

Detection & Classification of Voice Pathology using Electrical Circuit Parameters

Vikas Mittal, R. K. Sharma



ABSTRACT--- *The classification of pathological voice is a hot topic that has been expected significant consideration. Voice pathology is related with a vocal folds difficulty, and for this reason, the vocal tract area which is joined to vocal folds demonstrate random patterns in case of a pathological voice. This random pattern is considered to distinguish healthy and pathological voices. It is possible to utilize transmission line theory in discovering automatic voice pathology detection by taking into consideration the vocal tract as acoustic lines. The work concentrates on developing a feature extraction for detecting and classifying vocal fold polyp by investigating different vocal tract parameters. In this paper, the vocal tract length and area are utilized for computing electrical parameters of the vocal tract. Furthermore, these electrical parameters are used for the classification of pathological voice. Finally, using electrical parameters 97.3% accuracy is obtained with SVM classifier when compared with 88.2% with the acoustic parameters, 85.3% accuracy considering physical parameters and other methods used in the past. The outcomes demonstrate that electrical parameters of the vocal tract can be utilized all the more successfully with better precision in voice pathology identification.*

Keywords—Voice Pathology Detection (VPD), Vocal Tract Area, Vocal tract length, Support Vector Machine (SVM).

I. INTRODUCTION

Voice pathology detection system is used to find the pathology in the vocal folds from an information voice. The results can be subjective or objective. In subjected finding, an expert physician hears the voice and review whether the voice is usual or pathological dependent on his or her past information and knowledge. Be that as it may, this sort of appraisal may alter from doctor to doctor dependent upon the experience [2]. In this way, objective assessment of voice pathology is increasing more consideration. Lieberman proposed one of the principal acoustic voice parameters in obsessive voice examination in 1961 [3]. Voice displeasure and quality measures, for example, jitter (pitch irritation) and shimmer (amplitude changes),

rely upon precise extraction of essential recurrence and the amplitude of different waveform types. Notwithstanding, estimating principal recurrence (F0) is an exceptionally troublesome task; particularly on account of pathological voice [4]. A large portion of the work in voice pathology identification depends on the estimation of a continued vowel, especially, /a/sound, expressed by the subject/a/ is easy to speak for a patient with voice pathology; its formants are plainly recognizable, and crests are noticeable. These three traits of the supported /a/settle on it a justifiable choice for voice pathology identification [5]. Vasilakis and Stylianou built up a strategy and achieved 94.82 % accuracy [8]. Voice pathology finding is so far an open test. A patient with vocal folds polyps may express their voice as ruthless, croaky or rough. A vocal fold polyp prevents proper closing and opening of the fold while pronouncing a vowel sound. In proposed work, electrical circuit parameters of two tube vocal tract based on transmission line theory demonstrate that adjustments in electrical impedances concerning reactance as change in the physical parameters due to vocal cord disorder will help for detection of healthy and pathological subjects. This paper is prepared as follows. Section II describes the materials and methods used for this work. Section III Comprises results and discussion. Section IV provides some brief concluding remarks.

II. MATERIALS & METHODS

The proposed Voice Pathology Detection (VPD) method demonstrated in figure 1 comprises of four parts, which are voice database, physical parameters (length and vocal tract area), Electrical modeling of vocal tract and classification. With the help of vocal tract area and length of vocal tract, we calculated electrical parameters for making electrical model of vocal tract, A support vector machine (SVM) classifier decide whether the information voice is normal or pathological. Tube area and length are having a mathematical relation with the impedances of vocal tract which is analogous to a section of transmission line.

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* Correspondence Author

Vikas Mittal*, Ph.D. Scholar, School of VLSI Design and Embedded Systems, NIT, Kurukshetra, Haryana, India
(Email: vikasmittal2k7@gmail.com)

R.K. Sharma, Professor, Department of Electronics and Communication Engineering, NIT, Kurukshetra, Haryana, India.
(Email: mail2drks@gmail.com)

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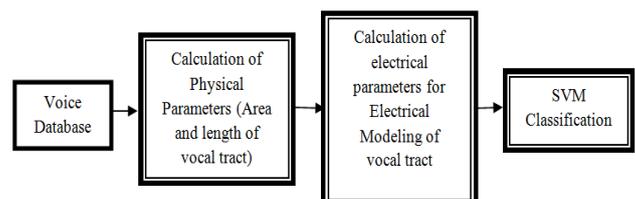


Figure 1: Blocks of proposed methodology .



