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Feature Extraction of Elderly Signals based on Bicoherence Estimation for Automated Medical Diagnosis System

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Abstract

Physiological changes in the vocal fold due to aging may change the pitch of the voice and the elderly signal can be automatically distinguished from the normal signal through various analyses. In case of most smart biomedical devices, the elderly voices have been neglected due to optimization which does not take into account the elderly. The objective of this study is to find the parameters that can distinguish the elderly signal. This paper suggests the mean of normalized skewness, the mean of normalized kurtosis, the ratio of the normalized skewness and kurtosis (RSK), and maximum bicoherence (MB) based on the linear predictive coding (LPC) residual. The parameters are based on the higher-order statistics (HOS) of the time and frequency domain. The mean of normalized skewness and MB parameter were useful and meaningful in an analysis between normal and elderly signals because they showed p-values <.05. In particular, it was believed that MB was very significant for the classification between two signals. And the mean of normalized skewness, RSK, and MB were significant for the objective classification among normal, female elderly, and male elderly signals. In most cases, MB is specially performs better statistically than do the other parameters. To improve the performance of speech interface in automated medical diagnosis system, an analysis of elderly signal is of great interest. These results will contribute to provide an easy access means for the elderly. Future investigations will incorporate multiple classification methods to implement more reliable detector for automated medical diagnosis system.

Keywords*: Elderly signal, Disorder voice, Bicoherence, Higher-order statistics, Linear predictive coding, Medical diagnosis system*

1. Introduction

The computerized smart training devices with speech interface have been made actively for education and community welfare facilities [1]. However, in case of most smart medical devices, the elderly voices have been neglected from the technology due to interface which does not take into account the elderly [2]. Speech interface that supports a smart device is currently using an optimized method based on the average speech pattern of young adults, middle-aged, and elderly people. If it is a little larger deviation from the standard, it may result in a phenomenon that degrades the performance of voice analysis and recognition [2]-[4].

The aging of the body beginning to move into adulthood brings morphological changes in the tissue of the vocal cords and larynx structure that is directly relevant to voice. Therefore elderly voice is to be understood in conjunction with the acoustic properties of the sound by the larynx change according to aging. It means voice changes caused by natural aging process as a result of the drying of the mucosal, the reduced flexibility of vocal ligament, and the nervous fibers atrophy, necrosis [5]-[6]. That is, anatomy and

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physiological changes in the larynx and the vocal cords may change the pitch of the voice and it is measured by fundamental frequency (F0). In conclusion, elderly voice is distinguished from the normal voice and it belongs to a part of speech disorder.

Although many studies related to elderly signals have been published, they are based on the acoustic analysis of the voice samples including jitter and shimmer [3][7]-[9]. However, since these parameters are based on the fundamental frequency, a very reliable pitch detection algorithm is necessary to measure voicing irregularities in elderly signals [10][11]. The perturbation analysis has been found to be sensitive to pitch variations in analysis tools such as multi-dimensional voice profile (MDVP), CSpeech, and TF32. Recently, Lee proposed the moving window method as an objective and reliable method of sample selection for Korean elderly signals. It utilized minimum perturbation value of perturbation measures such as jitter (%), shimmer (%), and SNR (dB) to extend perturbation analysis. It also compared minimum perturbation with average values of the acoustic parameters and investigated the impact of the moving window on perturbation measures generated from elderly signal samples [12].

This paper utilizes higher-order statistics (HOS) that is nothing to do with pitch estimation. Many studies have applied HOS to disordered voices since Alonso *et al.*'s publication on automatic detection of voice pathologies by HOS-based parameters [13]-[18]. Further, the combination of HOS analysis and the linear predictive coding (LPC) residual may help to effectively construct important information to distinguish the signal types of disordered voices [17]-[18]. Although HOS analysis holds promise as one possible method of distinguishing between normal/pathological voices and signal type classification [14]-[16], no studies have applied HOS analysis to analyze elderly voices. Therefore, novel HOS- based parameters estimated in frequency domain for analysis of elderly voices are proposed in this paper.

In this study, an author analyzes the speech of the elderly and finds the necessary correction factor by comparing the normal voices of young adults and middle-aged people. The HOS-based parameters in the time and frequency domains are presented in this paper in order to analyze the elderly voices and to improve the classification performance. This will enhance the speech recognition performance of existing smart medical systems for the elderly. This is also expected to help provide an easy access means of the elderly and people with disabilities who were excluded from the rapid socialization.

