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The Effect of Vocal Effort on Voice Quality in Occupations with High Vocal Load

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Phonation type identification and voice quality analysis are often performed using invasive methods such as laryngoscopy or fiberoscopy. This work aims to determine whether comparable results can be reproduced using acoustic analysis, a noninvasive method. The research consists of two series of experiments conducted on two separate groups of professional voice users to calculate the values of voice quality parameters (i.e., peak slope, normalized amplitude quotient, cepstral peak prominence, harmonics-to-noise ratio). The first experiment focused on recording voice in the sound studio (22 participants), while the second focused on collecting data using a dedicated mobile app outside the sound studio (20 participants). The collected samples were then analyzed to examine the effects of vocal load on voice quality and to determine variations between different groups of test participants. According to the results of the experiments, vocal load and working professionally with voice change the value of normalized amplitude quotient (NAQ). Furthermore, it has been shown that harmonics-to-noise ratio (HNR) and cepstral peak performance (CPP) vary with regular hydration status.

Keywords: voice quality; acoustic analysis; vocal load; vocal exhaustion; phonation type; hydration.

1. Introduction

During the COVID-19 pandemic, the lives of most of the global population changed drastically. The severe and abrupt restrictions implemented due public health concerns significantly affected many people's lives. Not only was a significant part of the population required to switch to remote work, but students also had to attend classes online. The latter shift affected both students and lecturers, with around half of the lecturers experiencing vocal fatigue beyond previously recorded levels [1, 2].

Many useful tools were developed to ease the change. Some facilitated online communication, others helped maintain social contact remotely, and still others helped in different ways. However, much of this technology inadvertently contributed to the increase and extended use of the vocal cords [3].

Potential speech loss or a sore throat can degrade in the quality of lessons. As research states [4–6], the voice can be strengthened and enhanced if it is regularly trained. It is also crucial to conduct classes in a proper environment as high noise levels lead to vocal degradation [7].

An examiner can use several possible methods to test a patient's voice. These methods can be divided into two groups: invasive (such as laryngoscopy or fibroscopy) and noninvasive [8]. Noninvasive can be further divided into perceptual, electric and acoustic analyses, the latter being the focus of this research.

At the beginning of the century, acoustic analysis was used only as an auxiliary toll in laryngological and phoniatric diagnoses [9]. However, its relevance has grown over the years. This is primarily caused by the introduction of advanced digital voice analyzers capable of running on simple end-user computer hardware and mobile devices.

Furthermore, acoustic analysis has proven successful in assessing certain voice features such as phonation type [10, 11] or nasality [12, 13].

Several studies suggest that acoustic analysis could rapidly develop and eventually replace some of the more conventional diagnostic methods [9, 14–16]. These conclusions are based not only on the speed and precision of these methods, but also on their accessibility to doctors and patients alike.

The research described in this paper was conducted to analyze the effects of vocal load on voice quality parameters. According to the Union of the European Phoniatricians, occupations with high vocal load comprise are those that place a considerable strain on the vocal apparatus, such as educators, interpreters, politicians, call center workers, customer service assistants.

Moreover, experiments were conducted to compare the voices of different groups of test subjects to identify factors (such as regular hydration) that impact voice quality.

2. Voice quality parameters

A collaborative voice analysis repository for speech technologies (COVAREP) is one of the best implementations for extracting voice acoustic parameters. Among all the available parameters, medical diagnostics typically rely on those that provide essential information about voice quality. Selecting the correct parameters greatly influences the outcome of the research. Every year, the accuracy of vocal parameters is proven with further experiments. Drawing inspiration from the works [10, 14, 16, 17], the following parameters were selected for this work: peak slope (PS), normalized amplitude quotient (NAQ), cepstral peak prominence (CPP), and harmonics-to-noise ratio (HNR). They are presented in the following sections.

The chosen parameters have been proven successful in detecting vocal disorders, such as Pompe disease [18] (PS, NAQ) or Morquio disease [19] (HNR, CPP).

In voice quality analysis, comparing voice parameters from an experimental group with those of a control group is common practice. The latter group is defined as a group of research subjects who exhibit no speech abnormalities and do not work professionally with their voice. This paper uses the control group data from [10], which consists of 50 males and 39 females.

