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Classification of Parkinson Disease Based on Analysis and Synthesis of Voice Signal

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ABSTRACT

The most important application of voice profiling is pathological voice detection. Parkinson's disease is a chronic neurological degenerative disease affecting the central nervous system responsible for essentially progressive evolution movement disorders. Seventy to ninety percent of Parkinson's disease (PD) patients show an affected voice. This paper proposes a methodology for PD based on acoustic, glottal, physical, and electrical parameters. The results show that the acoustic parameter is more important in the case of Parkinson's disease as compared to glottal and physical parameters. The authors achieved 97.2% accuracy to differentiate Parkinson and healthy voice using jitter to pitch ratio proposed algorithm. The authors also proposed an algorithm of poles calculation of the vocal tract to find formants of the vocal tract. Further, formants are used for finding the transfer function of vocal tract filter. In the end, the authors suggested parameters of the electrical vocal tract model are also changed in the case of PD voices.

KEYWORDS

Acoustic Parameters, Electrical Circuit, Glottal Parameters, Physical Parameters, Vocal Tract Filter

1. INTRODUCTION

In multiple aspects, neurodegenerative, psychiatric and developmental disorders will adversely impact humans at all levels. Not only will these illnesses adversely affect one's quality of life, but also shorten one's average life span. Importantly, mental disabilities are often followed by a progressive deterioration of mental and physical abilities, which can in turn lead to one becoming dependent upon public-private healthcare resources, one's family and/or extended social networks for life. A key contribution of this work is towards improving the overall standards of human life and wellbeing vis-à-vis ongoing societal interactions since early detection of these devastating diseases will lessen the impact of the adverse effects, allowing timely monitoring of the evolution of these diseases.

Parkinson disease (PD) is a neurodegenerative disorder affecting predominately dopamine-producing "dopaminergic" neurons (Singh, 2007). According to World Health Organization (WHO), PD currently has 0.351 Disability Adjusted Life Years (DALYs) (Braga, 2019). Moreover, rates of PD occurrence are now expected to grow with increased life expectancy. While no cure for PD has yet been found, the quality of life for infected patients may be significantly improved with early diagnosis and interventions (Lang, 1998).Today, we know that a decrease of dopamine producing cells in the brain causes PD, but the root cause of decrease in dopamine producing cells is still unknown. The decrease in these cells affects the role of the neural activities and results in PD (Ho, 1999).

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Typical indicators of PD consist of muscular inflexibility, resting shake, postural volatility and cognitive destruction (Ramaker, 2002). PD is most common characterized by quiet voice, heaviness, slow and monotonous expression, imprecise articulation, air shortage and voice tremor. Owing to a slow initiation, delays in responses can also be observed, which can also be followed by speech rushes. During the course of the disease, there is often a reduced rate of speech and reading (Martin,2016; Sachin, 2008). Speech and voice can be studied by voice analysis and by evaluating other parameters of speech and language, such as subtle variations in voice frequencies (jitter), voice cycle-to-cycle magnitude difference (shimmer), volume (amplitude), vocal cord opening pressure, and more. More specifically, individuals affected by PD tend to have shorter average phonation time, higher jitter and glow, lower pitch range and decreased phonation threshold pressure (Chenausky, 2011).

In this article, the detection of PD via acoustic, physical, glottal parameters, frequency response of vocal tract as well as its equivalent electrical parameters is explored. In order for IJHISI readers to better understand the proposed methodologies in the context of voice pathology and detection, we present first, a method for detection and classification of PD voice based on acoustic, glottal and physical parameters, then discuss a series of details of the circuit for vocal tract filter for PD voice classification, and finally, proposed equivalent electrical circuit of vocal tract to compute its electrical parameters. The varying values of these parameters have been successfully used to classify PD affected subjects.

The remainder of this paper is organized as follows. Section 2reviewsthe extant literature related to the detection of PD. Section 3details the speech database and the proposed study methodology used to explore PD detection. Section4 describes study results and practical implications of the findings. Finally, Section 5offers a summary of the key contributions of this work, highlights potential study limitations and provides insights into future work.

2. LITERATURE REVIEW

Over the years, increasing attention has been given to studying people suffering from PD on the basis of voice and speech patterns (Rusz, 2015; Saxena, 2014). To date, about 90% of PD patients are projected to suffer speech related problems (Little, 2009). Rouzbahani & Daliri (2011) defined a technique to diagnose PD in humans using voice signals. Saloni, et al. (2016) had proposed classifying PD via local angular frequency and instantaneous deviation in the waveform. In advance-stage PD, the voice is often neither audible nor intelligible, thereby leading to deterioration in the functioning of vocal folds. To identify the effects of speech and voice disorders in PD, there are many speaking exercises that could be used. Sustained phonation, freely spoken spontaneous expression are the most traditional of these (Mittal, 2020).

It is estimated that a PD patient would have some type of speech and language impairment (Robin, 2015). Significant differences of speech can be affected, such as spoken language production (dysprosody), voice production (dysphony), and articulation (dysarthria) (e.g., Galaz, 2016;. Pawlukowska, 2015;Lirani-Silva, 2015;Sapir, 2014).Recent research has also made great progress in speech-based measures for PD, producing interesting results due to the non-invasive nature of the methods. Polat, et al. (2020),presented a novel data sampling approach for the classification of PD based on the acoustic characteristics of speech signals. Some changes in vocal cords have been described in Parkinson's associated hypokinetic dysarthria, which can be observed by direct laryngoscopy (Blumin, 2004).

Prior research has focused on emerging approaches in the detection of PD. Several studies on the prediction and classification of Parkinson's disease via different approaches have been reviewed herein. A recent simple approach based on handwriting from people with PD has been advanced in (Gupta, et al.,2020).The combination of empirical mode decomposition and neural network (NN) method used for Parkinson's disease classification has also been advocated (e.g., Zeng, et al, .2019).

