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Perturbation analysis using a moving window for disordered voices

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Abstract— Voices from patients with voice disordered tend to be less periodic and contain larger perturbations. These perturbations are distributed randomly in the voice sample; therefore, the selection of a particular segment for analysis is extremely important. In this study we examine the potential of using a moving window to identify areas of minimum perturbation. This method allows for a standard method to select samples and may extend perturbation analysis to more disordered voices. A moving window 0.5 seconds in length was shifted through the sample by moving forward at 25 millisecond increments. Prior to analysis, voices were typed according to the guidelines proposed by Titze in 1995. Additionally, we added a category of type 4 voices which were considered primarily stochastic. Type 1, 2 and nearly all type 3 voices showed areas of stability where perturbation analysis was deemed valid. The type 4 signals did not have segments where the reliability measures indicated perturbation results were valid. Significant differences in the perturbation measures of the voice types were preserved after moving window segment selection. The moving window method allows the objective identification of low perturbation areas in type 1, 2 and some type 3 signals. This allows perturbation analysis to be extended to these more disordered samples. The moving window method may improve the reliability of perturbation analysis particularly for disordered voices.

Index Terms— Sample selection method, moving window, signal typing, perturbation analysis

I. INTRODUCTION

A considerable number of studies have applied acoustic analysis, including perturbation measures of jitter, shimmer, and signal to noise ratio (SNR), to voices of patients with laryngeal pathologies [1]-[4]. Many acoustic parameters are based perturbations of the fundamental frequency; therefore, a reliable pitch detection algorithm is essential [5]-[7]. Increasingly dysphonic voices exhibit irregular or a periodic waveforms leading to elevated and unstable perturbation values [8]-[11]. In a 1995 summary statement from the National Center for Voice and Speech workshop on acoustic analysis, Titze proposed that signals should be categorized as type 1, 2, or 3 according to their periodicity [4]. In his system, type 1 signals were nearly periodic and therefore suitable for perturbation analysis, type 2 signals contained strong modulations or sub-harmonics and type 3 signals were irregular and aperiodic. Type 2 and 3 voices were considered unsuitable for acoustic analysis [12]. Owing to the increased interest in nonlinear acoustic analysis we recently proposed the addition of a fourth type of voice to Titze's classification scheme [13]. The type 4 signal is primarily stochastic in behavior and is therefore unsuitable for both perturbation and nonlinear dynamic analysis.

Regardless of the voice type, the stability of sample varies over the duration of a single utterance [2]. Variability in the sample makes the method of selecting a segment for analysis vitally important to the outcome of acoustic analysis. Although the general consensus is to avoid the negative effects of onset and offset of phonation, the location and length of the selected segment varies and results in different perturbation values among studies [3], [4], [11], [14]-[17]. Many researchers select a portion of the voice signal visually deemed to be most stable. By selecting a portion of the sample that appears most stable, researchers can eliminate some of the characteristics of type 2 and 3 voices that preclude them from acoustic analysis. Visual selection often focuses on amplitude variability; however, frequency may vary independent of amplitude and samples selected using this method may not represent the most stable section of the sample with regard to frequency.

In this study, we propose the moving window method as an objective and reliable method of sample selection. The moving window employed in this study was 0.5 seconds in length and was shifted forward by 0.025 second increments. We suggest the use of the moving window to extend perturbation analysis to a larger subset of pathological voices by identifying areas of type 2, 3 or 4 voices that are suitable for acoustic analysis. We investigate the impact of the moving window on perturbation measures generated from these voice samples and evaluate the presence of areas of transient stability in type 1, 2, 3 and 4 voice signals.



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II. MATERIALS AND METHODS

A. Database

The voice samples examined in this study were selected from the Disordered Voice Database, model 4337, version 1.03 (Kay Elemetrics Corporation, Lincoln Park, NJ), developed by the Massachusetts Eye and Ear Infirmary Voice and Speech Lab (Kay Elemetrics Corp., 1993) [18]. Sustained /a/ phonations were recorded at a sampling rate of 44.1 kHz. Voice files excluded onset and offset and ranged from 0.8 to 1.3 seconds in length. 32 pathological voices (21 women and 11 men) were randomly selected. Subject characteristics are shown in Table I.

B. Signal typing

Signal typing was conducted by a group of 3 trained speech language pathologists. Narrow band spectrograms were generated using the Praat software version 5.1.02 (P. Boersma and D. Weenink, 2009, Amsterdam, Netherlands). Spectrograms were created with a window length of 50 milliseconds, a time step of 0.002 seconds, a frequency step of 5Hz, and a dynamic range of 40dB. A hamming window shape was used to generate the spectrograms.

Figure 1 shows spectrograms generated from voice data classified as type 1, 2, 3, and 4, respectively. In the spectrograms, type 1 signals showed clearly defined, nearly straight harmonics of a variable number and spacing. Noise between harmonics was minimal in type 1 voices and the signal was nearly periodic. For type 2 signals, noise between the harmonics formed clearly defined sub harmonics. In some cases modulations caused the harmonics to appear wavy. Areas of sub harmonics or modulations were often transient. Type 3 signals showed a smearing of energy across multiple harmonics. Although the fundamental frequency was often apparent, strong modulations were evident and higher harmonics could not be distinguished. Type 4 signals were characterized by an absence of harmonics and diffuse energy spanning the range of frequencies displayed.