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The description of each block is given below:

(A) Voice Database

To demonstrate the proposed work, we utilized the German database, Saarbrücken Voice Database (SVD)[23]. For our experiments, only files with the sustained vowel /a/ produced at neutral pitch belonged to vocal folds polyps vocal disorder 55 samples and healthy 20 voice samples of people older than age 30 were used. The other part of voice database obtained from MMIMSR, Mullana hospital. These 10 voice samples belong to patients having vocal fold polyps. The samples were recorded using Sony ICD –PX 333 Digital voice recorder.

Table 1 shows the distribution of a database used for analysis.

Table 1: Distribution of database

	Number of speakers		Age (in years)
	Male	Female	
Normal(healthy)	10	10	30 to 79
Pathological (Polyps) SVD	25	20	30 to 79
Pathological (polyps) MMIMSR	5	5	30 to 79

(B) Vocal Tract Tube length calculation:

Vocal tract length is calculated with the help of equations proposed by Kunwoo Kim [24].

(C) Vocal tract tube area calculation:

The vocal tract area is calculated using Levinson-Durbin recursive algorithm as follows [32]:

The vocal tract area of the m-th tube can be found using Eq. (1).

$$A_{M+1} = 1, \\ A_m = A_{m+1} \times \frac{1+k_m}{1-k_m}, \text{ for } m=M, \dots, 2, 1 \quad (1)$$

The vocal tract areas of m number of tubes are determined for each voice recorded.

(D) Electrical model of vocal tract:

A uniform tube-shaped section of vocal tract is practically equivalent to a segment of the transmission line [30]. The T-segment of impedances appeared in figure 2 shows one section of vocal tract and described by Eqs. (2) to (5). These impedances are quite independent of how the line segment is ended at either end.

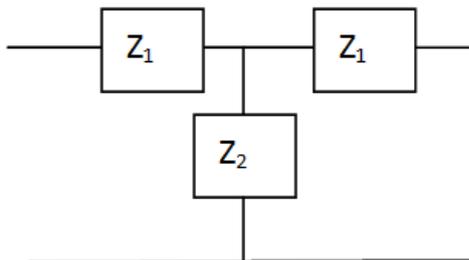


Figure 2: A cylindrical section of vocal tract represented by T-section of impedances [30].

$$Z_1 = Z_0 \tanh\left(\frac{\Gamma l}{2}\right), \quad (2)$$

$$Z_2 = Z_0 \operatorname{csch} \Gamma l, \quad (3)$$

$$Z_0 = \left(\frac{R+j\omega L}{G+j\omega C}\right)^{1/2}, \quad (4)$$

$$\Gamma = [(R + j\omega L)(G + j\omega C)]^{1/2} \quad (5)$$

In these equations l is the length of the section, ω is 2π times the frequency, and j is the imaginary unit, while R , L , G and C are, respectively, the distributed resistance, inductance, “leakance,” and capacitance, each per unit of length of the line. Z_0 is called the characteristic impedance of the line, and Γ the propagation constant. R and G are dissipative terms, representing in the acoustical case the viscous resistance and the absorption of energy by the wall of the cylinder. We will neglect both of them, with confidence that this will not greatly change the frequency position of the resonances. The acoustical equivalents of L and C are given by

$$L = \frac{\rho}{A}, \quad C = \frac{A}{\rho c^2}, \quad (6)$$

where, ρ is the density of air is given by $1.14 \times 10^{-3} \text{ g/cm}^3$, c is the velocity of sound given by $3.53 \times 10^4 \text{ cm/sec}$, and A is the area of cross section of the cylinder. Making these omissions and substitutions,

$$Z_0 \approx \frac{\rho c}{A}, \quad \Gamma \approx \frac{j\omega}{c}, \quad (7)$$

$$Z_1 \approx \left(\frac{\rho c}{A}\right) \tanh j\left(\frac{\omega l}{2c}\right) = j\left(\frac{\rho c}{A}\right) \tan\left(\frac{\omega l}{2c}\right), \quad (8)$$

$$Z_2 \approx \left(\frac{\rho c}{A}\right) \operatorname{csch} j\left(\frac{\omega l}{2c}\right) = -j\left(\frac{\rho c}{A}\right) \operatorname{csc}\left(\frac{\omega l}{2c}\right) \quad (9)$$

The reduction to circular functions was made possible by neglecting R and G . The impedances are reduced to reactances, we shall write:

$$X_1 = \left(\frac{\rho c}{A}\right) \tan\left(\frac{\omega l}{2c}\right), \quad X_2 = \left(\frac{\rho c}{A}\right) \operatorname{csc}\left(\frac{\omega l}{2c}\right), \quad (10)$$

$$Z_1 = jX_1, \quad Z_2 = -jX_2 \quad (11)$$

III. RESULTS AND DISCUSSION

(A) Analysis using Acoustic Parameters:

This paper presents analysis of few important set of acoustic parameters like fundamental frequency (F_0), Formants specially first two F_1 , F_2 over healthy and Pathological (vocal fold polyps) subjects. The Table 2 shows confusion matrix obtained after acoustic parameters analysis.