Tsanas et al. (2011) proposed the Relief and *Local Learning-Base Feature Selection* (LLBFS) techniques for the detection of PD.

Other classification algorithms and smart methods have also been suggested, for example, some researchers have argued the use of prediction support tools for PD classification (e.g., Affonso, 2017; Hrelja, 2013; Ficko,2010), but accurate predictions can only be made to a certain degree (Liu,2015). Alku(2011)discussed the idea of Glottal inverse filtering (GIF) for use infitting a model for the vocal tract filter, resulting in an estimate of the glottal flow signal. (Drugman, 2012; Sakar, et al. 2013) examined various kinds of sound recordings obtained from people with PD. The extracted features have been fed into Support Vector Machine (SVM) and k-Nearest Neighbor (k-NN) classifiers for PD diagnosis via a leave-one-subject-out (LOSO) cross-validation scheme and summarized Leave-One-Out.Also, several experiments on voice recordings were originally conducted at the University of Oxford (Little,2009).Shahbakhi, et al. (2014) presented the best PD classification results at 94.50% accuracy. A method for acoustical analysis of PD speech, the classification of the extent of speech impairment with the aim of improving speech therapy success rates described by (Baasch, et al.,2016)

Some published work using Random Forest (RF) algorithm to detect PD can also be found. Vaiciukynas, et al. (2017) recommended a technique for detecting PD using RF from sustained phonations. The possibility of combining the Multi-Edit-Nearest-Neighbor (MENN) and RF techniques to identify PD was discussed by Zhang, et al. (2016). To develop a classification model, Caglar, et al. (2009) used Machine Learning Programming (MLP). The supervised learning algorithm focused at separating massive amounts of data using the hyper plane and margin concept described by (Sewell, 2017).

Another body of research work discussed the detection of healthy and pathological voices via the electrical modeling of the vocal tract (Mittal, 2019). Wee, et al. (2008) presented the first experimental integrated-circuit vocal tract can be used to generate speech. Wee, et al.(2011) described an integrated-circuit vocal tract to create speech-locked loop. A two-mass model characterizing the properties of vocal folds was explored by Yao (2013). For the classification of normal and stressed voice, he used the vocal tract to simulate speech production. Dixit (2014) examined the variations between PD patients v. normal subjects using Praat as the software for extracting features from the voice signal, taking into consideration the voice parameter analysis.

With the overall goal to detect PD via voice analysis, this study investigates the detection of PD via acoustic, physical, glottal parameters, frequency response of vocal tract as well as its equivalent electrical parameters.

3. MATERIALS AND METHOD

3.1. Sampling

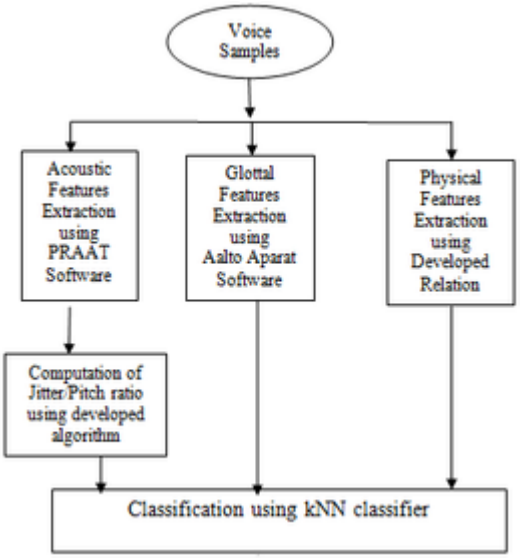
The dataset used in this work was drawn fromKing's College London (KCL) Hospital, Denmark Hill, Brixton, London SE5 9RS. KCL used a typical examination room with about ten (10) square meters area and a typical reverberation time of approximately 500ms to perform the voice recordings.

The dataset comprises phonation from 16 Parkinson and 21 control subjects. The samples were recorded with Motorola Moto G4 Smartphone using "Toggle Recording App". The recordings were done by test executor at a sampling frequency of 44.1 KHz with 16 bit resolution of spontaneous dialog with the participants. The test executor starts asking random questions about places of interest, local traffic, or personal interests, where and if acceptable. For each normal v. PD participant, the voice recordings are labeled in the following format:

SI_ HS_ HYR_ UPDRS II-5_UPDRS III-18

Where:

Figure 1. Proposed Methodology



- SI is subject identification in the form ID*NN*, *N* in [0, 9]
- HS is the health status label (Normal or PD accordingly)
- HYR is the expert assessed H&Y scale rating
- UPDRS II-5 is according to expert peer-reviewed score
- UPDRS III-18 is the according expert assessed score

3.2 Method

Figure 1 shows the proposed methodology used for PD detection.

Parameters used in proposed methodology are briefly described below.