C. Data analysis

Percent jitter, percent shimmer, and SNR were obtained using the TF32 software (P. Milenkovic, 2001, Madison, WI) [19]. The reliability of jitter, shimmer, and SNR was assessed using the TF32 generated values of “Trk” and “Err”. The “Trk” count provides an indication of the number of dramatic fluctuations in pitch, while “Err” quantifies the number of probably voice breaks in the sample [19]. As breaks in voicing may exaggerate jitter and shimmer values and diminish SNR, a large “Err” is an indication that a sample is ill-suited for acoustic analysis. In this study, an “Err” value of less than 10 was used to indicate a sample suitable for perturbation analysis. A window of 0.5 seconds was used and was shifted forward in 0.025 second increments across the duration of the signal as shown in Figure 2. Perturbation measures were calculated in each window frame.

D. Statistical analysis

Statistical analyses were conducted using SPSS 12.0 software. One-way repeated measure ANOVAs on ranks were performed to test differences among type 1, 2, and 3 voices for each parameter of interest. All of the type 4 and two of the type 3 voices were not included because the “Err” value was greater than 10 for all segments. An alpha of 0.05 was employed for all comparisons. Multiple pair wise comparisons were conducted with the Turkey method and an adjusted alpha of 0.017 ($p=0.05/3$)

Table I. Summary of subject information

Subject	Sex	Age (years)	Diagnosis	Signal Type
1	F	18	Vocal fold edema	1
2	F	39	Abnormal vocal process	1
3	M	29	Vocal fold polyp	1
4	F	18	Vocal nodules	1
5	F	25	Vocal nodules	1
6	F	24	Vocal fold edema	1
7	F	21	Nodular swelling	1
8	F	34	Vocal nodules	1
9	F	25	Vocal fold edema	2
10	F	25	Vocal fold edema	2
11	F	31	Polypoid degeneration	2

12	M	40	Scarring	2
13	F	38	Keratosi / leukoplakia	2
14	M	38	Bowing / sulcus vocalis	2
15	M	42	Keratosi / leukoplakia	2
16	F	42	Vocal fold edema	2
17	F	50	Chronic laryngitis	3
18	F	61	Vocal fold polyp	3
19	F	75	Parkinson's disease	3
20	F	43	Polypoid degeneration	3
21	M	76	Vocal fold polyp	3
22	F	65	Vocal fold polyp	3
23	M	39	Keratosi / leukoplakia	3
24	F	32	Paralysis	3
25	M	69	Paralysis	4
26	M	49	Paralysis	4
27	M	53	Paralysis	4
28	M	52	Paralysis	4
29	F	38	Spasmodic dysphonia	4
30	F	40	Generalized edema of larynx	4
31	F	47	Keratosi / leukoplakia	4
32	M	29	Papilloma	4