2. Research Method

2.1. Database

The elderly signal samples were collected in The Speech Information Technology&Industry Promotion Center (SiTEC). The database includes the elderly signals of 20 Korean subjects (10 female and 10 male) ranging in age from 70 to 80 years. Two sentences were used in this study. The normal signal samples were collected in the speech clinic, Otorhinolaryngology of Gangnam Severance Hospital. The database includes the normal signals of 10 Korean subjects (10 female) ranging in age from 20 to 30 years. Silence sections are manually deleted using information such as structure of waveform and spectrum. The signal samples were sampled at 22.5 kHz and the information is detailed in Table 1.

Table 1. Database Information

<table>
<tr><th></th><th>Sex</th><th>Number</th><th>Age</th><th>Korean sentences</th></tr>
<tr><td rowspan="2">Elderly signals</td><td>Female</td><td>10</td><td>70-79</td><td rowspan="2">1. 그때 누가 그녀의 책상 앞으로 다가왔다.
2. 그때 웬 낯선 사람이 다가와 물었다.</td></tr>
<tr><td>Male</td><td>10</td><td>70-78</td></tr>
<tr><td rowspan="2">Normal signals</td><td>Female</td><td>10</td><td>20-30</td><td>1. 무엇보다도 산에 오를 땐 더욱 더 그 빼어난 아름다움이 느껴진다.</td></tr>
<tr><td>Male</td><td>x</td><td>x</td><td>x</td></tr>
</table>

2.2. LPC Analysis

In previous study, Lee *et al*. introduced the LPC characteristics as acoustic parameters to classify normal and pathological signals [17]-[20]. They suggested HOS-based parameters obtained from the LPC residual for voice-quality assessment. The presented techniques demonstrated that it is possible to evaluate the extent of larynx diseases. Therefore, LPC analysis was introduced in this study to investigate its ability to automatically analyze the elderly signal.

Figure 1 shows the LPC residuals estimated for normal and elderly signals. Figure 1 (a) shows the LPC residuals estimated in normal signals. Then it is zoomed out as Figure 1 (b) to compare LPC residuals of elderly signals with same amplitude unit. Amplitudes of LPC residuals estimated in elderly signals are larger than those of normal signal. Only some of the residuals are harmonically related in Figure 1 (c) and (d). It can be seen that the residual errors tend to be high because of pulse regularity and noise between the signals in elderly voices. Therefore, the use of LPC residuals may yield information regarding the abnormal movement of vocal folds and turbulence noise, which is useful for elderly signals classification.