2.1. Peak slope (PS)

PS makes it possible to distinguish between breathy, modal and tense voice types [16]. According to [14], PS is more effective in differentiating voice quality and is more noise-resistant than other commonly used parameters (NAQ, H1-H2). At a noise-to-signal ratio of 25 dB PS achieved an accuracy of 77%, compared to 68% for NAQ. PS is defined through a wavelet transform, with the mother wavelet function given by the following formula [14]:

$$g(t) = \cos\left(2\pi f_n t\right) \cdot \exp\left(\frac{-t^2}{2\tau^2}\right),$$

where f_s is the sampling frequency (16 kHz in our case), $f_n = f_s/2$, and $\tau = 1/(2f_n)$.

After decomposing the speech signal into octave bands, the value of PS corresponds to the slope of a regression line fitted to the maximum amplitudes across different scales.

The PS value for the control group was estimated at -0.30 for female, and -0.33 for male voices [10].

2.2. Normalized amplitude quotient (NAQ)

NAQ, similarly to PS, is used to distinguish between phonation types [11]. This time-domain parameter measures the glottal closure phase using two amplitude-based measurements from waveforms estimated by inverse filtering [11]. The value of this parameter is calculated by using the following formula [11]:

$$\frac{A_{ac}}{T_{\mathrm{av}} \cdot d_{\min}} = \frac{A_{\max} - A_{\min}}{T_{\mathrm{av}} \cdot d_{\min}},$$

where $A_{\max}$ is the maximum amplitude for each period of the signal, $A_{\min}$ is the minimum amplitude for each period of the signal, T_{av} is the average fundamental period length, $d_{\min}$ is the minimum derivative of glottal flow, and A_{ac} is the maximum amplitude of airflow. The study in [11] proves that the NAQ parameter is resistant to noise, which makes it easier to estimate precisely.

The NAQ value for the control group was estimated at 0.12 for female voices, and 0.1 for male voices [10].

2.3. Cepstral peak prominence (CPP)

CPP is another parameter used to differentiate between phonation types. According to [20], early dysphonia can be detected due to good correlation between CPP and voice perception. This parameter defines the harmonic structure of a voice signal. Its value is equal to the difference in amplitude (in dB) between the cepstral peak and the corresponding value of the regression line directly below that peak [20].

The CPP value for the control group was estimated at 11.79 dB for female voices and 11.10 dB for male voices [10].

2.4. Harmonics-to-noise ratio (HNR)

HNR is a parameter that describes the degree of acoustic periodicity of the voice. According to [21, 22], HNR can describe the level of hoarseness and may be used to evaluate the effects of hoarseness treatment.

3. Methodology

Every test subject was recorded twice: before and after vocal load. Sessions were conducted in a specially silenced sound studio (ambient noise $<$30 dB). As recommended in [23–26], recordings consisted of continuous speech (about 2 minutes) and extended vowel phonation. Continuous speech was achieved by asking participants to read a short text of about 150 words, identical for all speakers. Before and after the continuous speech test, subjects were asked to phonate the prolonged vowel /a:/ three times at a sound pressure level of 60 dBA–80 dBA, measured at 1 m from the microphone, for a sustained period of at least 4 seconds each time. As a result, 12 samples were recorded for every participant, 6 before vocal load and 6 after. The first and last phonations of the vowel /a:/ were used for calculating acoustic parameters. All participants phonated neutrally. Phonations with higher or lower fundamental frequency (F0) values were not considered in the analyses. Figure 1 compares the NAQ values of one test subject before and after vocal load.

Voice recordings were made at 44.1 kHz sampling rate and 24-bit depth, using a RAZER SEIREN V2 PRO microphone placed about 0.5 m from the test subject's mouth with PRAAT software [27, 28]. The microphone's specifications

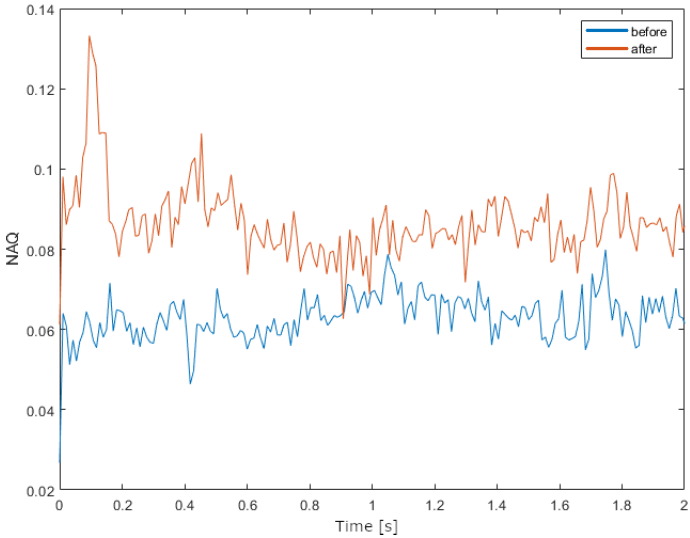

Fig. 1. Comparison of NAQ values before and after vocal load for one test subject.

include: frequency response of 20 Hz–20 kHz, sensitivity of –34 dB, max SPL of 120 dB, and a signal-to-noise ratio of 105 dB.