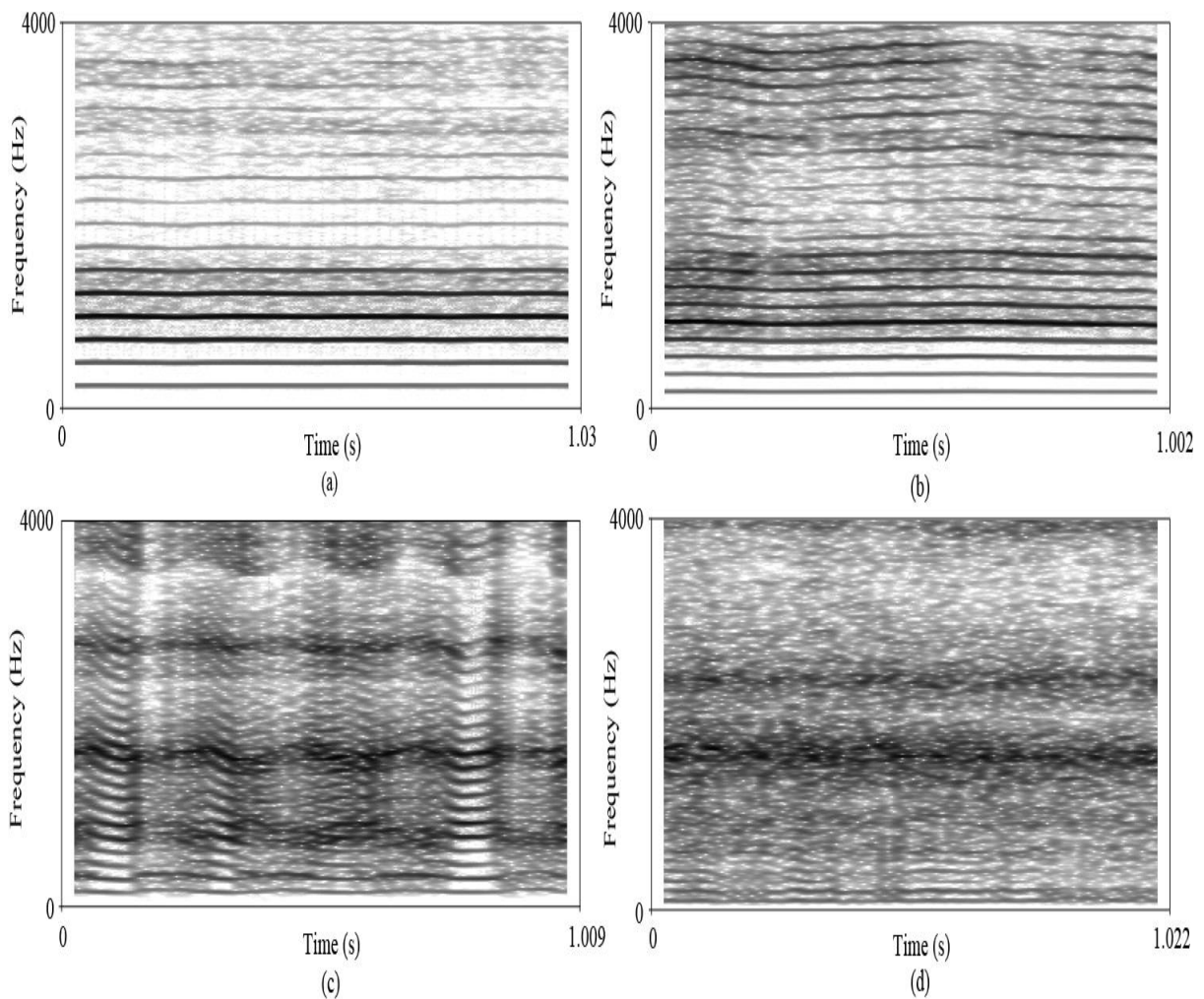


Fig 1. Spectrograms generated from voice data. (a), (b), (c), and (d) are classified as type 1, 2, 3, and 4, respectively.



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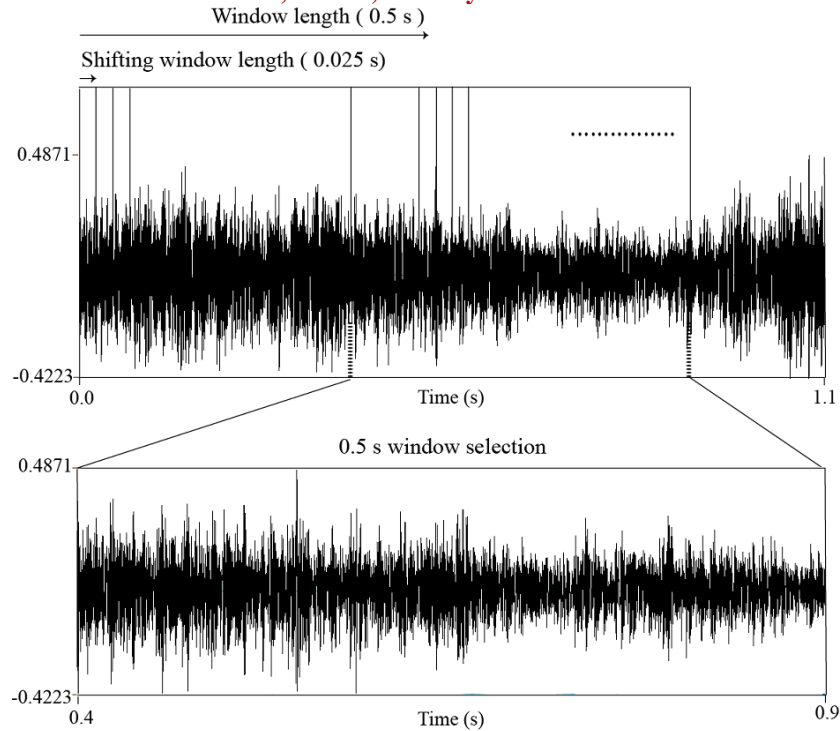


Fig 2. Selection of windows for the moving window method

III. RESULTS

Figure 3 shows “Trk” and “Err” estimated from the whole phonation. Both “Trk” and “Err” values increased dramatically from type 1 through type 4 voices. Using our pre defined cutoff of an “Err” less than 10, only type 1 and type 2 voices were appropriate for acoustic analysis.

Figure 4 shows the results of the moving window technique applied to the type 1 voices. The “Err” values were 0 in all frames. In most of the type 1 signals, perturbation parameters were stable across all frames; however, in some subjects these values changed depending on the location of the window. Table II shows the minimum perturbation values and their location for each voice signal. For type 1 voices, most samples achieved minimum values for the three parameters in similar places; however, even in type 1 signals, the location of minimum perturbation varied between subjects.

Figure 5 shows “Err”, percent jitter, percent shimmer, and SNR values calculated via moving window for the type 2 signals. Although all “Err” values for the type 2 signals were less than 10, perturbation measures appear slightly more unstable between frames as compared to the type 1 signals. In Table II, variation in the time points of the minimum perturbation measures, both between different parameters and between different individuals is evident. While “Err” values taken from the whole sample for type 3 signals were greater than our cutoff of 10 (Figure 3), moving window analysis detected areas where this value dropped below 10 and the segment could be used for acoustic analysis. Figure 6 shows “Err”, percent jitter, percent shimmer, and SNR values for the type 3 voices. Compared to type 1 and 2 signals, the type 3 signals showed abrupt changes in perturbation parameters between frames. Transient areas of stability were enough to generate minimum values for these perturbation measures and, as a rule, the locations of minimum perturbation corresponded to areas with “Err” less than 10. Minimum perturbation parameters are reported in Table II. In most of the type 3 signals, the locations of minimum perturbation varied for each of the parameters. In voices where “Err” was above 10 in all frames, perturbation analysis was not completed as was the case for two of the type 3 voices included (Table II).



