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Tracking age-related changes in voice and speech production with Landmark-based analysis of speech

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ABSTRACT:

Voice and speech production change with age, which can lead to potential communication challenges. This study explored the use of Landmark-based analysis of speech (LMBAS), a knowledge-based speech analysis algorithm based on Stevens' Landmark Theory, to describe age-related changes in adult speakers. The speech samples analyzed were sourced from the University of Florida Aging Voice Database, which included recordings of 16 sentences from the Speech Perception in Noise test of Bilger, Rzcezkowski, Nuetzel, and Rabinowitz [J. Acoust. Soc. Am. **65**, S98–S98 (1979)] and Bilger, Nuetzel, Rabinowitz, and Rzeczkowski [J. Speech. Lang. Hear. Res. **27**, 32–84 (1984)]. These sentences were read in quiet environments by 50 young, 50 middle-aged, and 50 older American English speakers, with an equal distribution of sexes. Acoustic landmarks, specifically, glottal, bursts, and syllabicity landmarks, were extracted using SpeechMark®, MATLAB Toolbox version 1.1.2. The results showed significant age effect on glottal and burst landmarks. Furthermore, the sex effect was significant for burst and syllabicity landmarks. While the results of LMBAS suggest its potential in detecting age-related changes in speech, increase in syllabicity landmarks with age was unexpected. This finding may suggest the need for further refinement and adjustment of this analytical approach https://doi.org/10.1121/10.0028175

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I. INTRODUCTION

Acoustic analysis has long been a core approach in speech science, offering invaluable insights into human speech production and perception (Kent and Kim, 2008; Stevens, 2000). Traditional approaches have primarily focused on describing the physical characteristics of speech signals, such as frequency, amplitude, and duration. While invaluable, currently available analytical tools have limitations, especially in terms of labor intensity, which have hindered its incorporation into clinical practice. In response to these challenges, there is a growing demand for an automated approach capable of not only capturing these basic acoustic properties but also delineating speech differences with greater specificity and efficiency. Systems developed based on the Landmark theory of speech have shown considerable promise in meeting this demand. These systems have demonstrated their utility in characterizing speech variations secondary to voice and speech disorders (Chenausky *et al.*, 2011; Ishikawa *et al.*, 2020; Liu and Chen, 2021; Speights Atkins and MacAuslan, 2022; Suthar *et al.*, 2022). Another critical factor influencing voice and speech production is aging, yet the extent to which landmark-based systems can account for these age-related differences remains underexplored. Distinguishing speech changes inherent to the normal aging process from those indicative of pathological conditions is essential for a clinical tool. Thus, understanding how a landmark-based system describes age-related changes in speech is a crucial step toward further developing a system specifically tailored for this purpose.

The landmark theory of speech, proposed by Kenneth Stevens (Stevens, 1981, 2002), describes speech perception through the lens of articulatory–acoustic and acoustic–perceptual mapping. Central to this theory is the concept of "landmarks," the temporal positions characterized by abrupt changes or extrema in the speech spectrum elicited by speech articulation. The theory posits that these landmarks serve as perceptual anchors for identifying the distinctive features of phonemes (Chomsky and Halle, 1968), providing the auditory system salient acoustic cues crucial for decoding the phonetic structure of speech (Slifka *et al.*, 2004). The Landmark theory has provided a framework for knowledge-based, automatic speech analysis systems (Boyce *et al.*, 2010, 2012; Howitt, 2000; Juneja and Espy-Wilson, 2008; Liu, 1996; Shi *et al.*, 2021).

The Landmark-based speech analysis systems typically extract the landmarks in a two-step process (Liu, 1996). The first phase involves marking the moments where abrupt changes in the speech signal occur. The second phase characterizes the acoustic patterns of these detected landmarks and classifies them into specific classes of landmarks based on the acoustic features corresponding to particular phonetic features.

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In SpeechMark® (Lexington, MA), a suite of software tools designed for research use (Boyce *et al.*, 2010, 2012), landmarks are divided into two primary classes: peak and abrupt. Peak landmarks are identified at points in speech where there is a peak in harmonic power or fractal dimension, representing the centers of vowels or fricated intervals. The abrupt landmarks are identified at moments in the speech signal where there is rapid change across multiple frequency ranges and time scales. For instance, an abrupt increase in amplitude above 3 kHz can indicate the onset of bursts, while an abrupt decrease can indicate the end of frication. The abrupt landmarks include glottal onset and offset [+/−g], burst onset and offset [+/−b], syllabic onset and offset [+/−s], voiced frication onset and offset [+/−v], unvoiced frication onset and offset [+/−f]. The detailed acoustic rules for the detection of each landmark type are described in Table I. An example of landmark analysis by SpeechMark® is shown in Fig. 1.

SpeechMark® has been employed in research to detect small, non-lexical differences in speech production, such as speech differences associated with speaking styles (Boyce *et al.*, 2013; Ishikawa *et al.*, 2023), sleep-deprived conditions (Boyce *et al.*, 2011), Parkinson's disease (Chenausky *et al.*, 2011), dysphonia (Ishikawa *et al.*, 2020), dysarthria (Liu and Chen, 2021), and speech sound disorders (Speights Atkins and MacAuslan, 2022; Suthar *et al.*, 2022). In normal speech, Ishikawa *et al.* (2017) analyzed the first 12 s of the "Rainbow Passage" (Fairbanks, 1960) from 15 adult females with a mean age of 37.8 years and 21 adult males with a mean age of 38.81 years. The results showed that 94% of all landmarks were primarily glottal, burst, and syllabic landmarks and highlighted the importance of sex effects on landmark analysis (Ishikawa *et al.*, 2017). This study was the first to characterize landmark expression in normal adult speakers and noted that the findings should be examined in a larger sample size, specifically for the effect of sex. Landmark-based analysis has also been used in the study of disordered speech that affects overall speech intelligibility. In their study on dysphonic speech, Ishikawa *et al.* (2020) extracted syllabic, glottal, and burst landmarks from the first sentence of the "Rainbow Passage" in 36 speakers with dysphonia and compared them to 33 speakers without dysphonia. This preliminary investigation reported that the average count of all landmarks was significantly greater in normal speech, and that dysphonic speech had more glottal and burst landmarks and fewer syllabic landmarks than normal speech. Most recently, Ishikawa *et al.* (2023) demonstrated the feasibility of differentiating conversational and clear speech in 27 individuals with muscle tension dysphonia. Specifically, clear speech resulted in a significantly greater number of burst onset landmarks and longer durations between glottal landmarks compared to casual speech; however, the number of syllabic landmarks did not significantly differ between clear and casual speech.

