Characterizing first and second language rhythm in English using spectral coherence between temporal envelope and mouth opening-closing movements

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Abstract

This study investigated the rhythmic differences between first and second language English from 19 native speakers of American English and an equal number of native speakers of Mandarin. Speech rhythm was viewed from Peter MacNeilage's frame/content theory. The spectral coherence between the temporal envelope and the mouth opening and closing kinematics was computed to operationalize the rhythmic frame. The spectral centroid, spread, rolloff, flatness and entropy were calculated to reveal the frequency distribution patterns in the coherence. Using a binary logistic regression model, these measures were collectively found to be effective in characterizing rhythmic differences between native and non-native groups ($A' = 0.71$ and $B''_D = -0.06$). Specifically, the native group was significantly higher than the non-native group in terms of spectral centroid and spread; whereas, the native group was significantly lower than its non-native counterpart in terms of spectral flatness and entropy. Both groups were not significantly different in spectral rolloff. Possible explanations for the result as well as the efficacy of employing the aforesaid coherence in speech rhythm research in general were discussed.

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I. INTRODUCTION

This paper characterizes speech rhythm from a joint perspective of acoustics and articulation. In particular, rhythmic differences between first and second language (L1 and L2 hereinafter) English were analyzed from 19 native speakers of American English and an equal number of Mandarin native speakers. Speech rhythm was viewed from the “frame/content” perspective where the mouth opening-closing cycles and thence the temporal modulations constitute the rhythmic *frame* in speech.¹ To characterize the rhythmic *frame*, spectral coherence between the temporal envelope and the temporal function of mouth opening-closing magnitude was analyzed in this study. In the upcoming sections, literature is reviewed in terms of (a) the history of and various approaches to speech rhythm (Sec. I.A), (b) the competency of the “frame/content” theory (Sec. I.B), (c) mouth opening-closing movements in the rhythmic frame (Sec. I.C), and (d) previous research on L2 rhythm (Sec. I.D). Sec. I.E outlines the current study.

A. Speech rhythm: history and approaches

Rhythm is ubiquitous in nature; so is it in speech. The crux of rhythmicity is nothing but cyclicity or regularity of diverse sizes and kinds. Early phoneticians intuited two major types of regularity – isochronous syllables and isochronous feet – in different languages, and referred to these languages as syllable-timed and stress-timed.^{2–5} Later attempts to instrumentally corroborate strict syllable- or foot-isochrony nevertheless failed,^{6–9} motivating researchers to explain the perceived rhythmic differences in terms of phonological mechanisms, such as syllable weight and vowel reducibility.^{8,10} Various rhythm metrics were then developed to capture the concomitant prosodic differences by calculating durational variabilities in different phonetic intervals – consonantal and vocalic in particular^{11–15} Rhythmic characteristics in different languages and language varieties,^{11–15}

speaking styles,^{16, 17} speakers,^{16, 18–20} developmental stages^{21, 22}, and pathological conditions^{23–25} have been examined using these rhythmic metrics. Other approaches to speech rhythm have also been proposed in the meanwhile and afterwards, focusing on different yet interrelated aspects which can be roughly grouped into “prominence,” “modulations,” and “coupling strengths”:

▪ *Prominence.* The speech signal is temporally organized into portions with varying degrees of prominence, giving rise to different rhythmicities. By calculating the syllable intensity variability across an utterance, rhythmic differences between language varieties,^{26–28} speakers,²⁹ and developmental stages³⁰ have been revealed. Inspired by the “primal sketch” in image perception,³¹ Todd³² constructed an auditory filterbank to sieve an audio signal; peak frequencies in each filtered channel were pinpointed and plotted on a time $\times$ frequency plane, appearing as a (semi-)regular pattern. The pattern demonstrates the rhythmic skeleton of the signal, analogous to primitive edges in images. This approach was initially developed to distill rhythm structures in music,³² and was later found to be effective in revealing between-language rhythmic differences as well.³³