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As seen in Figure 3, “Err” values for type 4 signals were well above 10. As can be seen in Figure 7, “Err” remained above 10 for all time points in all samples and the perturbation values were highly variable. Using our cutoff “Err” value, no segments were suitable for perturbation analysis; therefore, minimums were not reported and further analysis was not completed.

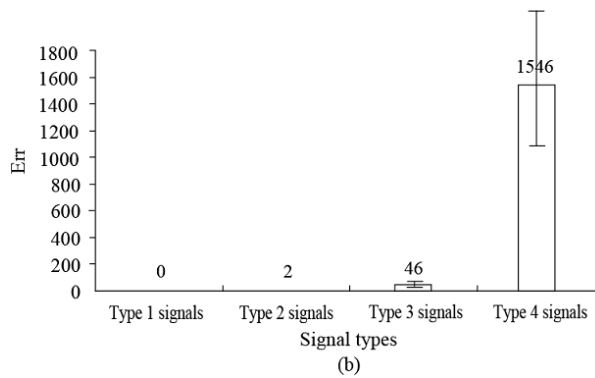
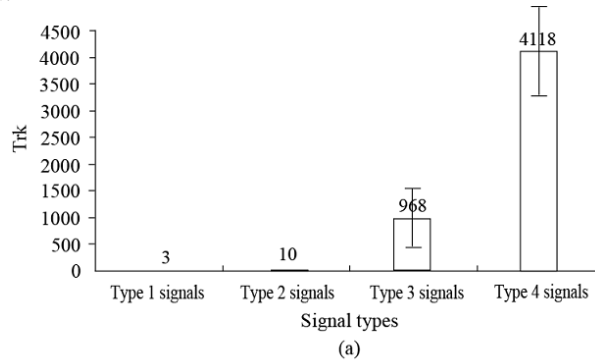


Fig 3. “Trk” and “Err” estimated from the whole phonation for each voice type.

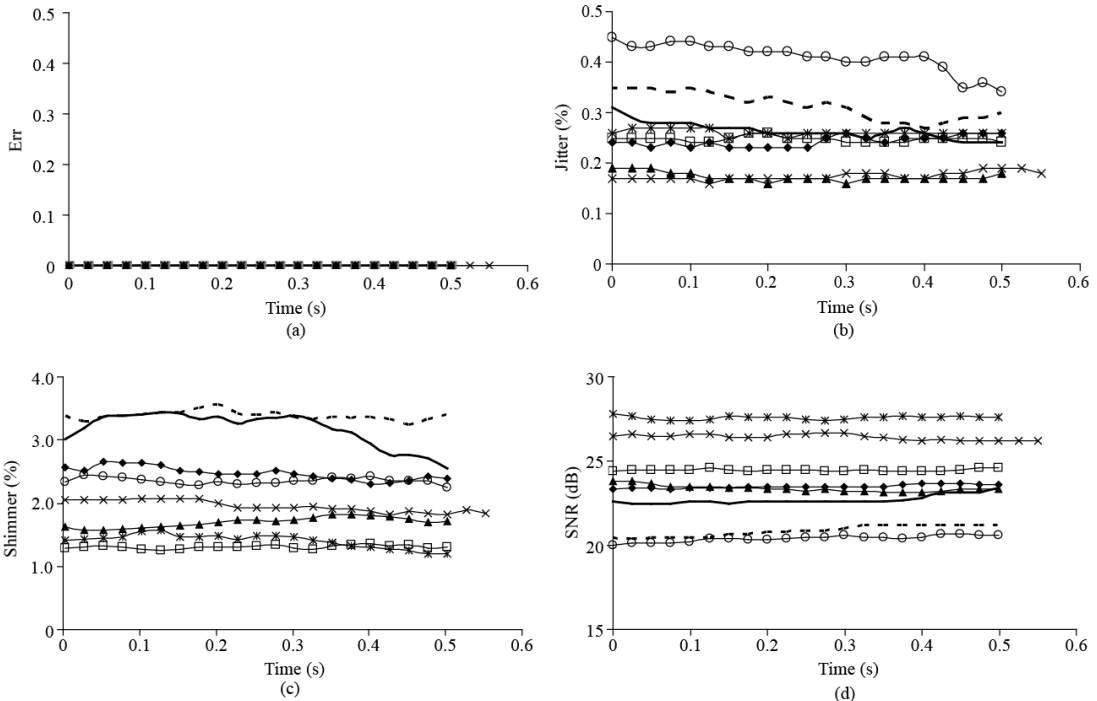


Fig 4. “Err”, percent jitter, percent shimmer and SNR values generated using the moving window method for type 1 voices. (.... : subject1, —□— : Subject 2, —*— : subject 3, —x— : subject 4, —○— : subject 5, — : subject 6, —◆— : subject 7, —▲— : subject 8)