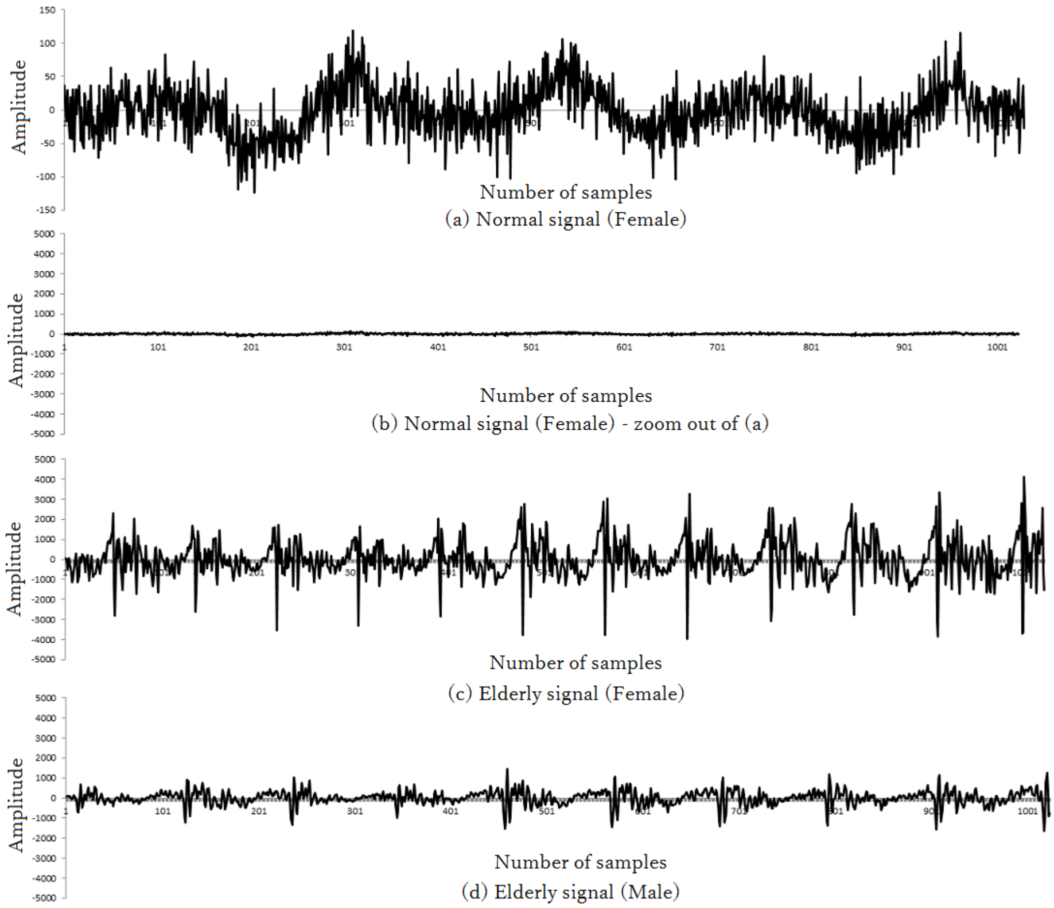


Figure 1. LPC Residuals Estimated for Normal and Elderly Signals

2.3. HOS Analysis

HOS analysis in the time domain has shown promise as a classification index for pathological signals and also has the advantage of not requiring a periodic or quasiperiodic signal to enable reliable analysis [7-9].

The normalized skewness (γ_{3t}) and kurtosis (γ_{4t}) are extracted in-frame, as shown in Equation (1):

$$\gamma_{3t} = \frac{\sum_{n=1}^{N} x_t^3(n)}{[\sum_{n=1}^{N} x_t^2(n)]^{1.5}}, \qquad \gamma_{4t} = \frac{\sum_{n=1}^{N} x_t^4(n)}{[\sum_{n=1}^{N} x_t^2(n)]^{2}} \tag{1}$$

where x(n) is the speech signal sample value of the t^{th} frame, and N is the number of samples.

Then, the means of the normalized skewness and kurtosis are applied for this study.

$$\overline{\gamma_3} = \frac{1}{N}\sum_{t=1}^{N} \gamma_{3t}, \qquad \overline{\gamma_4} = \frac{1}{N}\sum_{t=1}^{N} \gamma_{4t} \tag{2}$$

The proposed parameter is the ratio of the normalized skewness and kurtosis (RSK) as indicated in Equation (3):

$$RSK = \frac{(\overline{\gamma_3})^4}{(\gamma_4)^3} \tag{3}$$

HOS analysis in the frequency domain is mainly applied by using a bispectrum or trispectrum. A bispectrum is a function of two frequencies, whereas a trispectrum is a function of three frequencies. Both spectrums contain complex values. This investigation utilized the bispectrum shown in Equation (4):

$$B(f_1, f_2) = \sum_{\tau_1=-\infty}^{\infty} \sum_{\tau_2=-\infty}^{\infty} C_{3x}(\tau_1, \tau_2) e^{-j\sum_{i=1}^{2} fi\,\tau_i} \tag{4}$$

where $C_{3x}(\tau_1, \tau_2)$ are the third-order cumulants and are defined by Equation (4):

$$C_{3x}(\tau_1, \tau_2) = E\{x(t)x(t+\tau_1)x(t+\tau_2)\} \tag{5}$$

Given estimates of the power spectra and bispectrum, the bicoherence can be estimated as indicated in Equation (5):

$$bic_{auto}(f_1, f_2) = \frac{S_{xxx}(f_1, f_2)}{\sqrt{S_{xx}(f_1)S_{xx}(f_2)S_{xx}(f_1+f_2)}} \tag{6}$$

where S_{xx} and S_{xxx} are the power spectrum and bispectrum, respectively.

The proposed maximum bicoherence (MB) parameter results from the bicoherences. Thus the MB parameter is defined by Equation (7):

$$\max(Bicoherence) = \max\left(\sum_{f_1=0}^{\dim_x-1} \sum_{f_2=0}^{\dim_y-1} bic(f_1, f_2)\right) \tag{7}$$

where the dimensions of the bicoherence value are $\dim_x$ and $\dim_y$.