▪ *Modulations.* The temporal modulations in speech typically present themselves as (semi-)cyclical patterns. Calculating the intensity variability^{26–30} reveals rhythmic regularities to some extent, yet information about the recurring frequencies is not obvious. Tilsen and Johnson,³⁴ on the other hand, proffered an approach to decompose these frequencies by calculating the Fourier spectrum from the temporal envelope extracted from the frequency band containing mostly the vocalic energy,³⁵ revealing the underlying cyclic patterns. Peak frequencies in the amplitude envelope spectrum have recently been coined as “rhythm formants,” emphasizing the low-frequency, high-magnitude spectral zones in sonority fluctuations.³⁶ A similar method has been used in musical genre analysis, where the spectrum

of the same kind is referred to as the beat histogram.³⁷ Temporal modulation spectra have been demonstrated to help characterize rhythmic differences within and between languages³⁸ and in different motor speech disorders.³⁹

The phase relationship of different modulation rates has also been argued to be important in the perception of different rhythmic patterns. Using the pure tone vocoding, Leong et al.⁴⁰ found that a phase shift of π -rad between syllable modulation rates (~ 4 Hz) and stress modulation rates (~ 2 Hz) would alter a trochaic verse to iambic, and a 2π -rad phase shift would restore the trochee. By investigating the coordination between temporal modulations at the rates of the syllable and prosodic word using the joint recurrence analysis,⁴¹ Lancia et al.⁴² showed that German and English (quintessential stress-timed languages as per early phoneticians) possess a higher level of coordination between these two modulation rates than do Italian and French (quintessential syllable-timed languages as per early phoneticians).

▪ *Coupling strengths.* A similar approach to the coordination between different modulation rates was proposed based on the concept of coupled oscillation.^{43–45} A faster and a slower oscillator in the signal were established at the syllable and foot levels. The foot duration was regressed on the number of syllables therein; the intercept/slope ratio yielded the coupling strength of the two oscillators. A ratio greater than one indicates a dominant foot oscillator; otherwise a reigning syllable oscillator. Malisz et al.⁴⁶ showed that as speech tempo increased, the coupling strength dwindled in Polish, yet remained rather stable in Finnish.

In terms of phonological theorization, the rhythmic pattern has been demonstrated using the metrical grid, where prominence was assigned (based on the researcher's auditory impression and

linguistic knowledge) and organized into hierarchical layers of prosodic units for phonological abstractions.^{47–49} This metrical structure (referred to as micro-rhythm by Jun⁵⁰) serves as the anchor of intonational phrasing.^{51, 52} The temporal regularity in f_0 variation is called the tonal or macro-rhythm,⁵⁰ and has been found to be useful in discriminating prosodically different languages.⁵³ Arguably, speech rhythm can be viewed as a (semi-)regular pulse train with alternating beats differing in prominence degrees (an AM process³⁶), upon which the melody of intonation can develop (an FM process³⁶), in the similar vein as music.

B. Speech rhythm: the frame/content perspective

Despite the multifarious approaches to speech rhythm, agreeing on a unifying perspective that encapsulates them has been infrequently talked about. Here I argue that the frame/content theory of speech evolution¹ is the tenet of these different approaches. It is also the theoretical footing of the method to speech rhythm which I am pursuing in the present study.

MacNeilage¹ held that speech rhythm is a primordially developed phenomenon in speech production. It evolved from pre-existing cyclical mandibular movements in ancestral primates in the form of lip-smacking,¹ serving perhaps a more primitive and essential function in sociality and survival.⁵⁴ Later ethological research confirmed that such cyclical lip movements were important visuo-facial gestures in extant non-human primate communications.⁵⁵ It is also believed that the coupling between mouth opening-closing cycles and vocalization emerged en route to human evolution: the sonority of speech typically waxes and wanes with mouth opening and closing gestures.^{1, 55, 56} Such opening-closing alternations are organized into syllable-sized units corresponding to the temporal modulations, which constitute the rhythmic *frames*; the open and closed phases are filled with vocalic and consonantal *contents*.¹ More recently, Fitch⁵⁷ endorsed the frame/content mechanism and argued that it affords the evolution of the language system at large.