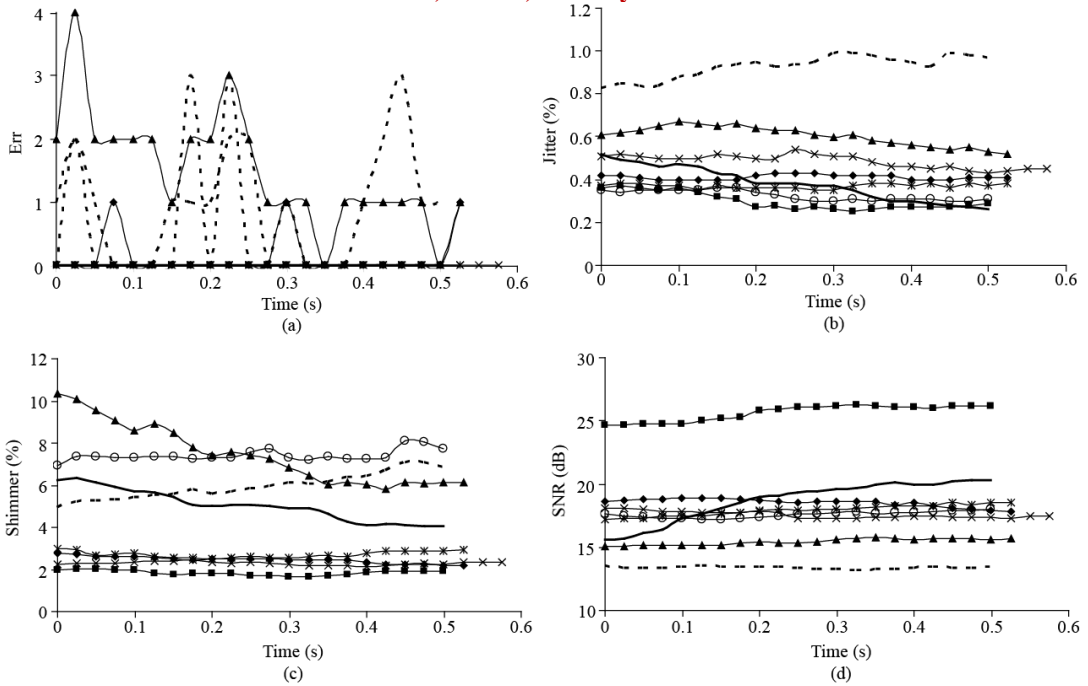


Fig 5. “Err”, percent jitter, percent shimmer and SNR values generated using the moving window method for type 2 voices. (—×— : subject 9, . . . : subject 10, —*— : subject 11, —▲— : subject 12, — : subject 13, —○— : subject 14, —■— : Subject 15, —◆— : subject 16).

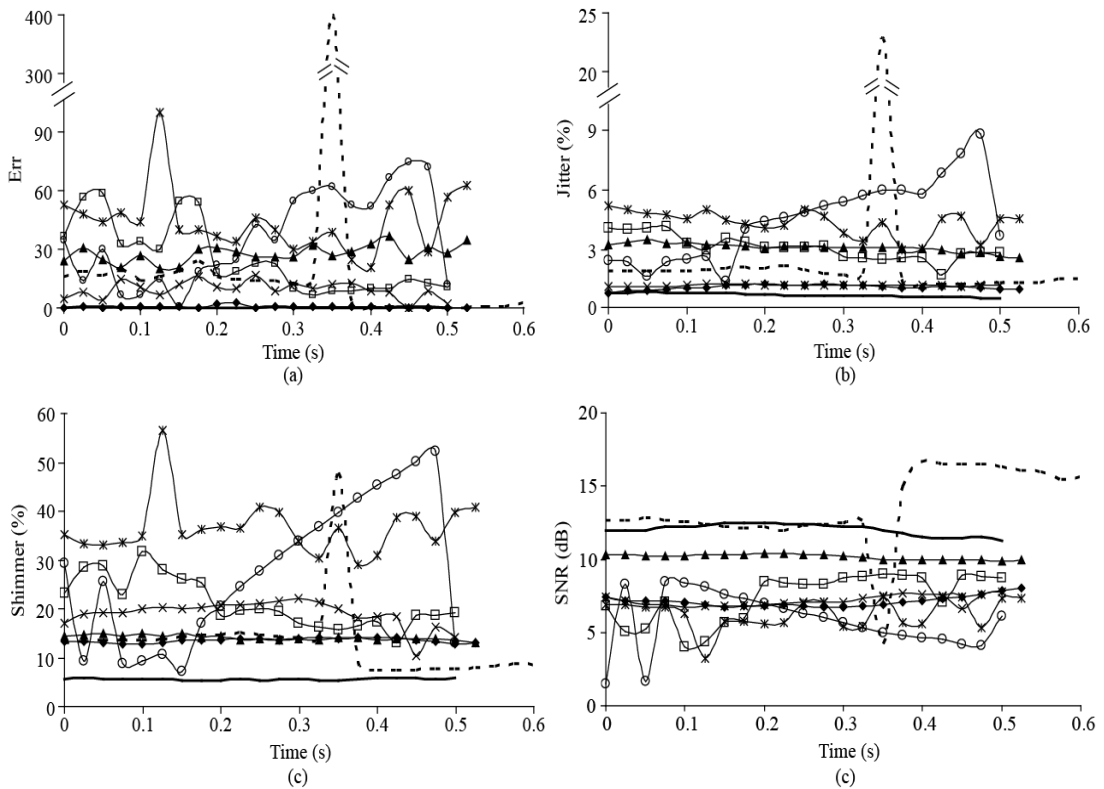


Fig 6. “Err”, percent jitter, percent shimmer and SNR values generated using the moving window method for type 3 voices. (. . . : subject 17, —◆— : subject 18, —*— : subject 19, — : subject 20, —□— : Subject 21, —×— : subject 22, —▲— : subject 23, —○— : subject 24)



