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Effects of Low-pass Filtering on Acoustic Analysis of Voice

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Abstract

Objective/Hypothesis—Low-pass filtering is often applied to eliminate effects of environmental noise when preparing voice recordings for acoustic analysis. This study tested the effects of low-pass filter cutoff frequency on the results of acoustic voice analysis, with a particular interest in the effects of low cutoff frequencies on nonlinear dynamic parameters.

Study Design—A crossover randomized controlled trial was performed using voice recordings of sustained vowel phonation obtained from the Disordered Voice Database.

Methods—A second-order Butterworth filter was applied to the voices at cutoff frequencies ranging from 5000 to 40Hz. Percent jitter, percent shimmer, fundamental frequency (F_0), signal-to-noise ratio (SNR), D_2 , and K_2 were calculated for each signal.

Results—Traditional acoustic parameters were validly measured at cutoff frequencies as low as 300Hz. SNR and percent shimmer were improved by cutoff frequencies of 300Hz or higher; F_0 and percent jitter were unaffected by filtering at these frequencies. D_2 and K_2 were measured stably for signals filtered at cutoff frequencies as low as 100Hz.

Conclusion—To ensure accuracy in acoustic voice analysis, setting the cutoff frequency of a low-pass filter at least one octave above the fundamental frequency (minimum of 300Hz) is recommended. Nonlinear dynamic measures of correlation dimension (D_2) and second-order entropy (K_2) proved more robust and maintained accuracy at lower frequencies.

Keywords

correlation dimension; second-order entropy; filter; cutoff frequency

INTRODUCTION

Acoustic and perturbation measures such as jitter and shimmer have been used to describe both normal and pathological voices for over thirty years¹. Originally, expensive hardware was needed to obtain acoustic parameters of voice, restricting analysis to research institutions. Technological achievements have made it possible to analyze the voice with simple computer software systems, increasing the potential use of vocal analysis to the clinical setting. In addition to increasing the aperiodicity of vocal fold vibration, vocal pathologies increase noise. This is detected by computer software systems, which are thus able to help determine diagnoses, treatment goals, procedures, and termination criteria¹. Although such systems offer increased convenience, they are error-prone. The signal can be affected by factors such as the type of equipment used, equipment placement and environmental noise, none of which existed in sound-proof research rooms with old,

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standardized analysis hardware^{1,2}. Much research has been devoted to eliminating problems with computer-analyzed voice with variable results regarding the best method to use^{1,2}. The lack of a standardized methodology decreases the applicability and reliability of this potentially useful system.

The presence of environmental noise in a voice signal affects acoustic measurement of perturbation and nonlinear dynamic voice properties, as increased noise has been shown to inflate values of jitter, shimmer, and correlation dimension (D_2), among other parameters^{1,2}. Environmental noise introduces the potential risk of false-positive diagnoses of vocal fold pathologies due to artificially high noise levels¹. Because the components of vocal analysis can be found at relatively low frequencies, reducing the high frequency component of environmental noise can improve vocal analysis results³. Low-pass filtering is a technique often applied in preparing voice recordings for acoustic analysis. The parameters of interest in voice analysis are commonly derived from properties of the voice source, which is vibration of vocal folds initiated and sustained by glottal airflow¹. Low-pass filtering is applied before acoustic analysis in order to filter out high-frequency components of the recording, including environmental noise². It has been shown to isolate fundamental frequency (F_0), removing external noise, while maintaining reliable jitter and shimmer measures at certain cutoff frequencies. Low-pass filters allow waves with frequency components lower than a specified cutoff frequency to pass through the filter unaffected. Waves with frequency components greater than the cutoff are severely attenuated, effectively removing them from the output signal⁴.

In preceding years, low-pass filters have been applied before perturbation analysis on a regular basis. While some studies use a high cutoff frequency^{5,6}, presumably to eliminate high-frequency noise from the analyzed signal, others apply moderate to low cutoff frequencies^{7,8}. A procedural statement indicating low-pass filter usage in a study of nonlinear dynamic measures of voice was not encountered in the literature. Clear explanation of filtering techniques should be provided in papers discussing acoustic analysis of voice. A more methodological and uniform cutoff approach to low-pass filter application in voice analysis would reduce inaccurate diagnoses and discrepancies in study results.