The rhythmic *frame* is one of the earliest acquired attributes in first language development. Intra-uterine hydrophone recordings from both women and ewes in gestation^{58, 59} revealed a strong attenuation of higher frequencies (*content* details thus eliminated), preserving the *frame* information in the extra-uterine speech for fetal hearing in the last prenatal trimester.⁶⁰ The rhythmic *frame* helps infants detect their mother tongue after birth, playing a crucial role in language acquisition by way of phonological bootstrapping.^{61–64}

How are different approaches to speech rhythm related to the frame/content theory? The rhythm metrics quantifying the durational variability of vocalic and consonantal intervals^{11–25} typically focused on the *content* perspective. Whereas the modulation-based approaches targeted the *frame* perspective with different emphases: recurring frequencies in the temporal envelope,^{34, 38, 39} and coordination between envelopes at slower and faster rates.^{40, 42} The prominence-based approaches principally capture the undulating pattern of the rhythmic *frame*, but the computations require *content* information, such as syllable boundary placements,^{26–30} and the filterbank response of acoustic details constituting the segmental *content*.³³ The coupled oscillator^{43–46} and the metrical grid^{47–49} approaches also work at the *content* level in terms of locating syllables and stresses, yet the aim is to portrait the higher level *frame* patterns.

The rhythmic *frame* in the form of the modulation envelope also facilitates the brain to parse the incoming speech signal for comprehension. It has been demonstrated that the auditory cortex entrains to the speech temporal envelope at the stress and syllable rates in terms of a window structure.^{65–68} Within these windows, *content* information encoded in finer timescales (e.g. phonemes up to ~40 Hz, corresponding to the γ -oscillation) can then be processed to achieve comprehension.

^{65, 67}

C. Speech rhythm: integrating mouth movements

The rhythmic *frame* emerged from the mouth opening and closing cycles according to MacNeilage,¹ yet the majority of the existing *frame*-based approaches to speech rhythm solely operated either on the acoustic signal or at the symbolic level, passing over the articulatory aspect. Arguably, the mandible performs the role of a carrier articulator responsible for lower modulation frequencies that constitute the rhythmic *frame*⁶⁸ to which the slower neuronal oscillations are phase-locked, not only in the auditory cortex, but also in the visual cortex.⁶⁹ Seeing an interlocutor's mouth movements facilitates comprehension particularly in adverse conditions with excessive noise.⁶⁹ In the era of the COVID-19 pandemic, people in general find it more challenging to understand each other wearing masks in a noisy environment, which has been scientifically attested.⁷⁰ The mouth movements play the role of visual scaffolding to help listeners visually access the rhythmic structure. The temporal windows facilitating the neural tracking of the speech temporal envelope must therefore be discoverable in the mouth movement cycles as well.

Erickson and colleagues⁷¹⁻⁷³ demonstrated that the jaw displacement well explained the metrical structure and subjective prominence ratings in a number of languages (English,⁷¹⁻⁷³ French,⁷⁴ Mandarin,⁷⁵ and Japanese^{73,76}), where a more prominent syllable was typically associated with a lower jaw position. These studies revealed that English exhibited more irregular jaw cycles compared with the other languages. From the perspective of the dynamical system, the change of speech rate (a perturbator which effectively shrinks or expands the rhythmic *frame*) resulted in re-organized mandibular movements in the space-time profile in reiterated syllables^{77,78} and in natural speech.^{79,80} Such changes in the movements were believed to be self-organized without cognitive instruction.^{78,79}

To integrate both temporal modulation and the opening and closing cycles of the mouth for the characterization of the rhythmic *frame*, spectral coherence has been used.^{81,82} The coherence is

calculated from the spectra of two signals to show the connectivity between them in terms of their correlation in the frequency domain. It synergizes both signals into one system. Chandrasekaran et al.⁸¹ demonstrated that in the coherence between the mouth area and the temporal envelope, the 2–7 Hz range was most prevalent. This frequency range overlaps with the cortical δ - and θ -oscillations, upholding the connections among mouth movements, temporal modulation, and neural processing.^{65–68, 81} It has further been demonstrated that in the coherence, the frequency density in the lower range (0.5–3 Hz) and higher range (3–9 Hz) are different between longer and shorter utterances.⁸² Spectral coherences have also been calculated between the surface electromyographic signals at the lips and the jaw and the temporal envelopes; they were found to be more effective to outline the rhythmic structure in speech than from a single domain.⁸³