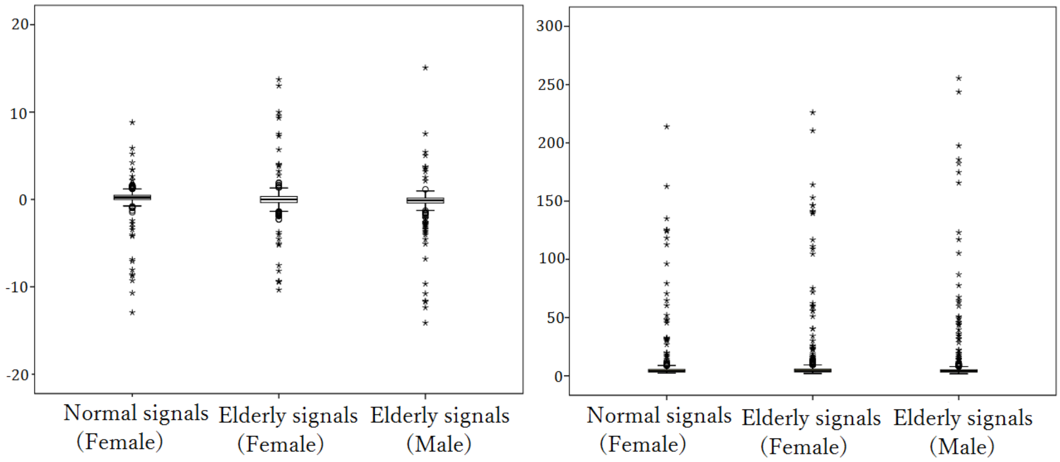
3. Results and Analysis

3.1. Distributions of HOS-Parameters Estimated In Time Frequency

Figure 2 shows the distributions of the normalized skewness and kurtosis estimated from the LPC residuals in normal and elderly signals. The signals were divided into frames of 20 ms with an overlap of 10 ms to extract an LPC residual. Each frame was then windowed by using a hamming window. The reflection coefficients (12^{th} order) were calculated from the 12^{th}-order autocorrelation coefficients by using the Levinson-Durbin algorithm. The output of the all-zero analysis filter was the residual signal.

Figure 2(a) and (b) present the normalized skewness and kurtosis in the form of box plots to provide better visualizations of normal and elderly signals. As may be seen from Table 2, the normalized skewness estimated in normal signals tends to be greater than zero. That is, the mean of normal signals (Female) is 0.233 and the means of elderly signals (Female) and (Male) are -0.005 and -0.173, respectively. Also the mode of normal signals (Female) is 0.34. There is a difference between the distribution of the normalized skewness of normal and elderly signals. In case of the normalized kurtosis, one estimated in elderly signals tend to be larger than one estimated in normal signals. That is, the mean of normal signals (Female) is 6.583 and the means of elderly signals (Female) and (Male) are 7.229 and 7.103, respectively. But the mode of normal signals (Female) is 1.93 and the means of elderly signals (Female) and (Male) are 1.97 and 1.85, respectively. Also the median of normal signals (Female) is 4.074 and the means of elderly signals (Female) and (Male) are 4.260 and 4.040, respectively. So there is little difference between the distribution of the normalized kurtosis of normal and elderly signals.

In particular, in normal signals, the distributions of the normalized skewness and kurtosis tend towards higher values and are slightly broader than those of elderly signals. Overall, it is evident that the normalized skewness is sufficiently distinct to analyze between the normal and elderly signals and can be used as a basis for automatic classification of the normal and elderly signals.



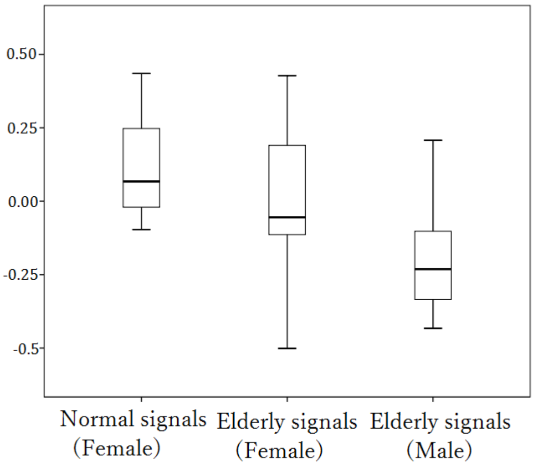
(a) The distribution of the normalized skewness (b) The distribution of the normalized kurtosis