In a previous study measuring effects of low-pass filtering on perturbation measures of voice, Titze *et al.* found that low-pass filtering the voice signal at cutoff frequencies above the F_0 had little effect on jitter measures. At cutoff frequencies of 150Hz and below, however, the jitter values decreased from the expected jitter. Though shimmer measures of signals low-pass filtered at cutoff frequencies between 2kHz to 10kHz showed no error-generated trend, measures decreased at cutoff frequencies below 2kHz. It was found that the peak-picking method of F_0 extraction was very error-prone when speech was filtered below 500Hz, due to the extreme flattening and smoothing of the voice waveform. The authors concluded that low-pass filtering was acceptable, but that perturbation measures were affected when the cutoff frequency was less than an octave above the F_0 ⁹.

Nonlinear dynamic parameters, such as fractal dimension, can be applied to characterize both normal and pathological voice^{10, 11}. Previous work has applied low-pass filtering to measure its effects on nonlinear dynamic parameters in areas other than laryngology. Shelhamer found that the calculated D_2 of an optokinetic nystagmus eye movement signal increased with decreasing cutoff filter frequency¹². This work corroborated previous results showing D_2 increase with decreasing cutoff frequency of a computer-simulated filter¹³. The study also demonstrated that measures of second-order entropy (K_2) are unaffected by low-pass filtering. However, to our knowledge, no research has yet investigated the effects of low-pass filtering on nonlinear dynamic characteristics of voice.

The Butterworth filter is a type of digital filter that must be applied to a stationary signal; otherwise, it is unable to eliminate noise⁴. In this study, we applied a second-order Butterworth filter to twenty normal voice signals at multiple cutoff frequencies. Acoustic analysis was performed for all original and low-pass filtered signals; traditional parameters of F_0 and SNR, perturbation parameters of percent jitter and percent shimmer, and nonlinear dynamic parameters of D_2 and K_2 were collected. Beyond the study of Titze *et al.*, no further investigation has been completed to determine the effects of low-pass filtering on acoustic analysis of voice. To our knowledge, no study has yet applied low-pass filtering at different levels to determine its effects on nonlinear dynamic analysis of voice. Our objective regarding this work was to compare the results of our perturbation analysis with that of Titze *et al.* and to ascertain if nonlinear dynamic parameters of voice exhibited the same trends resultant to low-pass filtering as those determined in non-laryngeal studies.

MATERIALS AND METHODS

Subjects

The voice samples examined in this study were obtained from the Disordered Voice Database, model 4337, version 1.03 (Kay Elemetrics Corp., Lincoln Park, New Jersey), developed by the Massachusetts Eye and Ear Infirmary Voice and Speech Lab. Twenty normal voices from healthy, nonsmoking, native English speakers were included. The subjects, ten male and ten female, ranged in age from 24 to 47 years (mean = 33.85).

Experimental Methods

During recording, subjects were asked to sustain the vowel /a/ at a comfortable pitch and intensity as steadily and as long as possible. Voice recordings were made in a soundproof booth on a DAT recorder at a sampling rate of $f_s = 44.1$ kHz and were digitized by a Computerized Speech Lab system, model 4300 (Kay Elemetrics Corp., Lincoln Park, New Jersey) at a sampling rate of $f_s = 25$ kHz. A middle stationary segment $x(t_i), t_i = i\Delta t, \Delta t = 1/f_s$, $i = 1, 2, \dots$, with a length of one second was selected, as both nonlinear dynamic analysis and the Butterworth filter require signal stationarity for accurate operation. Voice onset and offset were excluded to avoid confounding effects of speech intonation or interactions between the larynx and vocal tract on analysis.

Data Analysis

Voice samples were then low-pass filtered using GoldWave software, version 4.23 (GoldWave Inc., St. John's, Canada). A second-order Butterworth filter was applied to each signal at the following cutoff frequencies: 5000, 4000, 3000, 2000, 1000, 900, 800, 700, 600, 500, 400, 300, 200, 100, 90, 80, 70, 60, 50, and 40Hz. A total of 400 low-pass filtered signals were generated in this manner; these and the twenty original voice signals were then analyzed. Cutoff frequencies below 100Hz were included because D_2 has exhibited inflationary behavior when signals are filtered at very low cutoff frequencies^{12,13}. Forty Hz is the minimum cutoff frequency for low-pass filtering with GoldWave.