3.2.1 Acoustic Parameters:

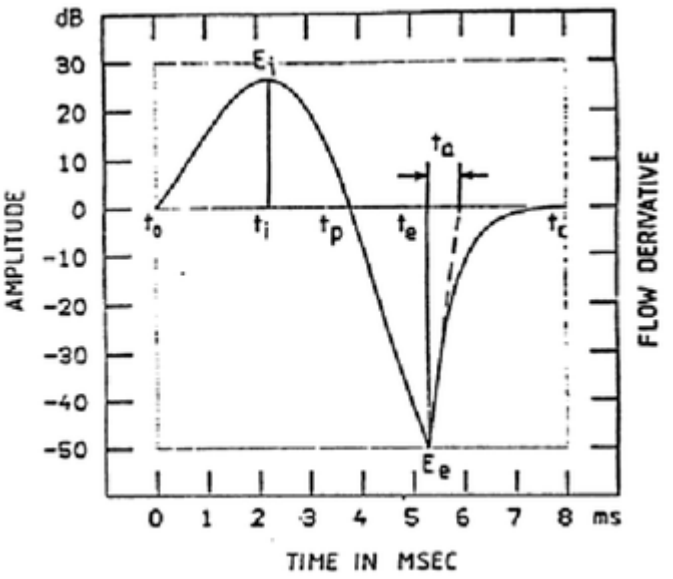
- *Pitch*: In phonetics, the "pitch" is the frequency (or harmonic height) of the lowest tone wave in voice (Forero Mendoza, 2014).
- *Jitter:* The cycle-to-cycle variance of the basic frequency, that is, the average absolute difference between successive cycles, express as a jitter(Forero Mendoza,2014).

$$\text{Jitter} = \frac{1}{N-1}\sum_{i=1}^{N-1}\left|T_i - T_{i+1}\right| \quad (1)$$

where, Ti is the i^{th}extracted F_0 period length and N is the number of extracted F_0 periods.

- *Shimmer:* Variability in decibels (dB) of peak-to-peak amplitude. The process used to evaluate the shimmer is similar to jitter, the only difference being that the jitter takes into account intervals and shimmer takes into account the full signal amplitude (Forero Mendoza,2014).

Figure 2. Waveform of Glottal Flow Derivated(Finkelhor,1988)



$$\text{Shimmer (local, dB): } = \frac{1}{N-1}\sum_{i=1}^{N-1} 20 * log\left(\frac{A_{i+1}}{A_i}\right) \tag{2}$$

where, A_i is the i^{th} extracted F_0 period amplitude.

- *Jitter to Pitch Ratio (JPR):* It is defined as ratio of Jitter to the Pitch of voice signal.

3.2.2 Glottal Parameters:

The QOQ and NAQ are often selected as the glottal parameters as they are robust to measuring noise and do not require the difficult task of estimating the glottal opening moment (Fant, 1985).

- *Normalized Amplitude Quotient(NAQ)*: The NAQ is computed as:

$$\text{NAQ}= \frac{\text{AQ}}{\text{T}} \tag{3}$$

- *Quasi Opening Quotient (QOQ):*This is defined as the time interval during which the glottal flow is 50% above the minimum flow.
- *L-F model Parameters:* The LF model is used to represent the glottal flow derivative (GFD) (Finkelhor,1988).

Typically, the four parameters are three time points $\mathbf{t_e}$, $\mathbf{t_p}$, $\mathbf{t_e}$ and one amplitude parameter $\mathbf{E_e}$. As shown in **Figure2**,$\mathbf{t_e}$ is the glottal closing instant, $\mathbf{t_a}$ is related to return phase, **tp** is positive peak of glottal flow and $\mathbf{E_e}$ is negative peak of derivative function.

3.2.3 Physical Parameters:

- *Stiffness (**k**):*

Stiffness is related to muscle tension and fundamental frequency. In the Ishizaka-Flanagan (1972) model, the standard value of m_1 can be considered to be equal to 0.125g.Moreover,Dejonckere(1984) relates m_1& m_2 and k_1 & k_2 as:

$$m_2 = \frac{m_1}{5} \text{ and } k_2 = \frac{k_1}{10} \tag{4}$$

where, $\mathbf{k_1}$is lower spring stiffness and $\mathbf{m_1}$ is lower mass. Similarly, $\mathbf{k_2}$ is upper spring stiffness and $\mathbf{m_2}$ is upper mass.

F_0, as a function of **k** and **m** can be defined as:

$$F_0 = \frac{1}{2\grave{A}}\sqrt{\frac{k}{m}} \tag{5}$$

where $k = k_1 + k_2$ and $m = m_1 + m_2$.Consequently, F_0 reduces to:

$$F_0 = \frac{1}{2\grave{A}}\sqrt{\frac{1.1k_1}{1.2m_1}} \tag{6}$$

From equation (6), $k_1$may be computed as:

$$k_1 = \frac{\left(F0*2\grave{A}\right)^2 * \left(1.2m_1\right)}{1.1} \tag{7}$$

- *Viscosity:*

Viscosity of vocal foldsmay be calculated as[38]:

$$r_1 = 2\zeta_1\sqrt{m_1 k1} r_2 = 2\zeta_2\sqrt{m_2 k_2} \tag{8}$$

where ζ_1, ζ_2 refer to damping ratios for the viscous resistances r_1 and r_2.

3.2.4 Classifier

Largely based on similarity feature, the kNN classifier is used for classification. Put simply, this classifier checks how similar any data point is to its neighboring data points, and it then classifies the objects automatically based on the principal of the computed minimum distance to the centroid (Agarwal, 2016).

4. RESULTS AND IMPLICATIONS

The acoustic, glottal and physical parameters results for every normal v. PD subject have been computed and provided in **Table 1**. In the case of a PD person's voices, it has been observed that the comparative values of *pitch* and the *fundamental frequency* are smaller whereas the *jitter* and *shimmer* values are bigger. The roughness in the voice is increased due to the increase in jitter in PD persons. An increase in shimmer means an increase in the amplitude of signal with increase inthe voice perturbation, resulting in a less clear voice in the case of PD.