The synergy between temporal envelope and the mouth movements is assumed to be more stable and informative than each of the two domains alone. Spurious frequencies that are randomly present in either the temporal envelope or the mouth movement will create artifacts in spectral analyses. Spurious frequencies are not expected in the connectivity between the two domains (otherwise they should be genuine), and therefore can be suppressed if not completely eliminated by the coherence (Fig. 2 serves as an example).

D. Speech rhythm in L2 speech

Speech rhythm in L2 has been most extensively investigated using the *content*-based rhythm metrics.^{11–14} The most popular target language was unsurprisingly English. It has generally been demonstrated that the durational variability increased in general as their L2 proficiency increased regardless of their L1.^{84, 85} Moreover, the durational variabilities in consonantal and vocalic intervals in the L2 speech were more similar to those of the L1 English, if the learners spoke a traditionally labeled “stress-timed” language (such as Dutch and German) as their L1, compared to those

1 speaking Spanish and French.^{84,86,87} For native speakers of the Chinese languages, however, it has
2 been reported that their L2 English rhythm as measured by the rhythm metrics was not significantly
3 different from L1 English rhythm, despite that the impressionistic rhythmicity was quite different
4 from that of the native English speakers.^{88,89} This may mean that these learners have acquired the
5 timing in producing phonetic *contents* (consonantal or vocalic), yet this does not necessarily entail that
6 they have acquired the rhythmic *frame*. When the intensity variability was calculated from the same
7 corpus, the rhythmic differences between L1 and L2 English surfaced,⁹⁰ further supporting the
8 pertinence of the *frame* aspect. One recent study⁹¹ strongly demonstrated the importance of the
9 temporal envelope in perceived nativeness using the envelope chimerization technique. Gut⁹² even
10 questioned the validity of the duration-based rhythm metrics, arguing that they may only capture
11 some phonological characteristics of these phonetic contents.

12 L2 rhythm from the perspective of the rhythmic *frame*, in particular the mouth opening and
13 closing movements, has been heeded by Erickson and colleagues.^{93–96} The jaw displacements were
14 recorded and compared between L1 and L2 speakers of English, Japanese and French, and it has
15 been found that L2 speakers exhibited some tendency to carry their jaw oscillation patterns in the L1
16 over to the L2, resulting in misplacements of syllable prominence.^{93–96} It has also been demonstrated
17 that by teaching the learners (L1 = Japanese) native-like jaw cycles visually, the speech rhythm in the
18 L2 English can be more effectively improved.⁹⁵ A cap-like device mounted with an inductance-based
19 elastic strap is being developed to record and visualize jaw cycles in speech production, ushering in a
20 vast potential in both language pedagogy and basic research.⁹⁷

21 22 **E. The present study**

23 The present study investigated L2 rhythm from the *frame* perspective. Specifically, the
24 temporal envelope and the mouth opening-closing cycles were combined using the spectral

coherence which reveals the connectivity between these two related signals (Sec. II.B.4 shows computation details). By nature, the coherence is simply a power spectrum, whose magnitude shows the correlation of these two signals in the frequency domain. English sentences produced by both native American English speakers and native Mandarin speakers were analyzed. Five common spectral measures (centroid, spread, rolloff, flatness, and entropy) ^{98–101} were computed from the spectral coherence of each sentence, and a binomial logistic regression model was built to evaluate how well the coherence can characterize speech rhythm in L1 and L2 (Sec. III contains the details).