Landmark-based analysis is emerging as a potential approach for detection of disorders beyond dysphonia. Liu and Chen (2021) explored its application among adults with cerebral palsy (CP), analyzing 210 sentences from the TORGO database (https://www.cs.toronto.edu/~complingweb/data/TORGO/torgo.html, https://link.springer.com/article/10.1007/s10579-011-9145-0). Their study, involving 14 participants—seven with CP and seven typically developing adults matched for age and sex—revealed that those with CP produced a significantly higher number of landmark features. In the pediatric domain, Speights Atkins and MacAuslan (2022) assessed the SpeechMark® Automated Syllabic Cluster detection system's capability in identifying speech impairments through continuous speech samples from 4-year-old children. Their findings highlighted variations in speech rate and syllabic cluster

TABLE I. The acoustic rules for the detection of each landmark type. Reproduced with permission from Ishikawa *et al.*, J. Acoust. Soc. Am. **142**, EL441–EL447 (2017). Copyright 2017 Acoustical Society of America.

Symbol	Landmark type	Rule
+g	Glottal onset	The beginning of sustained vocal fold vibration, i.e., of periodicity or of power and spectral slope similar to that of a nearby segment of sustained periodicity
−g	Glottal offset	End of sustained vocal fold vibration
+b	Burst onset	At least three of five frequency bands show simultaneous power increases of at least 6 dB in both the finely smoothed and the coarsely smoothed contours, in an unvoiced segment (not between +g and the next g)
−b	Burst offset	At least three of five frequency bands show simultaneous power *decreases* of at least 6 dB in both the finely smoothed and the coarsely smoothed contours, in an unvoiced segment
+s	Syllabic onset	At least three of five frequency bands show simultaneous power increases of at least 6 dB in both the finely smoothed and the coarsely smoothed contours, in a voiced segment (between +g and the next g)
−s	Syllabic offset	At least three of five frequency bands show simultaneous power *decreases* of at least 6 dB in both the finely smoothed and the coarsely smoothed contours, in a voiced segment
+f	Frication onset	At least three of five frequency bands show simultaneous power increases at high frequencies and decreases at low frequencies (unvoiced segment)
−f	Frication offset	At least three of five frequency bands show simultaneous power decreases at high frequencies and increases at low frequencies (unvoiced segment)
+v	Voiced frication onset	At least three of five frequency bands show simultaneous power increases at high frequencies and decreases at low frequencies (voiced segment)
−v	Voiced frication offset	At least three of five frequency bands show simultaneous power decreases at high frequencies and increases at low frequencies (voiced segment)

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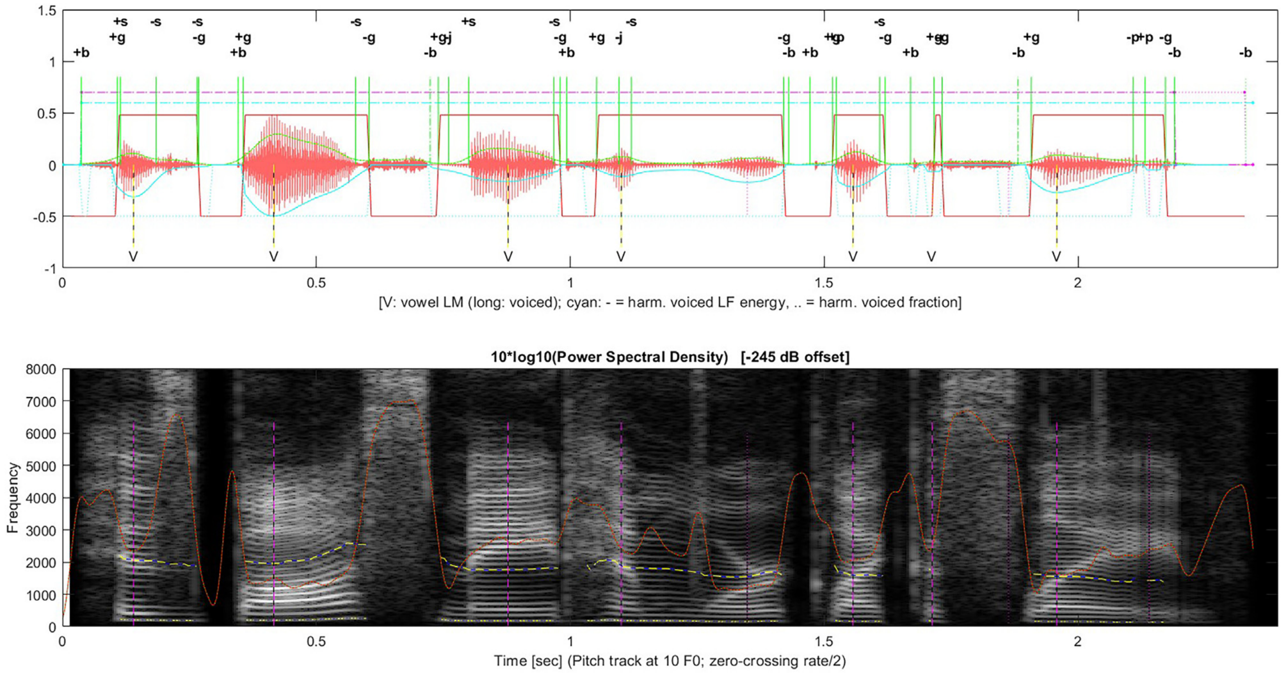