Figure 2. Distributions of the Normalized Skewness and Kurtosis

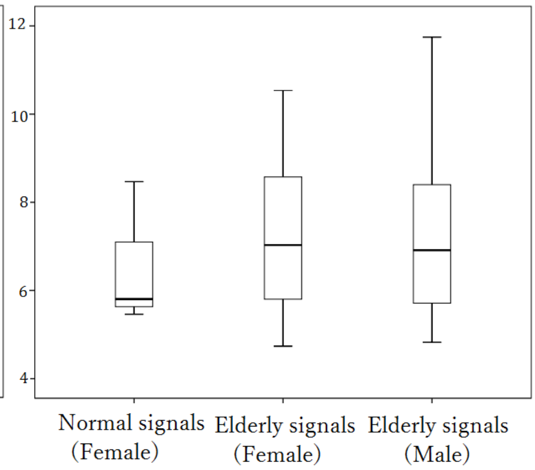
Table 2. Statistics of the Normalized Skewness and Kurtosis

The normalized skewness		Normal signals (Female)	Elderly signals (Female)	Elderly signals (Male)
Mean		0.233	-0.005	-0.173
Median		0.221	0.006	-0.094
Mode		0.34	-10.35	-14.13
Range		29.84	24.09	29.21
Minimum value		-14.65	-10.35	-14.13
Maximum value		15.20	13.74	15.07
Percentile	25	-0.024	-0.353	-0.412
	50	0.221	0.006	-0.094
	75	0.516	0.335	0.176
The normalized kurtosis		Normal signals (Female)	Elderly signals (Female)	Elderly signals (Male)
Mean		6.583	7.229	7.103
Median		4.074	4.260	4.040
Mode		1.93	1.97	1.85
Range		256.70	224.10	253.71
Minimum value		1.93	1.97	1.85
Maximum value		258.63	226.06	255.56
Percentile	25	3.206	3.289	3.290
	50	4.074	4.260	4.040
	75	5.568	5.742	5.182

Figure 3(a) and (b) describe the distributions of the means of the normalized skewness and kurtosis in the form of box. In the distribution of Figure 3 (a), the means of the normalized skewness estimated from normal signals tend to be greater than zero. The means of the normalized skewness measured in elderly signals are inclined to be lesser than zero, that is negative values. In particular, in elderly signals, the mean of the normalized skewness is slightly broader than those of normal signals. As may be seen from Table 3, in statistics of the mean of the normalized skewness, the mean of normal signals (Female) is 0.131 and the means of elderly signals (Female) and (Male) are 0.002 and -0.197, respectively. The range of normal signals (Female) is 0.53 and the range of elderly signals (Female) and (Male) are 0.93 and 0.64, respectively. The 25th, 50th, and 75th percentiles are -0.024, 0.067, and 0.290, respectively, for the means of the normalized skewness measured in normal signal (Female). The 25th, 50th, and 75th percentiles are -0.121, -0.054, and 0.226, respectively, for the means of the normalized skewness measured in elderly signal (Female). Finally, the 25th, 50th, and 75th percentiles are -0.343, -0.231, and -0.095, respectively, for the means of the normalized skewness estimated in elderly signal (Male). There is a clear difference between the distribution of the means of the normalized skewness for normal and elderly signals. In case of the mean of the normalized kurtosis, one estimated in normal signals is included in one estimated in elderly signals. It can be shown by the fact that the maximum, minimum, and range values of the mean of the normalized kurtosis estimated in normal signals are 5.46, 8.47, and 3.01, respectively, in shown as in Table 3. However, the mean of normal signals (Female) is 6.301 and the means of elderly signals (Female) and (Male) are 7.284 and 7.257, respectively. It shows a clear difference between the normal and elderly signals. Similarly, it is obvious that the mean of the normalized skewness sufficiently analyze the normal and elderly signals and can be used for automatic classification between the normal and elderly signals.