Traditional acoustic analysis was conducted on the voice segments with CSpeech software, version 4.0 (Milenkovic and Read, Madison, Wisconsin)¹⁴, which utilizes the peak-picking method to determine pitch periods for analysis. Traditional parameters of F_0 and SNR, as well as perturbation parameters of percent jitter and percent shimmer were collected. F_0 quantifies the vibratory frequency of the vocal folds. SNR describes the dominance of harmonic signal behavior over aperiodic noise. Jitter measures the cycle-to-cycle frequency variation of a voice signal, and shimmer measures the cycle-to-cycle amplitude variation of a signal.

Nonlinear dynamic analysis of the low-pass filtered samples was performed using software developed by the Laryngeal Physiology Laboratory at the University of Wisconsin School of Medicine and Public Health (Madison, Wisconsin). A voice signal was plotted against itself at some time delay to create a reconstructed phase space. The reconstructed phase space qualitatively illustrated the dynamic behavior of a signal, as a periodic signal produces a closed trajectory while an aperiodic signal appears irregular¹⁵. From the reconstructed phase space, the parameters of D_2 and K_2 were calculated. D_2 specifies the number of degrees of freedom needed to describe a system; a more complex system has a higher dimension and requires more degrees of freedom to describe its dynamic state. K_2 indicates the rate of loss of information about the state of a dynamic system over time. Perfectly periodic behavior has zero entropy, a chaotic system with a finite degree of freedom has a finite K_2 value, and the K_2 value of true random behavior approaches infinity.

Nonlinear dynamic calculations made by the software were based on the numerical algorithms described for studies analyzing pathological human voices¹⁶ and excised larynx phonations¹⁷. In brief, the time delay technique was applied to reconstruct an m -dimensional delay-coordinate phase space $\mathbf{X}_i = \{x(t_i), x(t_i - \tau), \dots, x(t_i - (m-1)\tau)\}$ ¹⁵, where m is the embedding dimension and τ is the time delay. The embedding theorem was applied to determine m ¹⁸. When $m > 2D+1$, where D is the Hausdorff dimension, the reconstructed phase space is topologically equivalent to the original phase space. The proper τ was estimated using the mutual information method proposed by Fraser and Swinney¹⁹. Theiler's improved algorithm was used to calculate the correlation integral $C(r)$, where r is the radius around $\mathbf{X}_i$ ²⁰. $C(r)$ measures the number of distances between points in the reconstructed phase space that are smaller than the radius r and has a power law behavior $C(r) \propto r^{D_2} e^{-m\tau K_2}$ which reveals the geometrical scaling property of the attractor. Using the calculated $C(r)$, D_2 and K_2 were estimated in the scaling region of r with the increase of m . For sufficiently large m , D_2 and K_2 , as well as standard deviations for both parameters, were derived using a curve fit to the curve of $\log_2 C(r)$ versus $\log_2 r$ in the scaling region. For reliable estimation of dimension and entropy in a signal, standard deviation of the values should be less than 5%.

Statistical Analysis

Repeated measure ANOVA was applied to elucidate any significant differences in acoustic analysis results between the unfiltered original signals and signals low-pass filtered at all cutoff frequencies. Because it was not predefined whether the groups were from normally distributed populations with equal variances, we applied the nonparametric Wilcoxon signed ranks test, comparing acoustic analysis parameters of the original signal group against those of each low-pass filtered signal group. Statistical significance was set at $p = 0.05$. SigmaStat 3.0 and SigmaPlot 8.0 software (SPSS Inc., Chicago, Illinois) were used to statistically analyze and graph data.

RESULTS

At cutoff frequencies from 5000 to 300Hz, percent jitter values for low-pass filtered signals were not significantly different from percent jitter for original signals ($0.750 \geq p \geq 0.113$). Signals filtered at cutoff frequencies from 200 to 40Hz demonstrated significantly higher percent jitter than original signals ($p \leq 0.004$); at these cutoff frequencies, percent jitter values increased with decreasing cutoff frequency. In the range of cutoff frequencies from 200 to 40Hz, mean percent jitter values were $\geq 105\%$ of the mean percent jitter for the original signals (Figure 1).