FIG. 1. (Color online) An example of LMBAS by SpeechMark®.

production between typically developing children and those with speech compromise, suggesting the system's potential for early detection of speech impairments. Expanding the scope of landmark analysis, Suthar *et al.* (2022) integrated machine learning techniques to enhance the detection of speech disorders in children. By employing both traditional and novel knowledge-based landmark features, their study showed the promise for increasing accuracy and efficiency of automatic screening tools. Collectively, these studies demonstrate the versatility and potential of landmark-based analysis in advancing our understanding and detection of speech production differences across different age groups and conditions.

Aging significantly affects voice and speech production, with changes manifesting as early as the fourth or fifth decade of life (Hixon *et al.*, 2014; Ramig *et al.*, 2001). These age-related alterations are attributed to structural, physiological, and neurological transformations affecting not only the cardiovascular, skeletal, and muscular systems, but also key speech subsystems, such as respiration, phonation, and articulation (Hoit and Hixon, 1987; Huber and Stathopoulos, 2015; Awan, 2006; Watts *et al.*, 2015; Liss *et al.*, 1990). Acoustically, the effect of aging on speech production has been documented across various languages as changes in speech and articulation rates, pause frequency and durations, and the acoustic properties of vowels and consonants (Bóna, 2014; Brückl and Sendlmeier, 2003; Eichhorn *et al.*, 2018; Jacewicz *et al.*, 2010; Rastatter *et al.*, 1997). For instance, a general decrease in speech rate occurs with advancing age, with variations observed based on the speaker's sex (Jacewicz *et al.*, 2009; Verhoeven *et al.*, 2004). Additionally, for English speakers, vowel centralization and the lowering of vowel formants have been reported, alongside greater variability in consonant production, particularly in voice onset time (VOT) (Morris and Brown, 1994; Sweeting and Baken, 1982; Xue and Hao, 2003). The importance of considering the sex difference in aging speech has been suggested by a study that examined formant frequencies and VOT of younger and older speakers (Torre and Barlow, 2009). Aging also affects the larynx. One of the common anatomical changes is atrophy of the vocal fold tissue, resulting in bowing and incomplete glottal closure. These physiological changes lead to a voice that may sound breathy, rough, or strained due to altered glottal flow dynamics. Acoustic manifestations of these laryngeal changes are often captured through measures, such as fundamental frequency, intensity, jitter, shimmer, harmonics-to-noise ratio, cepstral peak prominence, and spectral features, associated with breathy voice quality (Ramig, 1983; Linville, 2002; Buckley *et al.*, 2023; Kent *et al.*, 2023).

Current literature employing conventional acoustic measures has demonstrated discernible effects of aging on voice and speech production. Previous studies utilizing speech-based landmarks have illustrated their efficacy in delineating changes in voice and articulation. Leveraging this premise, our study assesses the efficacy of landmarks in discerning age-related alterations within a substantial dataset. Additionally, given the balanced distribution of sexes within our dataset, we also explore potential sex-based effects.

II. RESEARCH QUESTIONS AND HYPOTHESES

The central research question of the current study is: "Do speakers' age and sex affect the expression of landmarks, specifically the count of glottal, burst, and syllabicity landmarks?" Aging is anticipated to impact glottal function, potentially leading to observable changes in both glottal and syllabicity landmarks. Given that vocal fold tissue atrophy can disrupt the periodicity of vibration—wherein glottal landmarks denote the onset and offset of periodic moments—such disruption is hypothesized to result in an increased count of glottal landmarks.

The atrophy may also enlarge the glottal gap, introducing greater noise and reduce harmonicity in the acoustic voice signal. This alteration could consequently decrease the acoustic moments that qualify for syllabicity landmarks, as their detection is contingent on energy differences across various spectral bands in voiced segments. Additionally, the phenomenon of vowel centralization, which reduces the contrast in formant frequencies across vowels, might diminish the likelihood of syllabicity landmark detection, as the distinction between vowel sounds becomes less pronounced. Hence, we hypothesize a decrease in the count of syllabicity landmarks with age due to these physiological changes.

The noise resulting from vocal fold atrophy may mimic consonantal sounds, potentially leading to an increase in acoustic moments that qualify for burst landmarks in older adults, akin to patterns observed in dysphonic speech (Ishikawa *et al.*, 2020). Moreover, the documented general decrease in speech rate with advancing age (Verhoeven *et al.*, 2004; Jacewicz *et al.*, 2009) might afford older speakers more time to articulate consonants distinctly. To support this notion, Narayan (2023) demonstrated that decreased speaking rate increased burst amplitude in plosives. Accordingly, aging-related change in speaking rate may generate more instances of that qualify for burst landmarks. Consequently, we hypothesize an increase in burst landmarks among older adults.