(a) The means of the normalized skewness



(b) The means of the normalized kurtosis

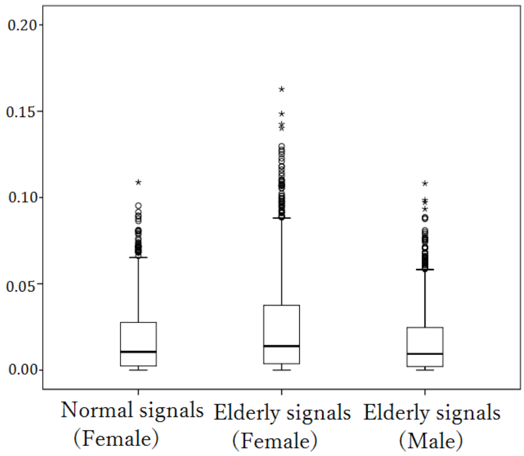
Figure 3. Distributions of the Means of the Normalized Skewness and Kurtosis

Table 3. Statistics of the Means of the Normalized Skewness and Kurtosis

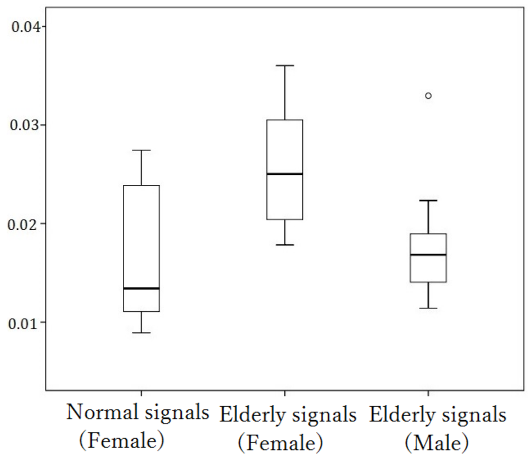
The means of normalized skewness	Normal signals (Female)	Elderly signals (Female)	Elderly signals (Male)
Mean	0.131	0.002	-0.197
Median	0.067	-0.054	-0.231
Mode	-0.10	-0.5	-0.43
Range	0.53	0.93	0.64
Minimum value	-0.10	-0.5	-0.43

Maximum value		0.44	0.43	0.21
Percentile	25	-0.024	-0.121	-0.343
	50	0.067	-0.054	-0.231
	75	0.290	0.226	-0.095
The means of normalized kurtosis		Normal signals (Female)	Elderly signals (Female)	Elderly signals (Male)
Mean		6.301	7.284	7.257
Median		5.804	7.030	6.913
Mode		5.46	4.74	4.82
Range		3.01	5.80	6.92
Minimum value		5.46	4.74	4.82
Maximum value		8.47	10.54	11.75
Percentile	25	5.600	5.790	5.677
	50	5.804	7.030	6.913
	75	7.113	8.659	8.450

Figure 4 shows the distributions of the RSK and their means in the form of box plot. There are similar dispersion among the RSK estimated from normal (Female), elderly (Female), and elderly (Male) signals. From statistics of the RSK in the Table 4, the mean of normal signals (Female) is 0.019 and the means of elderly signals (Female) and (Male) are 0.024 and 0.017, respectively. The 25th, 50th, and 75th percentiles are 0.002, 0.011, and 0.030, respectively, for the RSK measured in normal signal (Female). The 25th, 50th, and 75th percentiles are 0.003, 0.013, and 0.037, respectively, for the RSK measured in elderly signal (Female). So, the RSK estimated in normal signals include the one estimated in elderly signals. There is little difference between the distributions of the RSK in normal and elderly signals. Also it is definitely shown in statistics of the means of RSK in Table 4.



(a) The distribution of RSK



(b) The means of RSK

Figure 4. Distributions of the RSK and Their Means

Table 4. Statistics of the RSK

The RSK		Normal signals (Female)	Elderly signals (Female)	Elderly signals (Male)
Mean		0.019	0.024	0.017
Median		0.011	0.013	0.009
Mode		0.00	0.00	0.00
Range		0.11	0.16	0.19
Minimum value		0.00	0.00	0.00
Maximum value		0.11	0.16	0.19
Percentile	25	0.002	0.003	0.002
	50	0.011	0.013	0.009
	75	0.030	0.037	0.025
The means of RSK		Normal signals (Female)	Elderly signals (Female)	Elderly signals (Male)
Mean		0.017	0.025	0.018
Median		0.013	0.025	0.017
Mode		0.009	0.018	0.011
Range		0.019	0.018	0.021
Minimum value		0.009	0.018	0.011
Maximum value		0.027	0.036	0.033
Percentile	25	0.011	0.020	0.014
	50	0.013	0.025	0.017
	75	0.024	0.030	0.020

3.2. Distributions of HOS-Parameters Estimated In Time Frequency

Figure 5(a), (b), and (c) present clear distinctions between the bicoherence distributions of the different voice signals. In the bicoherence distribution of elderly signals, the greatest amplitude is observed, and the distribution tends towards higher values. Overall, the distributions become broader and more dispersed appearance with higher bicoherence values. In the bicoherence distribution of normal signals as shown in (a), the amplitudes tends to be lower values and a more assembled structure than those of the elderly signals.