At a cutoff frequency of 5000Hz, percent shimmer values for filtered signals were not significantly different from percent shimmer values for original signals ($p=0.250$). Percent

shimmer values for signals filtered at cutoff frequencies from 4000 to 400Hz were significantly lower than percent shimmer for the original signals ($p \leq 0.032$). Percent shimmer values decreased with decreasing cutoff frequency from 4000 to 300 Hz. At cutoff frequencies from 200 to 100Hz, percent shimmer values increased with decreasing cutoff frequency. Values of percent shimmer for signals filtered at cutoff frequencies from 300 to 200Hz were not statistically different from percent shimmer for original signals ($0.330 \geq p \geq 0.114$), while percent shimmer for signals filtered at cutoff frequencies of 100 to 40Hz were statistically higher than percent shimmer for original signals ($p < 0.001$). In the range of cutoff frequencies from 2000 to 300Hz, mean percent shimmer values were $\leq 95\%$ of the mean percent shimmer for the original signals, and from 200 to 40Hz, mean percent shimmer values were $\geq 105\%$ of the mean percent shimmer for the original signals (Figure 2).

SNR values for signals low-pass filtered at all cutoff frequencies were significantly different from SNR values for original signals ($p \leq 0.011$). SNR increased with decreasing cutoff frequency from 5000 to 300Hz. At 200 to 40Hz, SNR decreased with decreasing cutoff frequency. In the range of cutoff frequencies from 600 to 300Hz, mean SNR values were $\geq 105\%$ of the mean SNR for the original signals, while from 100 to 40Hz, mean SNR values were $\leq 95\%$ of the mean SNR for the original signals (Figure 3).

Signals low-pass filtered at cutoff frequencies from 5000 to 200Hz had F_0 values that were not significantly different from F_0 for the original signals ($1.000 = p$). At 200Hz, F_0 values begin to increase in comparison with F_0 values for original signals. ($p = 0.250$) F_0 values for signals filtered at cutoff frequencies of 100 to 40 Hz were significantly higher than F_0 values for original signals ($p = 0.004$). Mean F_0 values for all cutoff frequencies were within $\pm 5\%$ of the mean F_0 for the original signals (Figure 4).

Though minor intrapersonal variation occurred in D_2 and K_2 values for filtered signals, D_2 and K_2 values for signals filtered at nearly all cutoff frequencies were not significantly different than D_2 and K_2 values for the original signals ($0.985 \geq p \geq 0.083$). At cutoff frequencies of 50 to 40Hz, D_2 values were significantly higher than D_2 values for original signals ($p \leq 0.027$); these parameters increased with decreasing cutoff frequency. In the range of cutoff frequencies from 90 to 40Hz, mean D_2 and K_2 values were $\geq 105\%$ of the mean D_2 and K_2 for the original signals (Figures 5 and 6, respectively).

DISCUSSION

In this study, low-pass filtering was performed on normal voice signals to confirm the effects of low-pass filtering on traditional acoustic analysis and to determine the effects of filtering on nonlinear dynamic analysis of voice. We found that traditional parameters of F_0 , SNR, percent jitter, and percent shimmer were validly measured at cutoff frequencies of 300Hz and above. SNR and percent shimmer measures were improved with the implementation of the low-pass filtering technique at cutoff frequencies of 300Hz or higher, while F_0 and percent jitter were unaffected by filtering at these cutoff frequencies. At levels of filtering equal to or less than F_0 , the F_0 itself was eliminated from the analyzed signal, resulting in erroneous F_0 and pitch extraction and invalidating F_0 , SNR, percent jitter, and percent shimmer calculations.

Results of F_0 analysis show that this parameter is reliably calculated via peak-picking for signals low-pass filtered at nearly all cutoff frequencies. This indicates that noise-generated errors in F_0 calculation via peak-picking or formant effects on F_0 extraction are minimal to absent in these samples. Low-pass filtering does not demonstrate a deleterious effect on F_0 extraction until the frequency at which F_0 is manifested is removed by very low cutoff frequencies. At cutoff frequencies of 200 to 40Hz tested in this study, F_0 itself is filtered out

^{1, 3}. At cutoff frequencies from 200 to 40Hz, frequency perturbation levels are significantly increased. Because the calculation of percent jitter in CSpeech is derived from calculation of F_0 ¹⁴, invalid percent jitter results would be generated when the cutoff frequency of the low-pass filter eliminates F_0 , as evidenced by the results.