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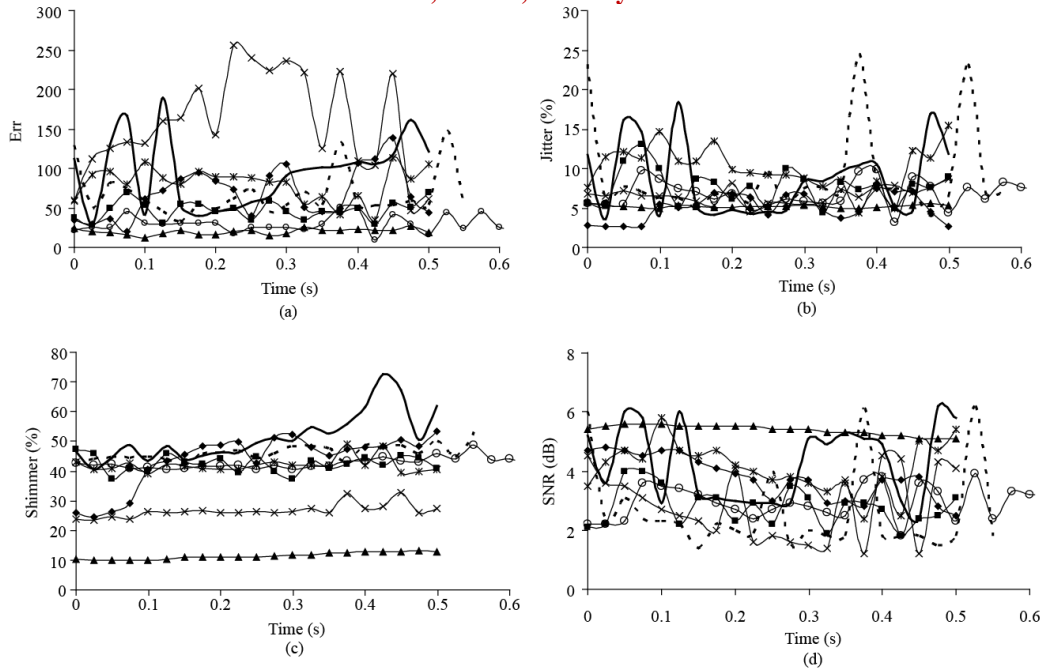


Fig 7. “Err”, percent jitter, percent shimmer and SNR values generated using the moving window method for type 4 voices. (.... : subject 25, —■— : Subject 26, —*— : subject 27, —▲— : subject 28, — : subject 29, —○— : subject 30, —×— : subject 31, —◆— : subject 32)

Table II. Minimum perturbation values and locations for type 1, 2 and 3 voices. “Err” values exceeded 10 for all segments in type 4 voices and two type 3 voice and therefore are not included.

Subject	Signal Type	Percent Jitter (Time Point)	Percent Shimmer (Time Point)	SNR (dB) (Time Point)
1	1	0.27 (0.4 s)	3.24 (0.45 s)	21.2 (0.45 s)
2	1	0.24 (0.125 s)	1.25 (0.125 s)	24.6 (0.125 s)
3	1	0.25 (0.225 s)	1.19 (0.5 s)	27.8 (0 s)
4	1	0.16 (0.125 s)	1.81 (0.425 s)	26.7 (0.3 s)
5	1	0.34 (0.5 s)	2.24 (0.5 s)	20.7 (0.5 s)
6	1	0.24 (0.5 s)	2.54 (0.5 s)	23.4 (0.5 s)
7	1	0.23 (0.25 s)	2.29 (0.4 s)	23.7 (0.4 s)
8	1	0.16 (0.2 s)	1.56 (0.025 s)	23.8 (0.025 s)
9	2	0.43 (0.5 s)	2.16 (0.4 s)	18.1 (0.025 s)
10	2	0.83 (0 s)	4.96 (0 s)	13.6 (0 s)
11	2	0.35 (0.275 s)	2.51 (0.2 s)	18.5 (0.45 s)
12	2	0.52 (0.525 s)	5.83 (0.425 s)	15.8 (0.35 s)
13	2	0.26 (0.5 s)	4.05 (0.475 s)	20.3 (0.475 s)
14	2	0.24 (0.275 s)	6.92 (0 s)	18.0 (0.5 s)
15	2	0.35 (0.325 s)	1.65 (0.325 s)	26.3 (0.325 s)
16	2	0.4 (0.125 s)	2.18 (0.525 s)	18.9 (0.125 s)
17	3	1.17 (0.4 s)	7.35 (0.4 s)	16.7 (0.4 s)
18	3	0.74 (0 s)	12.83 (0.075 s)	8.0 (0.525 s)
19	3	NA	NA	NA
20	3	0.48 (0.475 s)	5.23 (0.175 s)	12.5 (0.175 s)
21	3	1.63 (0.425 s)	13.0 (0.425 s)	9.0 (0.35 s)
22	3	1.04 (0.45 s)	10.33 (0.45 s)	7.8 (0.5 s)
23	3	NA	NA	NA
24	3	1.32 (0.15 s)	7.28 (0.15 s)	8.5 (0.075 s)