III. METHODS

A. Description of speakers/speech stimuli

The speech data utilized in this study were a subset sourced from the University of Florida Vocal Aging Database (UF-VAD) (Harnsberger *et al.*, 2008, 2010; Spiegl *et al.*, 2009), which comprises recordings of American English spanning the years 2003–2007. Stimulus materials consisted of a diverse set of speech samples read by 50 individuals in three distinct age groups: chronologically young (18–30 years), middle-aged (40–55 years), and older adults (62–92 years). Each age group comprised 25 male and 25 female speakers/talkers (Table II). The speech samples included "The Rainbow Passage" (Fairbanks, 1960), "The Grandfather Passage" (Van Riper, 1963), 16 sentences taken or adapted from the Speech Perception in Noise test (SPIN) sentences (Bilger *et al.*, 1979, 1984), three sustained vowels ([a], [i], and [u]), and two diadodes ([/patəkə/], [/ʃəpupi/]). SPIN sentences are standardized speech stimuli commonly used in hearing research (e.g., Wong *et al.*, 2009). For this database, no noise was added to the recordings. Recordings were made in a quiet environment using a head-worn microphone (Shure SM10A, Shure Inc., Niles, IL) fixed at a constant distance from the corner of the mouth. All recordings, captured on a Sony DAT recorder (Sony Corp, Tokyo, Japan), were later transferred to a computer for analysis (sampling rate = 22.05 kHz; quantization = 16 bits). The entire collection of 150 normal voices is referred to as the UF-VAD. A list of 16 SPIN sentences was used for the current study (the Appendix).

B. Landmark extraction

The SpeechMark® MATLAB Toolbox Ver 1.1.2 was used for landmark-based analysis (Fig. 1). Following the software's guidelines, the speech recordings were downsampled to 16 kHz. Additionally, the frequency limit for the high-pass filter was set at 75 Hz, the standard setting for adult speakers. The maximum fundamental frequency limit was adjusted to 220 Hz for male speakers and 350 Hz for female speakers. Due to redundancy in the detection algorithm, voiced and unvoiced fricative landmarks occur less frequently than glottal, burst, and syllabic landmarks (Ishikawa *et al.*, 2017). Therefore, although all types of landmarks were generated, this study's analysis predominantly focused on the three most frequently occurring landmarks: glottal [g], burst [b], and syllabic [s] onset and offset landmarks. The counts of landmarks were obtained from the 16 sentences for each speaker and were then used as the dependent variable in the statistical models.

C. Statistical method

The acoustic values were obtained for each sentence and then averaged across 16 sentences for each speaker. To assess the effects of two independent variables (age and sex) on the dependent variable (the count of each landmark), a two-way analysis of variance (ANOVA) was utilized. The interaction between age and sex was also evaluated. When the model indicated significant effects of age and/or sex on the landmark count, pairwise *t*-tests were conducted. These tests were aimed at investigating differences in the landmark count across different age groups, stratified by sex, and across different sexes, stratified by age. The *p*-values from these tests were adjusted using the Bonferroni method to account for multiple comparisons. The effect sizes were computed as partial eta-squared. The effects were considered trivial (<0.01), small (0.01-0.06), medium/moderate

TABLE II. Mean, minimum (min), and maximum (max) chronological ages for males and females in each age group of the UF-VAD.

Talker group and sex	Chronologic age (years)		
	Mean	Min	Max
Young			
Male	22	18	29
Female	20	18	24
Middle			
Male	49	41	55
Female	48	40	55
Older			
Male	78	62	92
Female	79	65	89

(>0.06–0.14), or large (>0.14) (Richardson, 2011). All statistical analyses were conducted with *R* version 2022.07.1 (R Studio Team, 2022).

IV. RESULTS

A descriptive statistics of the landmark count is displayed in Table III.

A. Glottal onset landmarks

The result of two-way ANOVA indicated a significant effect of age on [+g] [$F(2, 144) = 3.958$, $p = 0.021$, $\eta_p^2 = 0.051$.] The effect of sex on [+g] was not statistically significant [$F(1, 144) = 3.294$, $p = 0.072$, $\eta_p^2 = 0.021$]. The interaction between age and sex was not significant [$F(2, 144) = 0.203$, $p = 0.816$, $\eta_p^2 = 0.003$]. A series of pairwise *t*-tests with Bonferroni correction across three age groups indicated that there was no significant difference in the mean levels of the dependent variable between the middle-aged and older groups, $t(49) = -1.39$, $p_{adj} = 0.516$ and between the middle-aged and young groups, $t(49) = 1.41$, $p_{adj} = 0.498$. However, there was a significant difference between the older and young groups, $t(49) = 2.83$, $p_{adj} = 0.020$ (Fig. 2).

B. Glottal offset landmarks

The result of the two-way ANOVA indicated a significant effect of age on [−g] [$F(2, 144) = 4.004$, $p = 0.0203$, $\eta_p^2 = 0.051$]. The effect of sex on [−g] was not statistically significant [$F(1, 144) = 3.472$, $p = 0.0645$, $\eta_p^2 = 0.022$]. The interaction between age and sex on [−g] was also not significant [$F(2, 144) = 0.193$, $p = 0.8248$, $\eta_p^2 = 0.002$]. A series of pairwise *t*-tests with Bonferroni correction across three age groups indicated that there was no significant difference in the mean levels of the dependent variable [−g] between the middle-aged and older groups [$t(49) = -1.40$, $p_{adj} = 0.507$] and between the middle-aged and young groups [$t(49) = 1.41$, $p_{adj} = 0.495$]. However, there was a significant difference between the older and young groups [$t(49) = 2.84$, $p_{adj} = 0.019$], indicating that the mean levels of [−g] significantly differed between these age groups (Fig. 2).

C. Burst onset landmark

The result of the two-way ANOVA revealed a significant effect of age on [+b] [$F(2, 144) = 4.755$, $p = 0.010$, $\eta_p^2 = 0.058$]. Additionally, the effect of sex on [+b] was found to be statistically significant [$F(1, 144) = 7.702$, $p = 0.006$, $\eta_p^2 = 0.047$]. The interaction between age and sex, however, did not reach statistical significance [$F(2, 144) = 1.474$, $p = 0.233$, $\eta_p^2 = 0.018$], indicating that the combined effect of age and sex does not significantly influence [+b].