Table 1. Computed values of Acoustic Parameters

Normal Subjects				Parkinson(PD) Subjects			
Pitch (Hz)	**Jitter (%)**	**Shimmer (dB)**	**(Jitter/Pitch) Ratio**	**Pitch (Hz)**	**Jitter (%)**	**Shimmer (dB)**	**(Jitter/Pitch) Ratio**
217.3	1.42	0.67	0.65	154.6	3.73	1.44	2.42
217.9	2.59	0.95	1.19	157.8	3.21	1.66	2.04
211.7	1.57	0.75	0.74	179.7	2.70	1.46	1.5
183.9	1.98	0.85	1.08	176.4	4.44	1.62	2.52
204.4	1.56	0.74	0.76	160.2	2.80	1.11	1.75
183.2	2.12	0.84	1.15	174.5	2.76	1.42	1.58
207.8	2.67	0.96	1.28	165.3	2.74	1.14	1.66
275.4	2.67	1.27	0.97	148.2	2.95	0.84	1.99
266.0	2.69	1.08	1.01	141.0	2.84	1.02	2.01
263.8	2.72	1.36	1.03	196.0	3.36	1.38	1.71
214.6	2.02	1.26	0.94	225.7	3.79	1.63	1.68
186.4	2.71	1.06	1.45	226.4	3.85	1.75	1.70
187.9	1.65	0.77	0.88	179.2	3.37	0.97	1.88
189.8	2.60	0.96	1.37	177.5	3.05	1.12	2.07
195.4	1.52	0.78	0.77	147.6	3.43	1.64	2.33
189.4	1.51	0.83	0.79				
191.5	2.59	0.71	1.35				
260.2	2.93	1.18	1.12				
254.4	1.96	0.83	0.77				
283.4	2.81	0.58	0.99				
395.8	2.52	0.62	0.63				

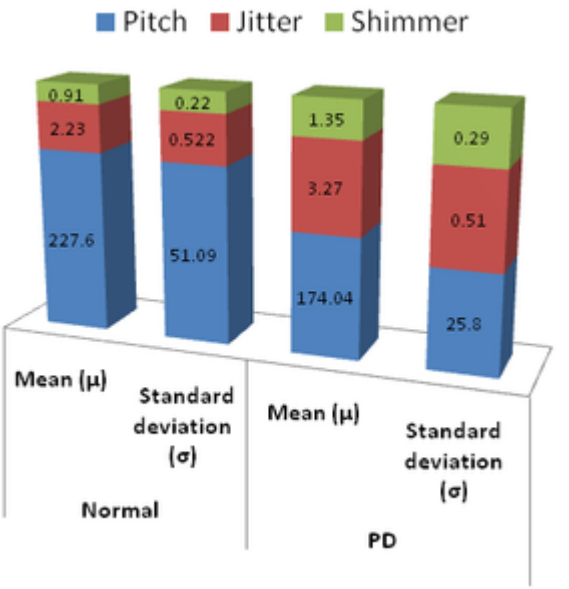
As shown in **Table 2** and **Figure 3**, mean values of shimmer and jitter tend to be bigger with the pitch being smaller in case of PD group. **Table 2** depicts the mean and standard deviation values of the acoustic parameters. The standard deviation value of shimmer is greater while the*pitch* and *jitter* are smaller in the case of the PD group.

Figure 3 shows the bar graph of mean **(μ)** and standard deviation **(σ)** values of each acoustic parameter.

Table 2. Mean and Standard Deviation of Acoustic Parameters

Acoustic Parameters	Normal		PD	
	Mean (μ)	Standard deviation (σ)	Mean (μ)	Standard deviation (σ)
Pitch	227.6	51.09	174.04	25.8
Jitter	2.23	0.522	3.27	0.51
Shimmer	0.91	0.22	1.35	0.29

Figure 3. Mean (μ) and Standard deviation (σ) of acoustic parameters



NAQ is an estimation of the duration of the glottal closing phase. It is the most effective measure for describing voice qualities. **Table 3** shows the variations of glottal parameters for normal v. PD subjects' voices.In the case of PD subjects, values of **NAQ** are higher.

An increased **NAQ** indicates a breathy phonation. The variation in the values of Quasi Opening Quotient (QOQ) quantify the glottal cycle in the case of normal v. PD subjects. In the case of PD subjects, the positive peak time(T_p) of glottal wave is large and changes the period of glottal wave. The glottal closing time (T_e)is increased in the voice of the PD subjects.

Table 4 represents the values of mean and standard deviation of glottal and LF parameters. As shown in**Figure 4**, in the case of PD subjects, the mean values of NAQ, QOQ, Tp and T_e parameters and standard deviation of T_p and T_e increased; also, from **Figure 4** and **Table 4**, it is apparent thatthe standard deviation of NAQ and QOQ decreased in the case of PD.

Table 5 shows the values of stiffness ($\mathbf{k_1}$) and viscous resistance ($\mathbf{r_1}$) in voices of normal v. PD subjects. In the case of PD subjects,the values of stiffness(k_1)and viscous resistance (r_1) are smaller.

From **Table 6** and **Figure 5**, it is apparent that the mean value of physical parameters is smaller while the standard deviation of physical parameters is bigger in the case of PD subjects.