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Table III. Multiple pair wise comparisons of percent jitter, percent shimmer and SNR values generated using the moving window method and their minimum perturbation values. “Err” values exceeded 10 for all segments in type 4 voices and two type 3 voice and therefore are not included.

	Type 1	Type 2	Type 3
Percent Jitter (p=0.002*)			
Type 1	-	P=0.335	P=0.001*
Type 2	-	-	P=0.026
Type 3	-	-	-
Percent Shimmer (p<0.001*)			
Type 1	-	P=0.230	P<0.001*
Type 2	-	-	P<0.001*
Type 3	-	-	-
SNR (p<0.001*)			
Type 1	-	P=0.011*	P<0.001*
Type 2	-	-	P<0.001*
Type 3	-	-	-

Table III shows the comparison of percent jitter, percent shimmer, and SNR values generated using the moving window method for type 1, 2 and 3 voices. “Err” values exceeded 10 for all segments in type 4 voices and two type 3 voices, therefore these samples were not included. The one way repeated measure ANOVA on ranks showed significant variability in the percent jitter, percent shimmer and SNR (P=0.002, p<0.001 and p<0.001, respectively, Table III). Multiple pair wise comparisons revealed significant differences between type 1 and type 3 voices for percent jitter. Percent shimmer detected significance between type 1 and type 3 voices and between type 2 and type 3 voices. SNR detected difference between all pairs.

IV. DISCUSSION

Pathological voices show large variations in cycle to cycle pitch period and amplitude [5]-[7]. Commonly used segmentation methods include selecting the mid-portion of phonation, visually selecting a steady portion or analyzing the whole recording excluding onset and offset [3], [4], [11], [14]-[17]. As seen in the present study, increasingly disordered voices show large variability in jitter, shimmer and SNR depending on the particular segment selected. This result highlights the importance of consistent and reliable voice segmentation, particularly in pathological voices. Segment selection methods based only on the location within the voice sample cannot account for variability in local stability. Moreover, we observed that locations of minimum perturbation vary between signals suggesting a need to select samples based on local stability. Individual perturbation measures varied in the locations of their respective minimums indicating that methods of determining an area of greatest stability based only on apparent amplitude stability may not be adequate [20]. Furthermore, there may not be a single segment that achieves a minimum for all perturbation measures. The moving window method provides an objective method for determining minimum values regardless of their location within the voice sample and allows researchers to select samples used in the calculation of each parameter independently.

In this study we suggest a moving window method to extend perturbation analysis to samples classified as type 2, 3 or 4. Both the “Err” and “Trk” values increased with voice type indicating increasing levels of instability in the signals [13]. A large “Err” is an indication that a sample is ill-suited for acoustic analysis and in this study, an “Err”



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value of less than 10 was used to indicate a sample suitable for perturbation analysis. Although whole sample analysis found “Err” values below our defined cut off of 10 only for type 1 and type 2 samples, the moving window was able to identify areas of transient stability in all the type 2 samples and six of the eight type 3 signals. Moreover, minimum perturbation measures were located within these windows, thus, by using the moving window and monitoring the “Err” values for each segment we can extend perturbation analysis to type 2 and even type 3 samples. The type 4 voices, defined as primarily stochastic in nature, contained no windows where the voice was stable enough to generate reliable perturbation parameters. The high level of noise in type 4 voices precludes the use of most nonlinear dynamic techniques; therefore, a method to objectively analyze these voices is a valuable subject of future research.

Although the moving window method determines an area of minimum perturbation, differences in these perturbation measures persisted between voice types. These results indicate that the moving window technique preserves enough of the variability in perturbation measures to facilitate voice type differentiation. Future investigations will endeavor to determine the impact the moving window method exerts on the stability of acoustic measures and their ability to differentiate voices of patients.

V. CONCLUSION

Segment selection methods have varied between studies. No current method is both repeatable and receptive to the changes in stability during the course of a phonation sample. In this study, voices were classified according to Titze’s recommendations as type 1, 2 or 3 with the addition of a type 4 voice characterized by high-dimensional or stochastic behavior. Percent jitter, percent shimmer, and SNR were calculated from a moving window of 0.5 seconds shifted at 0.025 seconds. Despite initial “Err” values suggesting that only type 1 and type 2 voices were suitable for acoustic analysis, areas of transient stability were found in six of the eight type 3 voices. For all type 4 voices and two of the type 3 voices, no segment produced an “Err” value less than our cutoff of 10. The locations of minimums for the three parameters were increasing spread across the sample for higher voice types and varied dramatically among individuals. Analysis of the perturbation parameters demonstrated that the moving window method maintained significant differences among the voice types. The moving window permits the use of perturbation analysis on higher type voices; however, methods to analyze type 4 voices objectively, must still be developed.

