Classification of Central Obesity from Voice Signals

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Abstract. Central obesity has a direct relationship with fatal and critical diseases such as type 2 diabetes, metabolic syndrome, and cardiovascular disease. The aim of this study was to develop a method for diagnosing central obesity using voice characteristics. Totally, 4040 subjects were selected from a Korean population, and the classification models were built using Naïve Bayes and wrapper-based feature selection. The area under the receiver operating characteristics curve was 0.603 in women (aged 60-79 years) and 0.611 in men (aged 60-79 years). Many voice features were statistically significantly different between the normal weight and central obesity groups, between men and women in these groups. Our results are important for the development of advanced applications for prediction of health condition in u-healthcare and telemedicine.

Keywords: Central obesity, Voice, Classification, Data mining, Machine learning

1 Introduction

Central obesity (CO) has been shown to be associated with a significantly increased risk for type 2 diabetes, metabolic syndrome, cardiovascular disease (CVD), ischemic heart disease, stroke, and cancer [1-5].

The human voice is affected by a number of diseases, such as vocal fold pathologies and sleep apnea [7-13], and morphological differences, such as gender, weight, height, and age [1418]. For a long time, many studies have focused on voice signals for diagnosis of diseases.

In studies on the relationship between voice and disease, Garcia et al. [10] showed the differences between healthy voices, pathological voices, and esophageal voices by analyzing pitch, jitter, and shimmer and proposed an accurate method for the detection of regular cycles of laryngeal and esophageal voices. The study by Ghoraani and Krishnan [12] suggested an automatic pattern classification method of pathological voice based on interpretable features using adaptive time-frequency distribution and matrix factorization. The method using spectral and temporal characteristics of pathological and normal speech signals was applied to the

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Massachusetts Eye and Ear Infirmary voice disorders database and showed superior classification performance.

Regarding the relationships between human voice, morphological characteristics, and aging, Koziel et al. [16] revealed that respiratory functions are significantly affected by CO and obesity of the chest in men, based on their analyses of CO, BMI, waist-to-hip ratio, skin folds, forced expiratory volume in 1 s, and forced vital capacity. They argued that obesity tends to worsen respiratory function in men and women. The study by Steele et al. [17] revealed that respiratory mechanics have a stronger relationship with central fat distribution in men than in women, based on their analysis of association between obesity (measured by BMI), body fat percentage, WC, fat mass, and lung function. Willis and Kenny [18] argued that voice changes in vocal range, pitch-break frequency, and speaking fundamental frequency (SFo) were associated with certain weight ranges, based on an assessment of voice-change progress of 13-year-old girls.

We propose a novel method for the classification of normal weight and CO using only voice features, independent of WC measurement. Our method will allow further development of medical applications for real-time monitoring of patients with chronic illnesses related to CO. Furthermore, we determine useful voice characteristics obtained by the statistical analysis of voice features and CO in gender groups. These data will help find the best possible combination of features for use in medical science, forensics, and speech recognition.

2 Materials and Methods

2.1 Data Collection

A total of 4040 subjects participated in this study. Voice signals of men and women aged 60-79 years were extracted at the Korea Institute of Oriental Medicine (MOM) and several hospitals in the Republic of Korea.

Speaker's renditions were strictly constrained by a standard operating procedure. The configuration of the voice-recording room was as follows: noise intensity of 40-50 dB, no resonance, humidity of 40% ± 5%, room temperature of 20°C ± 5°C. Recording equipment used was as follows: a Blaster Live 24-bit external sound card, a Sennheiser e-835s microphone, and GoldWave recording software. Distance from the subjects' mouths to the microphone was 4-6 cm. We extracted 222 voice features based on the correlation coefficient between FO and intensity (CORR), pitch, shimmer, average ratio of pitch period, Mel-frequency cepstrum coefficients (MFCC), absolute jitter (JITA), and other features, from 5 vowels and 1 sentence. Detailed contents of the features used in this study are described in a referenced article [19].