Table 3. Computed values of glottal parameters

Normal Subjects				Parkinson(PD) Subjects			
NAQ	QOQ	T_p (ms)	T_e(ms)	NAQ	QOQ	T_p (ms)	T_e(ms)
0.08	0.17	0.89	2.53	0.18	0.45	5.53	7.58
0.06	0.38	0.006	0.01	0.15	0.58	4.43	7.01
0.11	0.23	2.17	3.36	0.08	0.28	8.05	14.8
0.09	0.32	0.01	0.02	0.051	0.16	0.09	0.21
0.07	0.29	2.28	5.01	0.09	0.49	1.45	3.39
0.05	0.24	0.03	0.03	0.12	0.34	0.021	0.027
0.02	0.09	0.01	0.04	0.11	0.45	0.09	0.12
0.21	0.60	1.15	3.50	0.13	0.49	0.07	0.11
0.07	0.31	2.79	3.86	0.23	0.58	3.61	7.81
0.14	0.55	3.47	5.38	0.12	0.20	1.67	2.27
0.14	0.42	4.94	7.15	0.17	0.49	4.72	7.00
0.04	0.34	1.96	2.97	0.15	0.30	0.03	0.13
0.07	0.39	3.18	4.44	0.10	0.40	0.04	0.06
0.04	0.12	0.28	0.53	0.15	0.42	1.31	2.74
0.07	0.17	3.86	4.86	0.08	0.49	2.54	3.88
0.05	0.30	0.001	0.002				
0.06	0.22	0.04	0.05				
0.07	0.39	0.009	0.017				
0.21	0.40	1.25	3.40				
0.08	0.21	2.49	3.66				
0.12	0.45	3.37	3.38				

Table 4. Mean and Standard Deviation of Time-based and LF-Model Glottal Parameters

Glottal Time-based and LF-Model Parameters	Normal		PD	
	Mean (μ)	Standard deviation (σ)	Mean (μ)	Standard deviation (σ)
NAQ	0.09	0.05	0.13	0.04
QOQ	0.13	0.31	0.41	0.12
T_P	1.63	1.56	2.24	2.50
T_e	2.16	2.58	3.81	4.29

4.1 Classification

The aim of KNN classifying algorithm is to automatically distinguish normal v. PD subjects via discriminatory features derived from speech signals. In order to measure the performance of each parameter in distinguishing between normal v. PD speech signals, the receiver operating characteristic (ROC) and the area under curve (AUC) were used.

Figure 4. Mean (μ) and Standard Deviation (σ) of glottal parameters

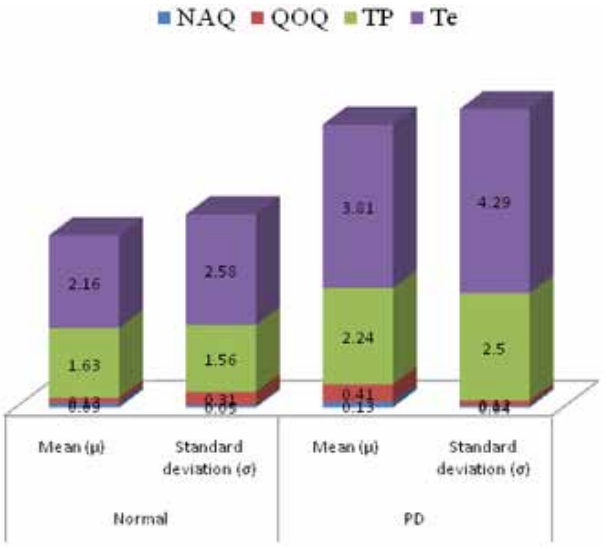


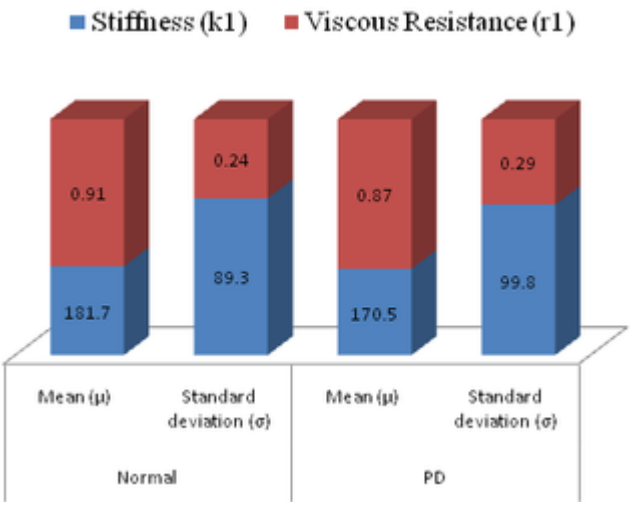
Table 5. Computed values of stiffness (k_1) and viscous resistance (r_1)

Normal Subjects			Parkinson(PD) Subjects		
Fundamental Frequency F_0 (Hz)	**Stiffness (k_1) (kdyn/cm)**	**Viscous Resistance (r_1)**	**Fundamental Frequency F_0 (Hz)**	**Stiffness (k_1) (kdyn/cm)**	**Viscous Resistance (r_1)**
180	174.2	0.93	91	44.5	0.47
183	180.1	0.94	122	80	0.63
118	74.8	0.61	62	20.6	0.32
261	223.5	1.05	142	108.4	0.73
141	106.9	0.73	251	338.8	1.3
242	314.9	1.25	229	282	1.18
267	383.3	1.38	180	174.2	0.93
242	314.9	1.25	193	200.3	1
178	170.3	0.92	116	72.3	0.6
144	111.5	0.74	228	279.5	1.18
127	86.7	0.65	121	78.7	0.62
188	190	0.97	179	172.3	0.92
136	99.4	0.70	228	279.5	1.18
234	294.4	1.21	193	183.6	0.95
73	28.6	0.37	213	243.9	1.10
191	196.1	0.99			
185	184	0.95			
174	162.8	0.90			
212	241.7	1.09			
158	134.2	0.81			
164	144.6	0.85			

Table 6. Mean and Standard deviation of Physical Parameters

Physical Parameters	Normal		PD	
	Mean (μ)	Standard deviation (σ)	Mean (μ)	Standard deviation (σ)
Stiffness (k_1) (kdyn/cm)	181.7	89.3	170.5	99.8
Viscous Resistance (r_1)	0.91	0.24	0.87	0.29

Figure 5. Mean (μ) and Standard Deviation (σ) of physical parameters



4.1.1 The Receiver Operating Characteristic (ROC):

In ROC, the false positive rate (FPR) indicates an incorrect observation by current classifier whereas the true positive rate (TPR) indicates the correct observation by the current classifier. As shown in**Table7**, the value of AUC is larger in case of acoustic parameters as compared to other parameters. Essentially, a larger AUC in acoustic parameters represents better performance for PD detection.