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REFERENCES

- [1] A.G. Askenfelt, B. Hammarberg, “Speech waveform perturbation analysis: a perceptual-acoustical comparison of seven measure,” *J. Speech Hear. Res.*, vol. 29, pp. 50-64, 1986.
- [2] M. Jafari, J. A. Till, L. F. Truesdell, C. B. Law-Till, “Time-shift, trial, and gender effects on vocal perturbation measures,” *J. Voice*, vol.7, no. 4, pp. 326-336, 1993
- [3] P. Yu, M. Ouaknine, J. Revis, A. Giovanni, “Objective voice analysis for dysphonic patients: a multiparametric protocol including acoustic and aerodynamic measurements,” *J. Voice*, vol. 15, pp. 529-542, 2001.
- [4] Y. Zhang, J. J. Jiang, “Acoustic Analyses of Sustained and Running Voices from Patients with Laryngeal Pathologies,” *J. Voice*, vol. 22, pp. 1-9, 2008.
- [5] I. R. Titze, “Workshop on Acoustic Voice Analysis: Summary Statemen,” National Center for Voice and Speech, Denver, CO, 1995.
- [6] S. Bielamowicz, J. Kreiman, B. R. Gerratt, M. S. Dauer, G. S. Berke, “Comparison of voice analysis systems for perturbation measurement,” *J. Speech Hear. Res.*, vol. 39, pp. 126-134, 1996.
- [7] R. D. Kent, H. K. Vorperian, J. F. Kent, J. R. Duffy, “Voice dysfunction in dysarthria: application of the Multi-Dimensional Voice Program,” *J. Commun. Disord.*, vol. 36, pp.281-306, 2003.
- [8] Y. Zhang, S. M. Wallace, J. J. Jiang, “Comparison of nonlinear dynamic methods and perturbation methods for voice analysis,” *J. Acoust. Soc. Am.*, vol/ 118, pp. 2551-2560, 2005.



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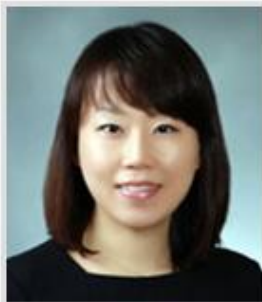
ISO 9001:2008 Certified

International Journal of Engineering Science and Innovative Technology (IJESIT)

Volume 3, Issue 1, January 2014

- [9] Y. Zhang, J. J. Jiang, L. Biazzo, M. Jorgensen, M. Berman, "Perturbation and nonlinear dynamic analyses of voices from patients with unilateral laryngeal paralysis," *J. Voice*, vol. 19, pp. 519-528, 2005.
- [10] E. P. Ma, Yiu EM, "Suitability of acoustic perturbation measures in analysing periodic and nearly periodic voice signals," *Folia Phoniatr. Logop.*, vol. 57, pp. 38-47, 2005.
- [11] D. A. Rahn, M. Chou, J. J. Jiang, Y. Zhang, "Phonatory Impairment in Parkinson's disease: Evidence from Nonlinear Dynamic Analysis and Perturbation Analysis," *J. Voice*, vol. 21, pp. 64-71, 2007.
- [12] A. Behrman, C. J. Agresti, E. Blumstein, N. Lee, "Microphone and Electroglottographic Data from Dysphonic Patients: Type 1, 2 and 3 Signals," *J. Voice*, vol. 12, pp. 249-260, 1998.
- [13] A. Sprecher, Y. Zhang, A. Olszewski, "Updating signal typing in voice: addition of type 4 signals," *J. Acoust. Soc. Am*, vol. 127, no. 6, pp. 3710-3716, 2010.
- [14] M. N. Vieira, F. R. McInnes, M. A. Jack, "On the influence of laryngeal pathologies on acoustic and electrographic jitter measures," *J. Acoust. Soc. A*, vol. 111, pp. 1045-1055, 2002.
- [15] J. L. Robinson, S. Mandel, R. T. Sataloff., "Objective Voice Measures in Nonsinging Patients with Unilateral Superior Laryngeal Nerve Paresis," *J. Voice*, vol. 19, pp. 665-667, 2005.
- [16] Lim Jae-Yol, Choi Jae-Nam, Kim Kwang-Moon, Choi Hong-Shik, "Voice analysis of patients with diverse types of Reinke's edema and clinical use of electroglottographic measurements," *Acta OtoLaryngol.*, vol. 126, pp. 62-69, 2006.
- [17] M. Petrović-Lazić, S. Babac, M. Vuković, R. Kosanović, A. Ivanković, "Acoustic Voice Analysis of Patients with Vocal Fold Polyp," *J. Voice*, 2010.
- [18] Kay Elemetrics Corp., "Multi-dimensional voice program: software instruction manual," Pine Brook: NJ: Kay Elemetrics Corp, 1993.
- [19] P. Milenkovic, TF32 User's Manual. Madison, WI, 2001.
- [20] E. H. Buder, E. A. Strand, "Quantitative and graphic acoustic analysis of phonatory modulations: the modulogram," *J. Speech Lang. Hear. Res.*, vol. 46, no. 2, pp. 475-490, 2003.

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