Figure 6 shows the characteristics of the MB parameters estimated for normal and elderly signals. The MB values have significantly lower ones in case of normal signals, similarly to the behavior shown in Figure 5. These distributions also presents clear distinctions between normal and elderly signals.

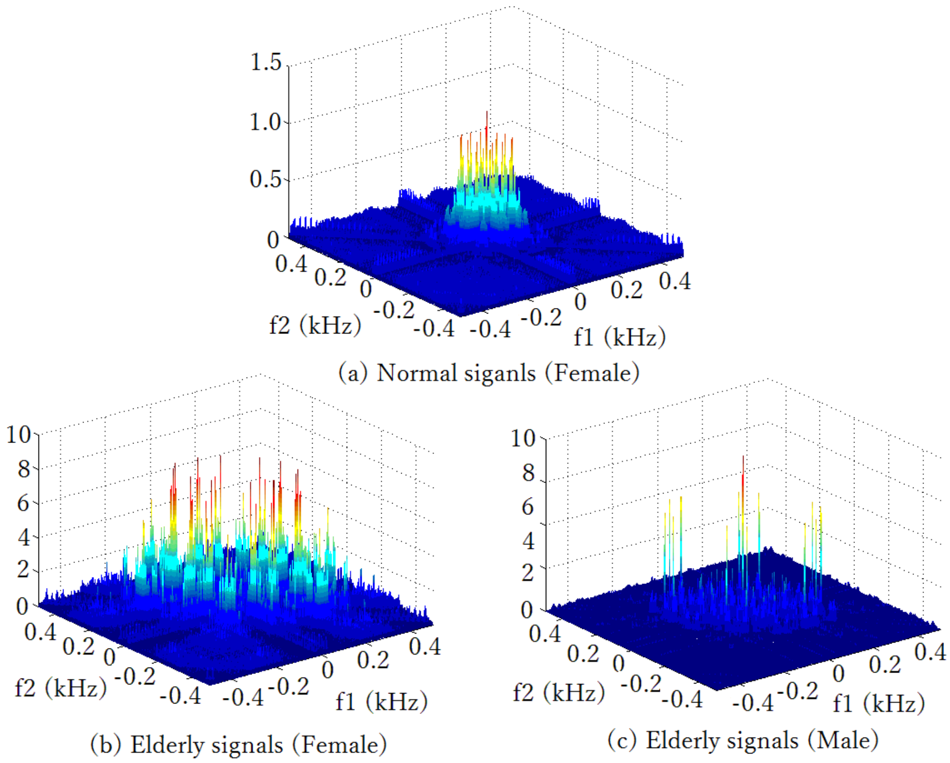


Figure 5. Bicoherence Distributions of Different Signals

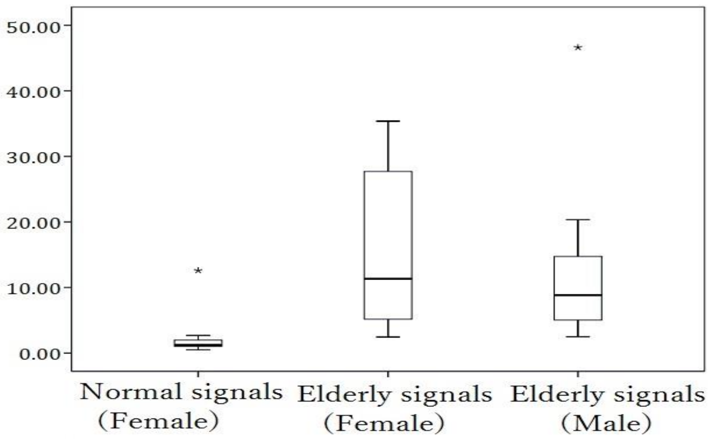


Figure 6. Distributions of MB parameter among Different Signals

3.3. Statistical Analysis

Table 5 shows the statistical analysis between normal and elderly voice signals. The purpose of a Mann-Whitney U test is to determine if significant differences exist in the dependent variables such as the mean of normalized skewness, the mean of normalized kurtosis, RSK, and MB that are used for automatic classification between normal and elderly voice signals. In Table 5, since the mean of normalized skewness and MB show p-values <.05, it is said that they are useful and meaningful for the classification of elderly voice signal. In particular, MB performs better statistically than do the other parameters.