The collected samples (prolonged vowel /a:/) were then resampled to 16 kHz. Voice quality parameters were calculated using PRAAT software (for HNR) as well as MATLAB and the COVAREP repository (for PS, NAQ, and CPP) [16]. Parameter values were then aggregated into a single file, which we used to conduct statistical analysis using Python [29]. Due to the relatively small sample size, both the parametric Student's t-test [30] (for dependent and independent samples) and nonparametric tests [31] were used. The level of significance for all tests was set to 0.05.

4. Test subjects

Twenty-two academic teachers and ten students participated in the experiment, all performing some kind of vocal load on the day of recording. The research focuses on the voice quality of teachers, so additional data was collected from them.

For teachers, vocal load can be described as conducting any type of class (e.g., lectures, seminars, laboratories). The total duration of the vocal load of the teachers ranged from 90 to 540 minutes, with an average of 286 minutes. However, the number of classes conducted by each teacher on the day of recording was not recorded. For students, vocal load consisted of performing a short (about 15–30 minutes) recording session (dubbing) in a sound studio.

The average age of the teachers was 42 years, while the students averaged years 22. Among the teachers, 13 male teachers and 9 female teachers participated in the experiment. Seventeen teachers claimed that they regularly hydrate during vocal load. It is worth noting that a correlation between regular hydration and the age of the teachers was found.

5. Experiments

We collected voice samples and conducted four experiments to study voice quality using acoustic analysis. The following sections present the aims and results of each experiment.

5.1. How does vocal load affect voice quality?

Prolonged vocal load may cause changes in voice quality. We compared voice samples before and after vocal load to validate that using Student's t-test for dependent samples and the Wilcoxon test. Table 1 describes the test results for a group of 22 teachers.

Table 1. Comparison of voice quality parameters before and after vocal load.

Parameter	PS	NAQ	CPP [dB]	HNR [dB]
Mean ± standard deviation before vocal load	−0.271 ±0.063	0.077 ±0.025	9.962 ±1.171	18.687 ±2.987
Mean ± standard deviation after vocal load	−0.273 ±0.067	0.089 ±0.029	9.73 ±1.374	19.358 ±3.415
Mean ± standard deviation of control group males	−0.389 ±0.046	0.102 ±0.021	11.102 ±0.410	–
Mean ± standard deviation of control group females	−0.301 ±0.041	0.124 ±0.024	11.789 ±0.333	–
p-value for Student's t-test	0.643	0.025*	0.437	0.201
p-value for Wilcoxon test	0.949	0.046*	0.949	0.235

* Statistically significant at $p = 0.05$.

For both tests no statistically significant differences were found for PS, CPP, and HNR. However, such difference was found for NAQ, thus we can assume that the value of NAQ changes after vocal load.

5.2. The impact of hydration on voice quality

It is believed that proper hydration may reduce the negative effects of vocal load. To verify this, we compared the voice quality of teachers who regularly hydrated themselves during vocal load (17 people) with those who did not (5 people). Table 2 presents the result of the Student's t-test for independent samples and the Mann–Whitney test.

Table 2. Comparison of voice quality parameters between teachers who regularly hydrate themselves during vocal load and those who do not do so.

Parameter	PS	NAQ	CPP [dB]	HNR [dB]
Mean ± standard deviation for hydrating teachers	−0.266 ±0.068	0.078 ±0.027	9.382 ±1.056	19.608 ±2.704
Mean ± standard deviation for non-hydrating teachers	−0.297 ±0.044	0.089 ±0.016	10.789 ±0.706	16.396 ±2.810
Mean ± standard deviation for control group males	−0.389 ±0.046	0.102 ±0.021	11.102 ±0.410	–
Mean ± standard deviation for control group females	−0.301 ±0.041	0.124 ±0.024	11.789 ±0.333	–
p-value for Student's t-test	0.360	0.413	0.012*	0.031*
p-value for Mann–Whitney test	0.493	0.446	0.009*	0.048*

* Statistically significant at $p = 0.05$.