For the analysis stratified by sex, the pairwise *t*-tests among females showed no significant difference in [+b] between the middle-aged and older groups [$t(24) = -0.074$, $p_{adj} = 1.000$]. However, significant differences were observed between the young and middle-aged groups [$t(24) = 3.41$, $p_{adj} = 0.007$], and between the young and older groups [$t(24) = 3.32$, $p_{adj} = 0.009$], indicating that age significantly affects [+b] in females. For males, no significant differences were found in [+b] across all age group comparisons: middle-aged vs older [$t(24) = 0.725$, $p_{adj} = 1.000$], young vs middle-aged [$t(24) = 1.08$, $p_{adj} = 0.873$], and young vs older [$t(24) = 0.646$, $p_{adj} = 1.000$].

For the analysis stratified by age, the pairwise *t*-tests revealed no significant differences in [+b] between females and males in the middle-aged [$t(24) = -1.32$, $p_{adj} = 0.200$] and older [$t(24) = -0.633$, $p_{adj} = 0.533$] groups. However, a significant difference was observed in the young group, with females showing a significantly different score in [+b] compared to males [$t(24) = -3.22$, $p_{adj} = 0.004$] (Fig. 3).

TABLE III. Average, standard deviation (SD), standard error (SE), and confidence interval (CI) of all landmark counts.

Age	Sex	N	Average count	SD	SE	CI
			[+g]			
Young	Female	25	94.56	8.01	1.60	3.30
Middle-aged	Female	25	96.36	8.76	1.75	3.62
Older	Female	25	99.56	11.79	2.36	4.87
Young	Male	25	96.24	12.75	2.55	5.26
Middle-aged	Male	25	100.36	10.22	2.04	4.22
Older	Male	25	103.84	14.35	2.87	5.92
			[−g]			
Young	Female	25	94.44	7.98	1.60	3.29
Middle-aged	Female	25	96.24	8.60	1.72	3.55
Older	Female	25	99.52	11.74	2.35	4.85
Young	Male	25	96.24	12.75	2.55	5.26
Middle-aged	Male	25	100.36	10.22	2.04	4.22
Older	Male	25	103.80	14.38	2.88	5.93
			[+b]			
Young	Female	25	75.36	9.02	1.80	3.72
Middle-aged	Female	25	84.20	11.06	2.21	4.57
Older	Female	25	84.44	12.81	2.56	5.29
Young	Male	25	84.52	12.30	2.46	5.08
Middle-aged	Male	25	88.20	9.23	1.85	3.81
Older	Male	25	86.24	11.04	2.21	4.56
			[−b]			
Young	Female	25	46.56	7.82	1.56	3.23
Middle-aged	Female	25	56.68	13.86	2.77	5.72
Older	Female	25	67.04	13.32	2.66	5.50
Young	Male	25	69.80	16.75	3.35	6.92
Middle-aged	Male	25	75.40	15.14	3.03	6.25
Older	Male	25	73.44	11.76	2.35	4.85
			[+s]			
Young	Female	25	42.92	7.76	1.55	3.20
Middle-aged	Female	25	38.32	12.68	2.54	5.23
Older	Female	25	40.20	13.97	2.79	5.77
Young	Male	25	24.48	8.40	1.68	3.47
Middle-aged	Male	25	26.56	8.20	1.64	3.38
Older	Male	25	34.20	14.31	2.86	5.91
			[−s]			
Young	Female	25	60.36	7.80	1.56	3.22
Middle-aged	Female	25	52.64	12.61	2.52	5.20
Older	Female	25	51.72	11.90	2.38	4.91
Young	Male	25	34.08	10.85	2.17	4.48
Middle-aged	Male	25	32.20	11.62	2.32	4.80
Older	Male	25	41.68	13.88	2.78	5.73

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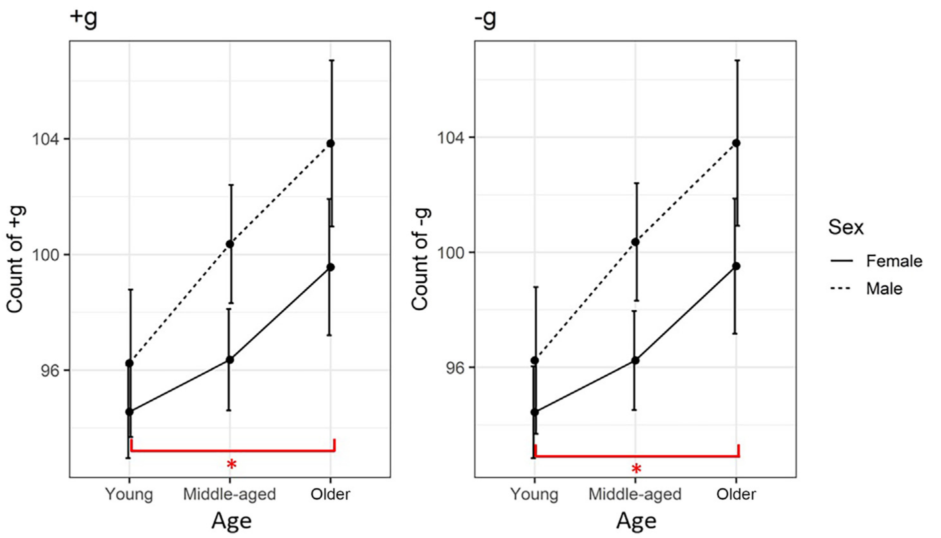

FIG. 2. (Color online) Line plot displaying the average counts of [+g] and [−g] landmarks, with error bars representing the standard errors. An asterisk indicates a pair with statistically significant difference.