In order to test the classifier performance, sensitivity (SE), specificity (SP), the overall accuracy (AUC) and Matthews's correlation coefficient (MCC) are all measured (Aggarwal,2016) as follows:

$$\text{Sensitivity} = \frac{TP}{TP + FN}$$

$$\text{Specificity} = \frac{TN}{TN + FP}$$

$$\text{Overall Accuracy} = \frac{(TP + TN)}{(TP + TN + FP + FN)}$$

$$\text{MCC} = \frac{(TP * TN) - (FP * FN)}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}}$$

Table 7. Computed values of AUC for different parameters

Parameters	TPR	FPR	Area Under Curve(AUC)
Acoustic	0.95	0.07	0.93
Glottal	0.71	0.40	0.60
Physical	1	1	0.53

MCC: Matthews's correlation coefficient is **1** for perfect prediction while **0** for extremely arbitrary prediction.

Table 8 shows the comparison of kNN classifier performance for acoustic, glottal and physical parameters. Result shows 97.2% accuracy with acoustic parameters.

The next subsections describe all pole and electrical modeling of vocal tract to differentiate between normal v. PD voices.

Table 8. Performance Analysis of kNN classifier

Parameters	Sensitivity (SE)	Specificity (SP)	Overall Accuracy (AUC) in %	MCC
Acoustic	0.95	0.93	97.2	0.88
Glottal	0.71	0.70	66.7	0.31
Physical	0.58	0	58.3	0

4.2 All Pole Modeling of Vocal Tract

The acoustic tube model of vocal tract is all-pole (Ali, 2016). Using LPC modeling of the vocal tract filter, its transfer function is computed. Thereafter, with the help of the transfer function, the values of components of vocal tract filter circuit are further computed. **Table 9** shows the computed values of transfer functions and formants for each normal v. PD subject.

4.2.1 Circuit Design of vocal tract filter

The transfer function of second order filter is given as:

$$H(s) = \frac{A}{s^2 + \frac{\omega_0}{Q} s + \omega_0^2} \tag{9}$$

The unity gain sallen-key low pass circuit shown in **Figure 6**.

The transfer function of the circuit is given by:

Table 9. Computed values of formants and transfer function

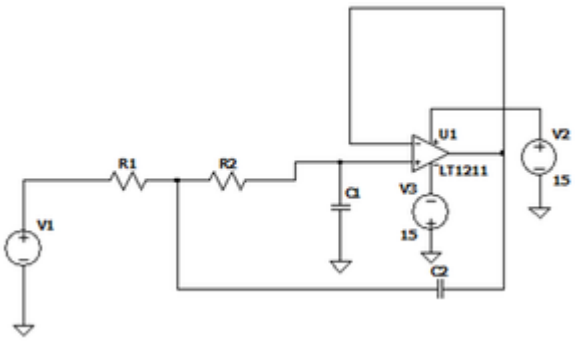
Normal Subjects				Parkinson(PD) Subjects			
F1	**F2**	**F3**	**Transfer Function H(s)**	**F1**	**F2**	**F3**	**Transfer Function H(s)**
351	9500	11420	$\frac{1}{s^2+1.322s+0.3367}$	4051	10400	12460	$\frac{1}{s^2+1.159s+0.1815}$
6435	10110	12890	$\frac{1}{s^2+0.99s+0.086}$	4484	9238	13250	$\frac{1}{s^2+1.383s+0.403}$
203	5341	9319	$\frac{1}{s^2+1.25s+0.27}$	6268	10230	13530	$\frac{1}{s^2+1.281s+0.310}$
520	6244	10040	$\frac{1}{s^2+1.096s+0.138}$	194	5599	10470	$\frac{1}{s^2+1.175s+0.175}$
502	6746	9589	$\frac{1}{s^2+1.19s+0.27}$	233	8256	8729	$\frac{1}{s^2+0.982s+0.017}$
7102	10610	14440	$\frac{1}{s^2+0.9128s+0.0137}$	425	5825	10430	$\frac{1}{s^2+1.082s+0.100}$
280	6923	10070	$\frac{1}{s^2+1.054s+0.0110}$	5646	9975	14170	$\frac{1}{s^2+0.978s+0.0137}$
5901	10230	12490	$\frac{1}{s^2+0.896s+0.119}$	2467	9381	10440	$\frac{1}{s^2+1.279s+0.297}$
594	5067	10150	$\frac{1}{s^2+1.21s+0.26}$	92	6348	8783	$\frac{1}{s^2+1.218s+0.238}$
8696	9279	12070	$\frac{1}{s^2+1.114s+0.200}$	342.2	5685	10550	$\frac{1}{s^2+1.095s+0.103}$
663	6301	9790	$\frac{1}{s^2+0.971s+0.061}$	4185	10250	13800	$\frac{1}{s^2+1.019s+0.039}$
6853	9709	14500	$\frac{1}{s^2+1.04s+0.134}$	261	6991	10380	$\frac{1}{s^2+1.129s+0.2553}$
7431	9635	12840	$\frac{1}{s^2+1.12s+0.25}$	1633	9449	13180	$\frac{1}{s^2+1.458s+0.4731}$
501	4469	9799	$\frac{1}{s^2+1.059s+0.974}$	352	5760	10150	$\frac{1}{s^2+1.143s+0.150}$

continued on next page

Table 9. Continued

Normal Subjects				Parkinson(PD) Subjects			
F1	**F2**	**F3**	**Transfer Function H(s)**	**F1**	**F2**	**F3**	**Transfer Function H(s)**
624	7309	10310	$\frac{1}{s^2+1.391s+0.435}$	253	6247	8966	$\frac{1}{s^2+1.167s+0.217}$
5918	11010	14140	$\frac{1}{s^2+0.841s+0.088}$				
395	8573	9846	$\frac{1}{s^2+1.08s+0.156}$				
7287	10720	11290	$\frac{1}{s^2+1.136s+0.1772}$				
2715	9805	12270	$\frac{1}{s^2+1.268s+0.3085}$				
4694	9725	13520	$\frac{1}{s^2+1.143s+0.172}$				
6477	10310	13700	$\frac{1}{s^2+1.002s+0.048}$				