Table 6 shows the one way ANOVA analysis among normal, female elderly, and male elderly voice signals. Scheffe is used as post hoc test. The mean of normalized skewness, RSK, and MB are significant for the objective classification among three voice signals because they show p-values <.05. RSK specially performs better statistically than do the other parameters. The mean of normalized skewness is especially meaningful for the classification between normal and male elderly signals. The RSK and MB are particularly significant for the analysis between normal and female elderly signals.

Table 5. Statistical Analysis between Normal and Elderly Signals

The mean of normalized skewness	p = 0.006*
The mean of normalized kurtosis	p = 0.104
The ratio of the normalized skewness and kurtosis (RSK)	p = 0.071
Maximum Bicoherence (MB)	p = 0.000*

Table 6. Statistical Analysis among Normal, Female Elderly and Male Elderly Signals

	Normal signals (Female)	Elderly signals (Female)	Elderly signals (Male)
The mean of normalized skewness (p = 0.008*)			
Normal signals (Female)	-	0.421	0.008*
Elderly signals (Female)	-	-	0.139
Elderly signals (Male)	-	-	-
The mean of normalized kurtosis (p = 0.334)			
Normal signals (Female)	-	0.426	0.445
Elderly signals (Female)	-	-	0.999
Elderly signals (Male)	-	-	-
The ratio of the normalized skewness and kurtosis (RSK) (p = 0.011*)			
Normal signals (Female)	-	0.018*	0.869
Elderly signals (Female)	-	-	0.058
Elderly signals (Male)	-	-	-
Maximum Bicoherence (MB) (p = 0.02*)			
Normal signals (Female)	-	0.026*	0.107
Elderly signals (Female)	-	-	0.790
Elderly signals (Male)	-	-	-

4. Conclusions

Speech interface is currently using an optimized method based on the average speech pattern of all aged people [2]-[3][11]-[12]. If it is a little larger deviation from an average value, it may have an effect on the performance degradation of voice analysis and recognition [14]-[15]. In case of most welfare smart devices, the elderly signals have been neglected due to interface which does not take into account the elderly [6]. Anatomy and physiological changes in the larynx due to aging may change the pitch of the voice and it can be distinguished from the normal signal as a part of speech disorder [2]-[5].

Many studies related to elderly signals have been based on the acoustic analysis of the voice samples including jitter and shimmer [3]-[4][6]-[8]. However, since these parameters are based on the fundamental frequency, a very reliable pitch extraction is necessary to measure voicing irregularities in elderly signals [12]. Recently, it is well known that higher-order statistics (HOS) which is not related to the pitch estimation is to be effective for the classification of signal type. Further, the combination of HOS analysis and the linear predictive coding (LPC) residual may help to effectively construct important information to distinguish between normal and elderly signals [13]-[17].

In this paper, the mean of normalized skewness, the mean of normalized kurtosis, the ratio of the normalized skewness and kurtosis (RSK), and maximum bicoherence (MB) are analyzed from LPC residual of normal and elderly signals. Distributions of the normalized skewness, the mean of the normalized skewness, the normalized kurtosis, the mean of the normalized kurtosis, the RSK, their means, bicoherence, and MB parameters are examined from normal, female elderly, and male elderly signals. The strong correlations between the HOS-based parameters and elderly signal are demonstrated.

The mean of normalized skewness and MB parameter are useful and meaningful in an analysis between normal and Elderly signals because they show p-values <.05. In particular, it is believed that MB is very significant for the classification between normal and elderly signals. One way ANOVA analysis is performed for various parameters estimated among normal, female elderly, and male elderly signals. The mean of normalized skewness, RSK, and MB are significant for the objective classification among three signals because they show p-values <.05. The mean of normalized skewness is especially meaningful for the classification between normal and male elderly signals. The RSK and MB are particularly significant for the analysis between normal and female elderly signals. Therefore, in most cases, MB is specially performs better statistically than do the other parameters.

These results will contribute to enhance the speech recognition performance of the existing smart medical systems for the elderly. This is also expected to help provide an easy access means for the elderly and the disabled who can be excluded from the rapid socialization.

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