Our results show that percent shimmer calculation is more greatly affected by the application of low-pass filtering than are other parameters, which is in accordance with the literature¹. At cutoff frequencies as high as 2000Hz, mean percent shimmer values differed by at least 5% from the mean percent shimmer for original signals. Amplitude perturbation measurements decreased with decreasing cutoff frequency to the 300Hz level. Again, at cutoff frequencies of 200Hz and below, this parameter's calculated values increased. Because percent shimmer calculation is related to pitch period extraction and therefore F_0 calculation, inflated measurements of this perturbation result when signals are filtered at cutoff frequencies lower than F_0 .

Repeated measurements of a signal's SNR over a range of cutoff frequencies demonstrate that low-pass filtering is effective in isolating and eliminating noise from the voice signal. Low-pass filtering increases the ratio of harmonic signal to noise, producing a signal with increasing amounts of harmonic signal and decreasing amounts of noise to a cutoff frequency of 400Hz. At 300 to 40Hz cutoff frequencies, the mean SNR begins to decrease relative to the SNR measured at the preceding cutoff frequency. This may indicate that essential harmonic components of the wave, such as F_0 , are filtered out at such low cutoff frequencies. Low-pass filtering can be applied to increase the SNR of a signal at cutoff frequencies of at least 400Hz.

Nonlinear dynamic parameters were least affected by low-pass filtering. No trends were noted as the cutoff frequency of the low-pass filter decreased, and no significant differences were found between the D_2 or K_2 values of original signals and signals filtered at cutoff frequencies from 5000 to 100Hz. This indicates that valid measurements of D_2 and K_2 parameters in voice are possible even with signal filtering at very low cutoff frequencies. Previous studies which produced results indicating an increase in D_2 as the cutoff frequency decreased implemented cutoff frequencies as low as 40Hz before D_2 inflation was noted^{12, 13}. To test this limit, signals were filtered at additional cutoff frequencies of 90, 80, 70, 60, 50, and 40Hz. Below 100Hz, D_2 and K_2 analysis may produce inflated analysis results, although significant inflation of D_2 did not occur until the cutoff was set at 50Hz. The capability of valid D_2 and K_2 measurement at cutoff frequencies as low as 100Hz should be sufficient for acoustic analysis purposes, given that low-pass filtering of voice signals is typically employed to minimize noise or eliminate the effects of formant frequencies on analysis, phenomena which occur at much higher frequencies.

In this study, only normal voices were used to assess how often a voice would be inaccurately deemed pathological at different filtering cutoffs. Because environmental noise affects diagnoses and because the algorithms of nonlinear dynamics parameters are intended for pathological subjects, repeating the study with both normal and pathological samples would allow for a more confident statement of the filtering threshold for each parameter. Due to the high frequency of environmental noise, our cutoff values are applicable in noisy settings, but future studies in noisy settings may prove beneficial.

To ensure accuracy in traditional acoustic analysis of voice, we reiterate the previous suggestion of Titze *et al.*⁹ Setting the cutoff frequency of a low-pass filter at a minimum of one octave above F_0 preserves the positive effects of the filtering technique while assuring measurement validity. Nonlinear dynamic analysis proved more robust in terms of cutoff frequency; parameters of D_2 and K_2 can be accurately calculated from signals low-pass

filtered at cutoff frequencies of at least 100Hz. These results indicate a potential cutoff threshold for low-pass filtering, which should allow for more useful and clinically applicable use of computer-assisted voice recording to diagnose and treat disorders with both traditional acoustic analysis and nonlinear dynamic analysis.

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Figure 2. Natural log-transformed mean percent shimmer values for the original signal group and each low-pass filtered signal group. Whiskers show standard deviation, and the dotted lines indicate $\pm 5\%$ of the mean percent shimmer for the original signals.

Figure 3. Natural log-transformed mean signal-to-noise ratio (SNR) values for the original signal group and each low-pass filtered signal group. Whiskers show standard deviation, and the dotted lines indicate $\pm 5\%$ of the mean SNR for the original signals.

Figure 4.

Natural log-transformed mean F_0 values for the original signal group and each low-pass filtered signal group. Whiskers show standard deviation, and the dotted lines indicate $\pm 5\%$ of the mean F_0 for the original signals.

Figure 5.

Natural log-transformed mean D_2 values for the original signal group and each low-pass filtered signal group. Whiskers show standard deviation, and the dotted lines indicate $\pm 5\%$ of the mean D_2 for the original signals.

Figure 6. Natural log-transformed mean K_2 values for the original signal group and each low-pass filtered signal group. Whiskers show standard deviation, and the dotted lines indicate $\pm 5\%$ of the mean K_2 for the original signals.