For both tests statistically significant differences were found for CPP and HNR, contrary to NAQ and PS.

5.3. The impact of vocal load type on voice quality

During lectures, teachers typically use their voice more extensively. We divided the test subjects into two groups based on the type of class they conducted on the recording day: lectures (8 teachers) and other types, such as laboratories, seminars or other (14 teachers). We compared voice quality in each group before and after vocal load in order to assess the impact of the type of vocal load on voice quality. The results of Student's t-tests for dependent samples and Wilcoxon tests are presented in Table 3 for lectures and Table 4 for the other types.

Table 3. Comparison of voice quality parameters before and after vocal load for teachers conducting lectures on the day of recording, level of significance $p = 0.05$.

Parameter	PS	NAQ	CPP [dB]	HNR [dB]
Mean ± standard deviation before vocal exhausion	−0.265 ±0.059	0.089 ±0.020	10.116 ±1.084	17.894 ±3.528
Mean ± standard deviation after vocal exhausion	−0.269 ±0.070	0.101 ±0.033	10.010 ±0.602	19.042 ±4.066
Mean ± standard deviation for control group males	−0.389 ±0.046	0.102 ±0.021	11.102 ±0.410	–
Mean ± standard deviation for control group females	−0.301 ±0.041	0.124 ±0.024	11.789 ±0.333	–
p-value for Student's t-test	0.759	0.236	0.790	0.074
p-value for Wilcoxon test	0.843	0.382	0.742	0.078

Table 4. Comparison of voice quality parameters before and after vocal load for teachers conducting other classes than lectures on the day of recording, level of significance $p = 0.05$.

Parameter	PS	NAQ	CPP [dB]	HNR [dB]
Mean ± standard deviation before vocal load	−0.275 ±0.068	0.070 ±0.025	9.875 ±1.249	19.141 ±2.665
Mean ± standard deviation after vocal load	−0.277 ±0.067	0.081 ±0.024	9.567 ±1.667	19.538 ±3.137
Mean ± standard deviation for control group males	−0.389 ±0.046	0.102 ±0.021	11.102 ±0.410	–
Mean ± standard deviation for control group females	−0.301 ±0.041	0.124 ±0.024	11.789 ±0.333	–
p-value for Student's t-test	0.749	0.065	0.476	0.600
p-value for Wilcoxon test	1.000	0.079	0.715	0.761

With such a distribution of test subjects, no statistically significant differences were found for any parameters.

5.4. The impact of working with voice professionally on its quality

As students took part in the experiment, we used their voices to measure the impact of professional voice use on voice quality. To do this, we compared the resting voice quality (before vocal load) of teachers and students. Because some voice quality parameters are known to vary with age, we selected only teachers under 40 years old, resulting in two equal-sized groups of teachers and students (10 people in each).

The quality of the resting voice was compared using the Student's t-test for independent samples and the Mann–Whitney test. The results are presented in Table 5.

Table 5. Comparison of resting voice quality between younger teachers and students.

Parameter	PS	NAQ	CPP [dB]	HNR [dB]
Mean ± standard deviation for younger teachers	−0.257 ±0.079	0.0754 ±0.024	10.032 ±0.995	19.530 ±3.695
Mean ± standard deviation for students	−0.290 ±0.050	0.119 ±0.041	9.012 ±1.485	18.479 ±3.688
Mean ± standard deviation for control group males	−0.389 ±0.046	0.102 ±0.021	11.102 ±0.410	–
Mean ± standard deviation for control group females	−0.301 ±0.041	0.124 ±0.024	11.789 ±0.333	–
p-value for Student's t-test	0.398	0.008*	0.297	0.644
p-value for Mann–Whitney test	0.473	0.017*	0.345	0.520

* Statistically significant at $p = 0.05$.

For PS, CPP, HNR no statistically significant differences were found in contrary to NAQ.

6. Using a mobile application to detect phonation type

In parallel with the described experiment, a mobile application was developed to measure voice quality before and after vocal load [32]. The first attempts to create such an application were mentioned by [10], and, hereby, this research attempts to confirm whether voice samples collected via mobile devices can be used for vocal analysis.

The application was created in Java for smartphones with the Android operating system. Using the app, users were able to record their voices before and after vocal load using a microphone built into their phone (Fig. 2).