D. Burst offset landmark

The result of the two-way ANOVA revealed a statistically significant effect of age on [−b] [$F(2, 144) = 10.422$, $p < 0.001$, $\eta_p^2 = 0.091$]. The effect of sex on [−b] was also found to be significant [$F(1, 144) = 54.198$, $p < 0.001$, $\eta_p^2 = 0.236$], suggesting that sex is a significant predictor of [−b]. Additionally, the interaction between age and sex was significant [$F(2, 144) = 5.281$, $p < 0.001$, $\eta_p^2 = 0.046$], indicating that the effect of age on [−b] varies by sex.

For the analysis stratified by sex, the pairwise *t*-tests among females indicated that there was no significant difference in [−b] between the middle-aged and older groups [$t(24) = -2.47$, $p_{adj} = 0.063$]. However, significant differences were observed between the young and middle-aged groups [$t(24) = 3.04$, $p_{adj} = 0.017$], and between the young and older groups [$t(24) = 6.58$, $p_{adj} < 0.001$]. For males, no significant differences were found in [−b] across the three age group comparisons: middle-aged vs older [$t(24) = 0.517$, $p_{adj} = 1.00$], young vs middle-aged [$t(24) = 1.32$, $p_{adj} = 0.594$], and young vs older [$t(24) = 0.982$, $p_{adj} = 1.00$].

For the analysis stratified by age, the pairwise *t*-tests indicated significant differences in [−b] between females and males within the young [$t(24) = -6.63$, $p_{adj} < 0.001$] and middle-aged [$t(24) = -4.68$, $p_{adj} < 0.001$] groups, with females showing significantly greater number of [−b] compared to males. However, no significant difference was observed between females and males in the older age group [$t(24) = -1.81$, $p_{adj} = 0.084$] (Fig. 3).

E. Syllabicity onset landmark

The result of the two-way ANOVA revealed that the effect of age on [+s] was not statistically significant [$F(2, 144) = 2.406$, $p = 0.0938$, $\eta_p^2 = 0.024$]. On the other hand, the effect of sex on [+s] was significant [$F(1, 144) = 43.193$, $p < 0.001$, $\eta_p^2 = 0.216$]. Additionally, the interaction between age and sex was significant [$F(2, 144) = 3.833$, $p = 0.024$, $\eta_p^2 = 0.038$], indicating that the effect of age on [+s] varies depending on sex (Fig. 4).

For the analysis stratified by sex for [+s], the pairwise *t*-tests showed no significant differences among females across all age group comparisons: middle-aged vs older [$t(24) = -0.540$, $p_{adj} = 1.000$], middle-aged vs young [$t(24) = -1.55$, $p_{adj} = 0.405$], and older vs young [$t(24) = -0.843$, $p_{adj} = 1.000$]. In males, no significant differences were observed between the middle-aged and older groups [$t(24) = -2.42$, $p_{adj} = 0.07$], and between the young and middle-aged groups [$t(24) = 0.888$, $p_{adj} = 1.000$]. However, a significant difference was found between the young and older groups [$t(24) = 3.23$, $p_{adj} = 0.011$].

For the analysis stratified by age for [+s], the pairwise *t*-tests indicated significant differences between females and males in the middle-aged [$t(24) = 3.95$, $p_{adj} < 0.001$] and young [$t(24) = 7.52$, $p_{adj} < 0.001$] groups. However, no significant difference was observed between females and males in the older age group [$t(24) = 1.32$, $p_{adj} = 0.201$].

F. Syllabicity offset landmark

The result of the two-way ANOVA revealed that the effect of age on [−s] was not statistically significant [$F(2, 144) = 2.580$, $p = 0.0793$, $\eta_p^2 = 0.020$]. In contrast, the effect of sex on [−s] was significant [$F(1, 144) = 99.837$, $p < 0.001$, $\eta_p^2 = 0.382$]. Additionally, the interaction between age and sex was statistically significant [$F(2, 144) = 6.291$, $p = 0.0024$, $\eta_p^2 = 0.048$], indicating that the effect of age on [−s] varies depending on sex.

For the analysis stratified by sex for [−s], the pairwise *t*-tests among females showed no significant differences between the middle-aged and older groups [$t(24) = 0.263$, $p_{adj} = 1.000$] and between the middle-aged and young groups [$t(24) = -2.38$, $p_{adj} = 0.077$]. However, a significant difference was found between the older and young groups [$t(24) = -2.91$, $p_{adj} = 0.023$]. In males, a significant difference was observed between the middle-aged and older groups [$t(24) = -2.80$, $p_{adj} = 0.030$], suggesting that age influences [−s] between these two groups. No significant differences were found between the middle-aged and young

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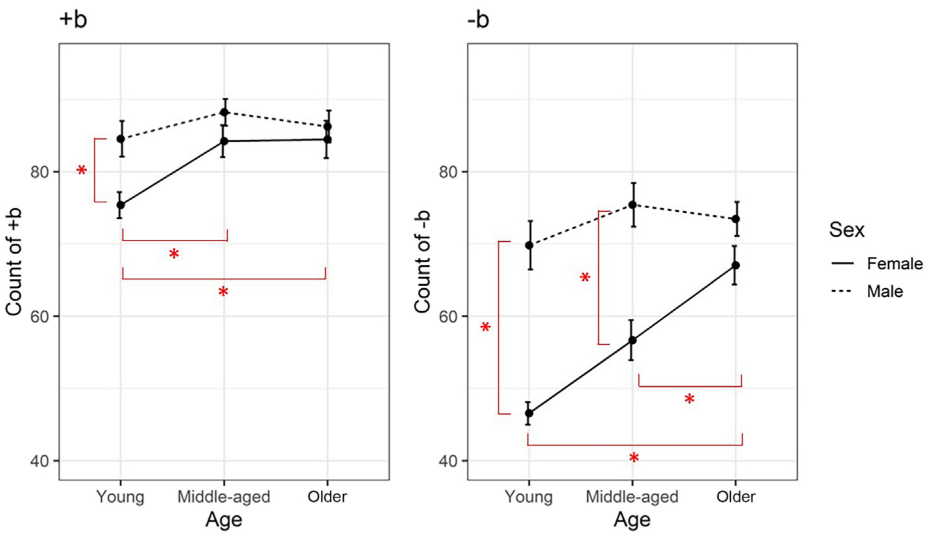