2.2 WC Cutoff Values and Feature Selection

Appropriate cutoff values for WC for diagnosis of CO vary by ethnic group [20, 21]. In this study, we have followed the suggestions of recent studies [22-24] in setting our cutoff values for Korean and Asian WCs. Therefore, the cut-off values for central obesity were defined as WC >85 cm for women and >90 cm for men.

Human voice is influenced by age, gender, and culture differences [25]. Therefore, we divided the subjects into 2 groups for gender-specific classification: the female 60-79 group (women aged 60-79 years) and the male 60-79 group (men aged 60-79 years). The basic characteristics of each group are described in Table 1.

For the selection of the combination of important features from an initial 222 features for each group, feature selection was performed as follows. First, we extracted all features that were significantly different (p value < 0.05 by independent two-sample t-test using the SPSS for Windows). Second, a wrapper-based subset selection approach using machine learning (logistic regression) and best first-search strategy (forward selection) were applied to the surviving features in each group from the previous step. The process was repeated for the 2 groups. We obtained 2 feature subsets for each group, and the surviving features in the 2 groups differed according to gender and a combination of features by wrapper-based subset selection. All classification experiments were performed using the Naive Bayes classifier of Weka software [26]. The results are based on 10-fold cross-validation.

Table 1. Basic statistics of the subjects in the 2 groups (standard deviation)

Group	Normal weight			Central obesity		
	N	Mean age (year)	Central measure	N	Mean age (year)	Central measure
Female	816	67.80(5.12)	79.17 (4.90)	1504	68.46 (4.95)	93.52 (6.07)
Male	1077	67.87 (5.27)	82.15 (5.89)	643	67.77 (4.99)	95.70 (4.72)

3 Results and Discussion

3.1 Performance Analysis

The performance analyses of the 2 groups are described in Table 2. Classification models showed AUC values ranging from 0.603 to 0.611. The female group had an AUC value of 0.603. Sensitivity and 1-specificity of normal weight were 0.516 and 0.357, respectively, and sensitivity and 1-specificity of CO were 0.643 and 0.484, respectively. In the male group, the classification model showed an AUC value of 0.611. Sensitivity of normal weight was 0.678 and that of CO was 0.476.

In elderly subject groups, the classification performance was better in the men than in the women. We think that one of the reasons for the lower performance in the elderly women was menopause, because after menopause women experience changes in body weight, shape, and fatty tissue distribution [27, 28].

Table 2. Detailed performance analysis of classification experiments (CO: central obesity)

Group	Class	Sensitivity	1-specificity	Precision	F-measure	AUC
Female-60-79	Normal	0.516	0.357	0.439	0.475	0.603
	CO	0.643	0.484	0.71	0.675	
Male-60-79	Normal	0.678	0.524	0.684	0.681	0.611
	CO	0.476	0.322	0.469	0.472	

3.2 Statistical Analysis of Surviving Features

In this study, features with p values of less than 0.05 were considered statistically significant, and features with p values less than 0.001 were considered highly statistically significant. Statistical analysis of the 2 groups is presented in Tables 3 and 4.

In the female group, 13 features were selected in feature selection, and differences in aMFCC12 (12th MFCC of a vowel A), eMFCC6 (sixth MFCC of a vowel E), iMFCC5 (fifth MFCC of a vowel I), and uMFCC12 (12th MFCC of a vowel U) were highly significantly different between the normal weight and CO groups ($p < 0.0001$, $p = 0.0010$, $p = 0.0001$, and $p < 0.0001$, respectively). Feature aF4, fourth formant frequency of a vowel A, was significantly different in the normal weight and CO groups ($p = 0.0068$).

In the male group, 14 features were selected through feature selection and were used in the classification experiment. Of these features, aRF4_F 1 (fourth formant frequency/first formant frequency of a vowel A), eRF60_120_240_480 (frequency band of 60-120 Hz/frequency band of 240-480 Hz of a vowel E), uF0 (basic pitch of a vowel U), iMFCC5 (fifth MFCC of a vowel I), and oMFCC4 (fourth MFCC of a vowel 0) were highly significantly different between normal weight and CO subjects ($p = 0.0001$, $p = 0.0003$, $p = 0.0009$, $p < 0.0001$, and $p = 0.0003$, respectively).

