicates a good separation between healthy and PD. NAQ was found to have the lowest performance for the IAIF method scoring an AUC value of 0.47 indicating this parameter could not distinguish between healthy and PD speech from this database.

The results for the QCP method show that the parameters QOQ and PSP perform the highest at separating healthy and PD speech for this technique with both obtaining AUC values exceeding 0.61. HRF has the lowest performance with an AUC value of 0.52 indicating this does not perform well at distinguishing between healthy and PD speech signals.

The performance of the two estimation techniques, IAIF and QCP, was analysed by comparing the AUC and SE values of the parameters obtained by both. The estimation technique that had higher AUC values was considered to perform better at separating healthy and Parkinsonian speech. IAIF obtained higher values for the AUC in all parameters except one, NAQ. For the parameter QOQ, IAIF scored a higher AUC value, obtaining 0.857 (SE=0.040) with QCP obtaining 0.631 (SE=0.057). The frequency domain parameter, PSP, also scored a higher value using the IAIF method. This indicates that overall, with these parameters, the IAIF method performs better at discriminating between healthy and Parkinsonian speech from the speech files in this database.

Laryngoscope studies on PD patients reported that vocal fold disorders are evident in Parkinsonian speech. It would be expected that vocal fold disorders could lead to pathological features in the glottal signal. The results found in this study suggest that the glottal flow exhibits different characteristics in Parkinsonian speech when compared with healthy speech. Hanratty et al. (2016) reported that the parameter QOQ scored a performance of over 90% at separating healthy and PD speech files when the glottal source was estimated by the IAIF method. In this study, the database was increased to include more PD speech files and QOQ still produced a high AUC value of 0.857 when distinguishing between healthy and PD.

4 CONCLUSIONS

Speech impairments are a common occurrence in PD patients and this could be related to the vocal fold abnormalities found in the patients. The results in this study indicate that different behaviour is evident in the glottal flow signal, with two glottal parameters showing separation between PD and healthy speech recordings from the test database.

The results indicate that the timing based parameter, QOQ, and the frequency domain parameter, PSP, show significant results when tasked with distinguishing between healthy and PD speech. According to the results from this experiment the estimation technique IAIF outperformed the QCP method with the selected glottal parameters. IAIF obtained higher AUC values for all parameters except one, indicating it is the appropriate method for estimating the glottal source from Parkinsonian speech

This experiment selected five glottal parameters and two glottal estimation techniques but note that many more possibilities exist that were not considered in this study. Estimating the glottal flow from speech signals can be a challenging task and is particularly difficult for pathological speech, such as that found in PD. Sources of variations exist in the test dataset, which include different recording protocols, severity of the disease in the PD group and age of participants not matched to the control group of healthy speech. Based on these critiques, there must be caution on drawing broader conclusions. Future work with an improved database with more participants will be considered to fully understand how parameters behave in the glottal flow of Parkinsonian speech.

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