Among these five spectral measures, the CENTROID calculates the “balancing point” in the coherence and serves as a point estimate of the coherence. The SPREAD calculates to what extent the coherence disperses around the centroid. The ROLLOFF indicates the degree of skewness in the coherence. The FLATNESS and ENTROPY quantify the amount of unpredictability or disorder in the spectrum. Taken together, they provide an overview of the shape of the spectral coherence which characterizes the rhythmic *frame* combining both mouth movements and the temporal envelope (Sec. II.B.5 shows the calculation details).

This paper is principally exploratory, yet several expectations were raised:

(i) The L2 group was expected to show a slower speech rate and thus a stretched rhythmic *frame*, and the CENTROID would be shifted towards lower frequencies as a result.

(ii) The L2 group was expected to transfer the more regular rhythmic *frame* of their L1 (= Mandarin) to their English speech production, so a more restricted SPREAD would be anticipated.

(iii) The L2 group was less fluent and higher frequency components might be more conspicuous in the coherence, so the ROLLOFF, FLATNESS and ENTROPY might be higher in the L2 group. However, if higher frequencies were excessively prominent, the CENTROID and SPREAD might be affected as well. For this reason, this study was more exploratory.

II. METHOD

A. Corpus

The Electromagnetic Articulography Mandarin Accented English (EMA-MAE) corpus^{102–104} was used. This gender-balanced corpus includes 20 native speakers of American English (group E) and 20 native speakers of Mandarin Chinese who speak English as an L2 (group M). One speaker in each group was excluded because of inadequate quality in the articulatory recordings. Both the speech audio data and articulatory kinematic data were recorded in synchrony using an AKG CS-1000 cardioid condenser microphone (AKG Acoustics GmbH, Vienna, Austria) and the NDI Wave system (Northern Digital Inc., Waterloo, Canada)¹⁰⁴ with respective sampling rates of 22.05 kHz and 0.4 kHz. For the present study, the part involving sentence reading was analyzed. Each speaker read 59 text-prompted sentences selected from the Harvard Sentences¹⁰⁵ and TIMIT Sentences.¹⁰⁶ Each sentence was cropped out and saved as an individual WAV file for the audio data and a tab-delimited file for the kinematic data. Altogether 2,232 sentences (amounting to ~99% of the available data) were retained after quality control (see Sec. II.B.3).

B. Signal processing

Unless otherwise mentioned, all signal processing steps were performed using PRAAT¹⁰⁷ with custom-made scripts. Essential ones are accessible from Appendix A.

1. *Calculating the temporal envelope*

First, the acoustic signal per sentence was band-pass filtered between 700 and 1,300 Hz (100 Hz smoothing) to keep the vocalic energy while removing the glottal energy and obstruent noise. This filter has been used to detect the P-centers or “beats” in the speech signal.^{34,35} Then, the filtered signal was full-wave rectified and downsampled to the Nyquist frequency of 20 Hz, yielding

the temporal envelope (hereinafter, ENV) which was subsequently saved as a PRAAT binary file (*.Sound) for the step in Sec. II.B.4.

2. Calculating the mouth opening-closing function (O_m)

The kinematic data from three NDI Wave sensors were employed: the UL and LL sensors (those glued at the upper and lower lips in the midsagittal plane at the vermilion borders), and the LC sensor (the one placed at the left cheilion). The area of the triangle formed by the three sensors was used to estimate the magnitude of mouth opening at each instant (hereinafter, O_m) based on their x , y and z coordinates, as formula (1) shows. A MATLAB script was written to calculate O_m per sentence, which was then imported to PRAAT, downsampled to the Nyquist frequency of 20 Hz, and saved as a PRAAT binary file (*.Sound) for the step in Sec. II.B.4.

$$O_m \simeq \frac{1}{2} \sqrt{\begin{vmatrix} y_{UL} & z_{UL} & 1 \\ y_{LL} & z_{LL} & 1 \\ y_{LC} & z_{LC} & 1 \end{vmatrix}^2 + \begin{vmatrix} z_{UL} & x_{UL} & 1 \\ z_{LL} & x_{LL} & 1 \\ z_{LC} & x_{LC} & 1 \end{vmatrix}^2 + \begin{vmatrix} x_{UL} & y_{UL} & 1 \\ x_{LL} & y_{LL} & 1 \\ x_{LC} & y_{LC} & 1 \end{vmatrix}^2} \quad (1)$$