Figure 6. Circuit for vocal tract filter



$$H(s) = \frac{\frac{1}{R^2 C_1 C_2}}{s^2 + \left(\frac{2}{RC_1}\right)s + \frac{1}{R^2 C_1 C_2}} \tag{10}$$

Comparing equations4&5

$$A = \omega_0^2 = \frac{1}{R^2 C_1 C_2} \tag{11}$$

Consider, R1=R2=R

$$C_1 = \frac{2Q}{\omega_0 R} \text{ and } C_2 = \frac{1}{2\omega_0 RQ} \tag{12}$$

Table 10 shows all the computed values of components for each normalv. PD subject obtained from the circuit as given in **Figure 6**using equations 10,11 and 12.

Viewing the computed values in **Table 11**, it is clearthat in the case of most of PD subjects, the 3-dB freuency is lower as compare to normal subjects. This means that the frequency response of the vocal tract filter is more stable at high values of frequency for normalsubjects.

4.2.2 An Electrical Analogue of the Vocal Tract

All speech sounds depend on the vocal tract configuration, glottal excitation and degree of coupling with the nasal tract. By making an electronic or electrical analogue of the vocal tract, it should be possible to synthesize its connected speech.

The vocal tract may be approximated as a cascade of short circular cylinders. The T-section electrical analogue for vocal tract is shown in **Figure 7**. The current (I) is analogous to volume velocity, inductances (L1, L2) are analogous to the inertance of air mass and capacitance(C) is analogous to the compliance of the air volume [33]. The resistance (R) represents the power dissipated in viscous friction at the tube wall, and the conductance (G) represents the power loss due to heat conduction at tube wall. Given that their values being small for the frequencies of interest, (R)and (G) may be neglected.

In the analogue, the glottis becomes a current source and current is given as:

$$i(t) = A(t)\sqrt{\frac{2P_{so}}{\rho}} \tag{13}$$

Where,

A(t) is the area of glottal opening, Pso is mean value of sub-glottal pressure and ρ is density of air.

The inductances are $L_n = \frac{\text{Á}l_n}{2kA_n}$ and the capacitances are $C_n = \frac{kl_n A_n}{\text{Á}c^2}$. The transmission line is terminated by $L_r = \frac{8\text{Á}}{3\text{À}}\sqrt{\pi A_n}$ and $R_r = \frac{128\text{Á}c}{9\pi^2 A_n}$, where A_n is the final (mouth) area.

Table 10. Computed values of components of vocal tract filter circuit for each Normal and PD subject

Normal Subjects					Parkinson(PD) Subjects				
R1(k)	**R2(k)**	**C1(nf)**	**C2(nf)**	**3dB Frequency(kHz)**	**R1(k)**	**R2(k)**	**C1(nf)**	**C2(nf)**	**3dB Frequency(kHz)**
10	10	1.8	1.8	5.6	10	10	4.7	9.8	2.4
10	10	.58	22	6.9	10	10	5.4	0.74	1.5
10	10	1.9	2.2	5.6	10	10	1.9	2	5.4
10	10	1.10	3.2	9.8	10	10	4.6	8	2.4
10	10	1.5	1.6	6.9	10	10	5	73	1.2
10	10	1.5	4.1	7.3	10	10	2.2	30	3.4
10	10	1.5	0.25	5.5	10	10	1.6	32	3.3
10	10	10	0.5	10.7	10	10	1.8	0.2	4.5
10	10	1.4	1.7	7.2	10	10	1.5	0.57	5.7
10	10	1.5	2.1	7.3	10	10	1.5	1.7	5
10	10	2.08	6.6	6.2	10	10	1.4	1.6	7.4
10	10	1.5	3.1	7.4	10	10	3.2	4	3.3
10	10	1.4	1.7	7.6	10	10	3.1	4.1	3.5
10	10	1.5	0.4	5.6	10	10	1.5	2.9	7.1
10	10	1.3	1.1	7.6	10	10	1.5	9.8	5.7
10	10	0.32	8.5	5.6					
10	10	1.8	1.6	5.5					
10	10	1.4	2.4	8					
10	10	1.4	1.4	7.2					
10	10	1.4	2.5	7.9					
10	10	1.6	9	5.8					

Table 11 shows the computed values of vocal tract length and area of each subject required for the computation of values of different components values of electrical equivalent of vocal tract.**Figure 7**. shows the equivent electrical circuit of the vocal tract.