FIG. 3. (Color online) Line plot displaying the average counts of [+b] and [−b] landmarks, with error bars representing the standard errors. An asterisk indicates a pair with statistically significant difference.

groups [$t(24) = -0.637$, $p_{adj} = 1.000$] and between the older and young groups [$t(24) = 2.32$, $p_{adj} = 0.088$].

For the analysis stratified by age for [−s], the pairwise t-tests revealed significant difference between females and males across all age groups [$t(24) = 9.96$, $p_{adj} < 0.001$ for the young group; $t(24) = 6.96$, $p_{adj} < 0.001$ for the middle-age group; $t(24) = 6.96$, $p_{adj} < 0.001$ for the older group] (Fig. 4).

V. DISCUSSION

This study examined the feasibility of detecting age-related changes in speech acoustics using the LMBAS. The results showed that the age affects expression of glottal and burst landmarks but not syllabicity landmarks. In contrast, the effect of sex was statistically significant for burst and syllabicity landmarks, but not significant for glottal landmarks. The interaction between age and sex was significant for burst offset landmark as well as syllabicity onset and offset landmarks.

The results of glottal landmarks corroborated our hypothesis: the count of [+g] and [−g] increased with age. However, the effect was small, and the difference was only seen between young and older groups. The lack of difference between young and middle-aged, and middle-aged and older groups implies that the functional changes in the vocal folds is more discernible across a wider age spectrum. The observed differences echo patterns noted in a large cohort study (Davids *et al.*, 2012), which reported the increasing prevalence of vocal fold atrophy among patients over 65 years, a demographic closely aligning with our older group. The greater number of glottal landmarks in a population with a physiological change in vocal fold tissue aligns with observations from previous studies on dysphonic speech (Ishikawa *et al.*, 2020).

Given previous reports highlighting differences in vocal fold vibratory characteristics between males and females, such as variations in the size and position of the glottal gap and vocal fold vibratory asymmetry, it might be reasonable to anticipate discernible effects of sex and the interaction

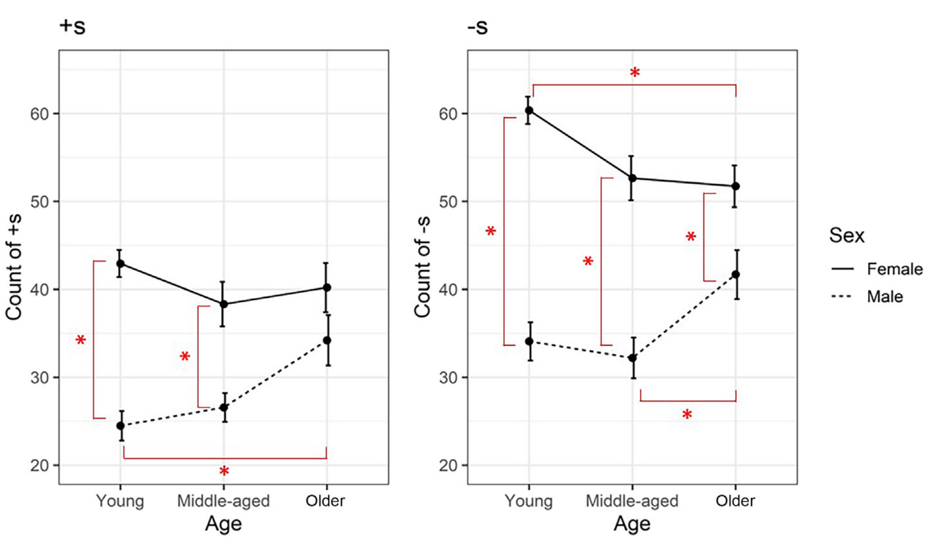

FIG. 4. (Color online) Line plot displaying the average counts of [+s] and [−s] landmarks, with error bars representing the standard errors. An asterisk indicates a pair with statistically significant difference.

between age and sex on glottal landmarks. However, acoustic studies have not consistently demonstrated these effects on periodicity (Buckley *et al.*, 2023; Stathopoulos *et al.*, 2011; Taylor, 2020). The absence of observed effects of sex or its interaction with age in our findings aligns with those studies that similarly did not observe them, suggesting a relationship between sex, age, and acoustic periodicity that may not be readily captured. This could also be attributed to the enhanced complexity of the SpeechMark® algorithm compared to conventional methodologies, or its capability to tailor speech analysis according to the sex of the speech sample. Additionally, it is possible that males and females in this database exhibited negligible differences in their vocal fold physiology.