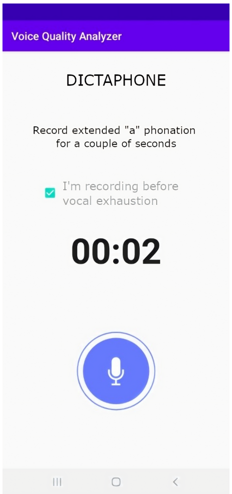

Fig. 2. Voice recording screen of the mobile application.

The recordings were then uploaded to cloud-based NoSQL database using Google Firebase and then processed using methods from the COVAREP [16] repository to calculate values of voice quality parameters. Afterwards, users were able to open a detailed page with calculated values for each recording (Fig. 3).

Eight teachers and twelve people who were not working professionally with their voices were given access to the mobile application and asked to record their voices before and after vocal load.

Participants were asked to record a single extended phonation of vowel /a:/, which was then segmented into smaller samples. We calculated the parameters PS, NAQ, and CPP for given samples and performed an acoustic analysis, com-

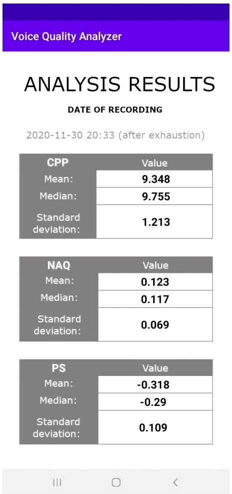

Fig. 3. Display of voice quality parameters for a single recording.

paring voice quality before and after vocal load for all participants. The results are shown in Table 6.

Table 6. Comparison of voice quality before and after vocal load using recordings from the mobile application.

Parameter	PS	NAQ	CPP [dB]
Mean ± standard deviation before vocal load	−0.378 ±0.054	0.143 ±0.040	10.915 ±0.362
Mean ± standard deviation after vocal load	−0.379 ±0.053	0.128 ±0.031	10.900 ±0.387
Mean ± standard deviation for control group males	−0.389 ±0.046	0.102 ±0.021	11.102 ±0.410
Mean ± standard deviation for control group females	−0.301 ±0.041	0.124 ±0.024	11.789 ±0.333
p-value for Student's t-test	0.398	0.008*	0.297

* Statistically significant at $p = 0.05$.

No statistically significant differences were found between PS and CPP. However, we can assume that the value of NAQ changes by about 10%.

7. Discussion

The results of the experiment presented in Subsec. 5.1 suggest that the NAQ value changes after vocal load. This may be interpreted as a change of phonation type [10, 11, 33, 34].

According to [35], the NAQ values of professional singers' voices was unaffected by the pitch of their voice. Because of this, we may assume that the observed changes in NAQ are in fact caused solely by vocal load. Further research is recommended to better understand the effects of vocal load on voice quality.

When test subjects were grouped by the type of vocal load on the recording day, no statistically significant differences were found. Further research is recommended to validate the results of the experiments described here. We recommend recording test subjects on two separate days, whereas one-day lectures are conducted. Then, the impact of class type may be assessed using repeated measures analysis of variance (ANOVA).

Regular hydration has also been shown to impact CPP and HNR. However, it is worth noting that a correlation between the age of tested teachers and their hydration habits was found. According to research [36, 37], the values of CPP and HNR change with the age. Therefore, further research is recommended to determine whether age or hydration causes changes in voice quality.

The experiment presented in Subsec. 5.4 suggests that regular vocal load causes a change in voice quality and potentially alters phonation type [10, 11, 33, 34]. Comparing the results of this experiment with those from [10], the hypothesis is partially supported as statistically significant differences were found in PS and NAQ for males, but not for females.

Additionally, the experiment described in Sec. 6 found an approximately 10% change in NAQ as a result of vocal load. This difference is consistent with [34] and can be interpreted as tense phonation [34].

8. Summary

It is possible to assess voice quality using voice recordings from either a recording studio or a mobile application. According to the results of the experiments, vocal load and working professionally with voice influence the NAQ value. It was also found that HNR and CPP differ depending on regular hydration. A correlation between hydration and age of test subjects was observed. Additional research is recommended to validate the obtained findings. We suggest recording the same test subjects on two separate days (e.g., with lectures and without lectures) to compare voice quality using complex acoustic analysis methods such as ANOVA.

Competing interests

The authors declare that they have no competing interests.

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