Table 11. computed values length and area of vocal tract

Normal Subjects				Parkinson(PD) Subjects			
L1= $\frac{C}{2F2}$ (cm)	L2 = (cm) $\frac{CF2}{20\pi^2 F1^2}$	A1 (cm^2)	A2 (cm^2)	L1= $\frac{C}{2F2}$ (cm)	L2 = $\frac{CF2}{20\pi^2 F1^2}$ (cm)	A1 (cm^2)	A2 (cm^2)
1.8	13.8	0.29	0.65	1.6	0.11	0.30	0.59
1.7	0.04	0.31	0.59	1.9	0.08	0.55	0.52
3.3	23.2	0.28	0.52	1.7	0.04	0.44	0.36
2.8	4.1	0.48	0.41	3.1	26.6	0.43	0.69
2.6	4.7	0.54	0.48	2.1	27.2	0.63	0.74
1.6	0.03	1.6	1	3	5.7	1.2	1.05
2.5	15.8	0.36	0.67	1.7	0.05	0.89	0.91
1.7	0.05	0.87	0.87	1.8	0.27	0.60	0.81
3.4	2.5	0.42	0.55	2.7	30.8	0.68	0.60
1.9	0.02	0.56	0.75	3.1	8.7	10.2	2.4
2.8	2.5	0.36	0.31	1.7	0.1	0.46	0.45
1.8	0.03	0.20	0.18	2.5	18.3	0.21	0.40
1.8	0.03	0.20	0.18	1.8	0.6	0.18	0.26
3.9	3.1	0.62	0.69	3	8.3	0.65	0.62
2.4	3.3	0.81	1.03	2.8	17.4	0.37	0.58
1.6	0.05	0.43	0.60				
2.0	9.8	0.60	0.86				
1.6	0.03	0.63	0.63				
1.8	0.23	0.73	0.73				
1.8	0.04	0.60	0.67				
1.7	0.04	0.47	0.66				

Figure 7. Electrical Equivalent circuit of Vocal Tract

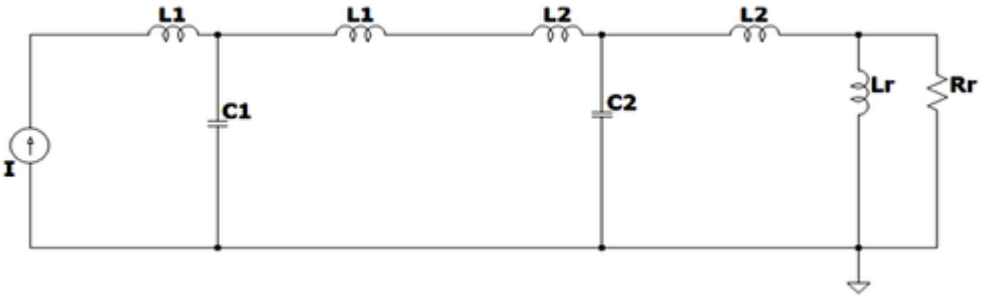


Table 12 shows the variation in component values of equivalent electrical circuit of the vocal tract for each normalv. PD subject.

Table 12. Computed values of all componets of equivalent electrical circuit for each subject

Normal Subjects						Parkinson's(PD) Subjects					
L1	**L2**	**C1**	**C2**	**Lr**	**Rr**	**L1**	**L2**	**C1**	**C2**	**Lr**	**Rr**
45.9	157	28	480	1.3	89	39.4	1.38	26	3.5	14	98
40.5	0.50	28	1.27	1.3	98	25.5	1.13	57	2.2	4.4	111
87.2	330	50	65	1.2	111	29.2	0.82	40	40	4.1	161
43.1	74	72	91	1.0	141	53.3	285	72	994	5.1	84
35.6	72.4	76	122	1.1	120	24.6	272	71	109	5.3	78
7.4	0.22	138	1.6	1.7	58	18.5	40.1	195	324	6.3	55
51.4	174	308	573	1.4	865	14.1	0.40	82	2.4	1.5	63
14.4	0.42	80	2.3	1.6	67	22.2	2.4	58	11	5.5	72
59.9	33.6	77	74	1.3	105	29.3	380	99	1.14	4.8	97
25.1	5.8	77	813	1.5	77	2.2	26.8	171	1131	9.6	24
57.5	0.32	42	42	95	187	27.3	1.64	42	86	4.1	128
66.6	3.3	19	292	72	322	88.1	338	28	14	3.9	145
66.6	3.3	19	292	1.4	322	74	17	17	8.4	3.1	223
46.5	0.49	131	115	1.4	84	34.1	99	105	278	4.8	93
21.9	1.1	105	184	4.7	56	56	222	56	547	4.7	100
27.5	0.01	52	1.6	1.3	97						
24.6	99.3	65	456	1.6	67						
18.8	0.01	54	1.02	1.4	92						
18.2	0.09	70	9.1	1.5	79						
22.2	0.01	58	1.4	1.4	86						
26.7	0.01	43	1.4	1.4	88						

5. CONCLUSION

Altogether, the current work investigates the detection techniques using the voice signals for PD. It has been successfully experimented with an understanding that the acoustic parameters are more effective in PD detection to present 97.2% accuracy with pitch/jitter ratio for the detection of Parkinson disease. As well, the authors argued for all pole filter model &equivalent electrical model of vocal tract design for detecting voices. Synthesized vocal tract filter results shows that in the case of PD subjects, the 3-dB frequency response is lower as compared to normal subjects. It is remarkably concluded that changing values of the components of equivalent electrical model of vocal tract have proved equally effective in the detction of PD.

Notwithstanding, several limitations should be noted. First, although KCL Hospital database may be comprehensive in terms of the number of people being recorded; still, the gender imbalance in the dataset should be reconciled in future research to yield more reliable and meaningful results. Second, the quantity of data needed can be a challenge to this sort of research, requiring excessive computational power and simplification. Finally, we did not conduct our experiments separately on split subsets of data for the different genders, which may yield other interesting findings.

Future research will involve the collection of more data and improvements on the feature selection strategy sothat an objective analysis tool may be designed for clinical practice.As well, the detection of PD can be effectively improved with possible combination of emerging methodologies and technologies by performing sound analysis.

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