Table 3. Statistical analysis of voice features in the female group

Feature	Class	Mean	Std.	t	Df	p-value
aF4	Normal	4044	313.3	2.708	2318	0.0068
	CO	4007	318.0			
aRF3_F2	Normal	2.190	0.302	2.626	2318	0.0087
	CO	2.155	0.303			
uRAP	Normal	0.077	0.038	-2.554	2205	0.0107
	CO	0.082	0.055			
uPPQ	Normal	0.128	0.058	-2.970	2157	0.0030
	CO	0.137	0.082			
aMFCC12	Normal	-3.921	5.528	-5.967	2318	<0.0001
	CO	-2.459	5.694			
eMFCC6	Normal	-16.83	7.546	-3.307	2318	0.0010
	CO	-15.77	7.304			
iMFCC5	Normal	0.791	6.615	-3.984	2318	0.0001
	CO	1.887	6.167			
uMFCC5	Normal	-14.04	6.958	-2.113	1524	0.0347
	CO	-13.43	6.242			
uMFCC12	Normal	-9.668	5.740	-5.810	2318	<0.0001
	CO	-8.244	5.580			
P10	Normal	161.9	32.51	1.995	2318	0.0462
	CO	159.2	31.31			
P90	Normal	216.7	31.64	3.101	2318	0.0019
	CO	212.3	32.69			
IHL	Normal	0.611	0.226	2.491	1493	0.0128
	CO	0.588	0.198			
SISTD	Normal	4.578	0.666	-2.002	2318	0.0454
	CO	4.635	0.638			

Table 4. Statistical analysis of voice features in the male group

Feature	Class	Mean	Std.	t	Df	p-value
aSTD	Normal	5.010	7.551	-2.201	1221	0.0279
	CO	5.909	8.552			
aBW2	Normal	321.9	226.3	-2.433	1718	0.0151
	CO	349.9	238.0			
aRF4_F1	Normal	6.510	2.158	3.996	1561	0.0001
	CO	6.128	1.760			
eRF60120240480	Normal	-0.301	1.229	3.651	1443	0.0003
	CO	-0.513	1.127			
iTO	Normal	6.982	1.511	-2.632	1718	0.0086
	CO	7.177	1.449			
uF0	Normal	150.3	35.42	3.335	1487	0.0009
	CO	144.8	31.14			
uPPQ	Normal	0.167	0.119	2.025	1718	0.0430
	CO	0.156	0.096			
aMFCC2	Normal	-2.230	5.405	2.458	1718	0.0141

Feature	Class	Mean	Std.		Df	p-value
	CO	-2.899	5.559			
aMFCC10	Normal	2.184	7.822	-2.729	1718	0.0064
	CO	3.234	7.557			
iMFCC5	Normal	10.51	7.133	-4.686	1718	<0.0001
	CO	12.17	7.018			
iMFCC10	Normal	-5.985	6.388	-2.113	1718	0.0347
	CO	-5.300	6.687			
oMFCC4	Normal	-4.625	8.073	-3.614	1430	0.0003
	CO	-3.235	7.493			
uMFCC9	Normal	-0.150	6.423	-2.433	1718	0.0151
	CO	0.623	6.289			
SISTD	Normal	4.660	0.678	-2.309	1718	0.0211
	CO	4.736	0.616			

4 Summary

We demonstrated that it is possible to predict CO using voice characteristics. We performed statistical analyses of the surviving features from wrapper-based feature subset selection and independent two-sample t-tests to reveal the relationship between CO and voice signals. Finally, we provide compact and significant feature subsets for building classification models for 2 gender groups. Our methods and results could help in developing advanced applications for use in voice pathology, remote healthcare, obesity, and voice recognition.

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