Table 2: Confusion matrix for acoustic parameters

True Class	Vocal Folds Polyps	50	5
	Healthy	6	14
		Vocal Folds Polyps	Healthy

(B) Analysis using Physical Parameters:

Some of the physical parameters characterizing the vocal tract are estimated in this work. We propose two parameters vocal tract length and cross-sectional area of the of vocal tract. The Table 3 shows the classification accuracy of 85.3 % is obtained with SVM classifier for the same input voice samples of healthy and pathological voices.

Table 3: Confusion matrix for physical parameters

True Class	Vocal Folds Polyps	53	2
	Healthy	7	14
		Vocal Folds Polyps	Healthy

C) Analysis using Electrical Parameters :

In proposed work, we consider the electrical analog of two tube of vocal tract for the classification of voice pathology. The table 4 show the confusion matrix of electrical parameters analysis for the classification of healthy and pathological voice using SVM classifier. The classification accuracy of 97.3 % is obtained with SVM classifier from same input voice samples of healthy and pathological voices. The result shows that Electrical parameters of vocal tract reflect more accurately about the vocal cord disease. The Electrical parameters of vocal tract are more important as to physical and acoustic parameters in the case of vocal cord disorder detection.

Table 4: Confusion matrix for Electrical parameters

True Class	Vocal Folds Polyps	53	2
	Healthy	0	20
		Vocal Folds Polyps	Healthy

In categorize to test the classifier performance, numerous procedures specifically; sensitivity (SE), specificity (SP) and the overall accuracy (AUC) are measured. These measures are calculated as of true positive (TP), true negative (TN), false positive (FP), false negative (FN) are presented [36].

Where,

$$\text{Sensitivity} = \frac{TP}{TP+FN} \times 100$$

$$\text{Specificity} = \frac{TN}{TN+FP} \times 100$$

$$\text{Overall Accuracy} = \frac{(TP+TN)}{(TP+TN+FP+FN)} \times 100$$

Table 5 shows the comparison of classifier performance with the analysis of acoustic, physical and electrical parameters. The performance of proposed electrical parameters obtained in Table 5 is better as compared to other parameters for the voice pathology classification.

Table 5: Comparison of Classifier Performance

Sr. No.	Parameters	Sensitivity (SE)	Specificity (SP)	Overall Accuracy (AUC)
1	Acoustic	88.3	87.5	88.1
2	Physical	89.2	73.6	85.3
3	Electrical	100	90	97.3

Performance comparison of the projected technique with other related techniques with overall accuracy given in table 5. Using SVD subset, the proposed electrical parameters of two tube vocal tract calculated and SVM classification

method for voice pathology detection performed better than the methods described in table 6.

Table 6: Performance Comparison of different methods

Sr. No.	Methods	Overall Accuracy (AUC)
1.	Proposed, electrical parameters of two tube vocal tract	97.3%
2.	J.I. Godino-Liorente et al., 2006 suggested short-term cepstral parameters method.	94.7%
3.	S.C. Costa et al., 2008 recommended parameteric cepstral analysis method.	90%
4.	Vasilakis and Stylianou , 2009 developed a method for short-time jitter and found the area under curve.	94.82%
5.	In the study of Arjmandi et al., 2010 recommended LDA method.	94.26%
6.	Markaki and Stylianou, 2011 suggested a modulation spectra method.	96.26%
7.	Martinez D et al., 2012 recommended MFCC and some other noise measurements method.	81%

IV. CONCLUSION

The investigate work obtainable in this text has successfully obtained classification of healthy and pathological voices with electrical parameters of vocal tract. SVM classifier has been used for classification and to compare performance of classification of electrical parameters with acoustic and physical parameters. The results show that Electrical model parameters are more important to discriminate pathologies of the vocal cord. Although the dataset used in this work included persons of different genders and ages, yet the results shows the accuracy of 97.3% with electrical modeling parameters which is better than other methods.

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