As predicted, age significantly increased the count of [+b] and [−b]; however, this effect was small to medium, and was observed only in females. Both glottal and burst landmarks demonstrated this age-related increase, suggesting that mechanisms. such as glottal noise, akin to those observed in dysphonic speakers (Ishikawa *et al.*, 2020), may play a role in the enhanced detection of burst landmarks among older speakers. The results also reveal complex patterns between sexes and across different age groups. It was anticipated that younger speakers would produce fewer burst landmarks due to their generally faster speech rate (Jacewicz *et al.*, 2009). This pattern was observed in young females who produced fewer burst landmarks compared to both middle-aged and older females. Previous studies have indicated that males generally speak faster than females (Jacewicz *et al.*, 2009; Verhoeven *et al.*, 2004), leading to the expectation that they might produce fewer burst landmarks due to a faster speech rate. Contrary to this expectation, however, the young male group generated more burst onset landmarks compared to the young female group. Results of the current study challenge the assumptions based on vocal fold atrophy and speech rate alone, suggesting that additional factors influence burst landmark production.

Contrary to our hypothesis, which predicted a decrease in syllabicity landmarks with aging, this effect was seen only from young to older females for [−s]. Aging did not affect [+s] for female speakers, and a significant increase was observed from young to older males for [+s] and middle-aged to older males for [−s]. On the contrary, the effect of sex was significant and large. Sex impacted the generation of [+s] and [−s] across the middle-aged and young age groups, with a greater number of these landmarks in females compared to males. In contrast, the older age group did not exhibit significant sex-related differences in [+s]. The age-related increase in the syllabicity landmarks may be associated with the age-related increase in glottal landmarks as syllabicity landmarks are detected between glottal onset and offset landmarks. The lack of sex difference in the older group may support a notion of convergence in voice characteristics that occurs over lifetime, though this convergence has been described primarily based on fundamental frequency (Decoster and Debruyne, 1997; Mysak, 1959; Nishio and Niimi, 2008).

Interestingly, [−s] occurred more frequently than [+s] in the current study, which contrasts with the findings of an earlier study by Ishikawa *et al.* (2017). In their research, which characterized normal adult speakers, [+b] and [+s] landmarks were observed to occur more frequently than [−b] and [−s]. The difference in the frequency of occurrence between [+s] and [−s] was attributed to the fact that while the acoustic rules for detecting these landmarks are symmetrically designed, the actual acoustic changes elicited by articulatory adjustments are not symmetric. This discrepancy between our study and the previous report could be attributed to differences in the phonetic context of the sentences used. The SPIN sentences cover a broader range of speech sounds and contexts compared to two sentences from the Rainbow passage used in Ishikawa *et al.* (2017). Thus, the choice of material for analysis–particularly in terms of its phonetic diversity–may be a critical factor in determining the frequency and distribution of specific landmarks in speech.

Regarding the effect sizes, our analysis revealed small to medium effect sizes (ranging from 0.02 to 0.09) for age and small to very large effect sizes for sex (ranging from 0.02 to 0.38). The interaction between age and sex consistently showed small effect sizes across landmarks. However, we are unable to compare our results with previous reports as the effect sizes were not reported. This limits direct quantitative comparisons, but the small effect size of age highlights the importance of having large sample sizes to obtain more reliable and generalizable results. The practical implication of our findings is still noteworthy. While some effect sizes observed in our study are small, they may still be practically significant, depending on the context. Small effect sizes may lead to meaningful differences in real-world applications, particularly in fields such as speech pathology (Bothe and Richardson, 2011; Gaeta and Brydges, 2020).

Limitations of this work include the requirement of SpeechMark® software to downsample stimuli to 16 kHz, leading to the loss of information above 8 kHz. The current study used the age function of SpeechMark®, which allows control for the sex (male vs female) of a speaker based on fundamental frequency. An increase in syllabicity landmarks with age was unexpected, potentially indicating the need for refinements to the algorithm. Furthermore, while samples of the current study were controlled for the phonetic context, the use of sentence reading samples limits the generalizability of results to everyday speech environments. Last, while the speakers included in the database were deemed to be normal based on self-reports, additional screening measures (through routine clinical examinations, perception. or imaging) were not conducted to verify their physiological status.

VI. CONCLUSION AND SCOPE OF FUTURE WORK

The current study has shown that age and sex of speakers affect landmark generation, demonstrating the potential utility of investigating speech production changes with aging using the landmark-based approach. The results also provide a baseline description of landmark expression in healthy aging speech, offering foundational knowledge for future research. Future studies comparing the magnitude of age and sex effects from landmark-based analysis and conventional acoustic measures on the same dataset may provide more insight into the utility of landmark-based analysis. By its design, this study was not configured to delineate the underlying causes of the observed changes. However, confirming these changes prompts further investigation to elucidate the relationship between specific articulatory variables and their corresponding landmarks. Such knowledge will be instrumental in guiding subsequent studies extending to disordered populations, including conditions more prevalent in older populations, such as Parkinson's disease, further enhancing the clinical and research utility of the landmark-based approach.

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AUTHOR DECLARATIONS

Conflict of Interest

The authors have no conflicts to disclose.

ETHICS APPROVAL

This study was approved by the Institutional Review Board at the University of Florida.

DATA AVAILABILITY

The data used in this study are not publicly available due to the sensitive nature of the participant information. However, upon request, the corresponding author can provide de-identified data to qualified researchers for the purpose of replication and further analysis.

APPENDIX: SPEECH PERCEPTION IN NOISE [(SPIN) SENTENCES (SS → SPIN SENTENCE]

ss01: His boss made him work like a slave.
ss02: He caught the fish in his net.
ss03: The beer drinkers raised their mugs.
ss04: I made the phone call from a booth.
ss05: The cut on his knee formed a scab.
ss06: I gave her a kiss and a hug.
ss07: The soup was served in a bowl.
ss08: The cookies were kept in a jar.
ss09: The baby slept in his crib.
ss10: The cop wore a bullet proof vest.
ss11: How long can you hold your breath?
ss12: At breakfast he drank some juice.
ss13: I ate a piece of chocolate fudge.
ss14: The judge is sitting on the bench.
ss15: The boat sailed along the coast.
ss16: The pirates buried the treasure.

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