3. NDI Wave tracking errors and solutions

The synchronization issue between the “master” and “slave” system control units of the NDI Wave¹⁰⁸ was of a lesser concern for this study, because the interested sensors were all connected to the “master” unit.¹⁰⁴ Nevertheless, tracking errors typically in the form of missing data points were observed in 282 sentences. Many of them were fixable using linear interpolations to the O_m functions (see Fig. 1). For the files that contained extended periods of missing points, they were discarded because interpolations were no longer trusted.

FIG. 1. (Color online). An example indicating that two portions in the O_m function contained missing data. They are displayed as pulse intervals because in PRAAT an undefined value was represented as a big-endian positive infinity. The linearly interpolated segments are indicated by the arrows.

4. Calculating the ENV- O_m coherence

First, DC-offsets in both ENV and O_m signals were removed, and a Tukey taper ($\alpha = 0.1$) was applied to mitigate spectral leakage.¹⁰⁹ Next, the signals were zero-padded to the nearest 2^M ($M \in \mathbb{Z}^+$) and fast Fourier transformed to obtain their corresponding spectra – FFT_{ENV} and FFT_{O_m} . The ENV- O_m coherence was calculated as the power of their cross spectrum (the product of the Fourier coefficients of FFT_{ENV} and the complex conjugate of the Fourier coefficients of FFT_{O_m}) normalized to the product of their individual amplitudes. The ENV- O_m coherence evaluates the common periodicities in both signals by revealing their correlation in the frequency domain (Fig. 2 illustrates an example).

FIG. 2. (Color online). An example illustrating an ENV- O_m coherence (right panel) calculated from the power spectra of both ENV and O_m (superimposed on each other in the left panel). It is evident that the power in the coherence is directly related to the amount of shared power in the spectra from which the coherence is derived. The power range has been rescaled to an arbitrary unit of 1 for a clearer illustration of shared frequencies because the spectra of ENV and O_m are in disparate scales. Frequencies above ~ 6 Hz appear spurious in both ENV and O_m , and are considerably subdued in the ENV- O_m coherence.

5. Variables extracted from the ENV- O_m coherence

The spectral CENTROID, SPREAD, ROLLOFF, FLATNESS, and ENTROPY were calculated from the ENV- O_m coherence using formulas (2) to (6), where n refers to the frequency index, or bin number in the ENV- O_m coherence; N refers to the total number of discrete frequencies in the coherence; Δf refers to the frequency granularity determined by the ratio between the sampling frequency (40 Hz) and the number of samples after zero-padding; and $C(n\Delta f)$ refers to the ENV- O_m coherence itself.

a. Spectral centroid. Spectral CENTROID [Hz] is calculated according to formula (2); it is the weighted average of the frequencies present in the coherence. It evaluates where the center of mass is in the coherence.

$$\text{centroid} = \frac{\sum_{n \in [0, N-1]} n\Delta f \cdot \mathbf{C}(n\Delta f)}{\sum_{n \in [0, N-1]} \mathbf{C}(n\Delta f)} \quad (2)$$

b. Spectral spread. Spectral SPREAD [Hz] (sometimes referred to as the spectral bandwidth) is calculated according to formula (3); it computes the square root of the second central moment of the coherence, and evaluates the extent to which the coherence is spread away from the centroid. In other words, it shows how dominant the centroid frequency is in the coherence.

$$\text{spread} = \sqrt{\frac{\sum_{n \in [0, N-1]} (n\Delta f - \text{centroid})^2 \cdot \mathbf{C}(n\Delta f)}{\sum_{n \in [0, N-1]} \mathbf{C}(n\Delta f)}} \quad (3)$$

c. Spectral rolloff. Formula (4) demonstrates the calculation of the spectral ROLLOFF [Hz]. A repeat-until loop iterates the coherence and sums up the power until 85% of the total power is reached; the frequency value at the termination point, $q\Delta f$, is the spectral rolloff. It is proportional to the degree of right-skewness of the coherence.

$$\sum_{n=0}^q \mathbf{C}(n\Delta f) \rightarrow 85\% \cdot \sum_{n \in [0, N-1]} \mathbf{C}(n\Delta f) \quad (4)$$

d. Spectral flatness. Formula (4) shows the calculation of the spectral FLATNESS [dB]. Essentially, it is the ratio between the geometric mean and the arithmetic mean of the coherence. Pragmatically, zero values were replaced by a small quantity of 10^{-10} to prevent the geometric mean, and subsequently the whole ratio from being evaluated to negative infinity as per formula (4). The

“iterated additions of natural logs” for computing the geometric mean was adopted instead of the more common “iterated multiplications” because it has been tested that looping multiplications of small numbers would yield erroneous zeros by PRAAT. The ratio thus obtained was small in numeric magnitudes compared to other spectral measures, causing convergence issues in statistical modeling; therefore, it was transformed using the common logarithm ($\lg\{\cdot\}$). If a spectrum is perfectly flat, the ratio will yield 1 ($\triangleq 0$ dB); if a spectrum contains a single spike, the ratio will yield 0 ($\triangleq -\infty$ dB). From the perspective of information theory, the flatter the spectrum is, the more unpredictable it becomes; thus the spectral flatness is also termed the Wiener entropy. ^{98,101}

$$\text{flatness} = \lg \left\{ \frac{\exp\left(\frac{1}{N} \sum_{n \in [0, N-1]} \ln \mathbf{C}(n\Delta f)\right)}{\frac{1}{N} \sum_{n \in [0, N-1]} \mathbf{C}(n\Delta f)} \right\} \quad (5)$$

e. Spectral entropy. Spectral ENTROPY [bits] is computed according to formula (6). It directly applies the Shannon’s entropy to a spectrum which is treated as a probability distribution. It quantifies the amount of unpredictability and disorder in a spectrum. A more uniformly distributed spectrum would yield a higher entropy compared to a spiky one.

$$\text{entropy} = - \sum_{n \in [0, N-1]} \mathbf{C}(n\Delta f) \cdot \log_2 \mathbf{C}(n\Delta f) \quad (6)$$

III. STATISTICAL ANALYSIS AND RESULTS

All statistical procedures were performed using R ¹¹⁰ and associated packages (*lme4* ¹¹¹, *car* ¹¹², *effects* ¹¹² and *ggplot2* ¹¹³). The generalized linear mixed model (binomial logit) with the “bobyqa” optimizer was used for data analysis. The five spectral variables extracted from the ENV- O_m

coherence (described in Sec. II.B.5) were modeled as the fixed-effect numeric predictors; LANG (speaker group, E for native speakers of English and M for native speakers of Mandarin) was modeled as the dichotomous response variable. Both groups produced the same set of sentences, and thus SENTENCE was modeled as a random factor.

High-leverage data points were first examined by plotting the hat-values, resulting in the removal of three data points (Eventually, 1,112 data points in group E and 1,117 in group M were enrolled). The variance inflation factors (VIFs) were calculated for all five predictors (all VIFs < 5) — the degree of multicollinearity was thus within tolerance. Table I summarizes the model-fitting results of all predictors, whose effects are visualized in Fig. 3.

To evaluate the prediction performance of the model, the fitted probability values were extracted. If the fitted probability was smaller than 0.50, the predicted category was assigned E, otherwise, M (fitted probabilities of exact 0.50 were non-existent in the data). The fitted probabilities were then arranged in ascending order and plotted in Fig. 4. A confusion matrix (**CM**) was built based on the actual and predicted categories (equation B1 in Appendix B). In general, 63.30% of the predictions were correct. To further look at the discriminability and prediction bias, the $\mathcal{A}'$ and B''_D (both are nonparametric and distribution-free)¹¹⁴ in the detection theory were calculated based on the sensitivity and specificity rates in **CM**: $\mathcal{A}' = 0.71$ and $B''_D = -0.06$. Appendix B shows the calculation details.

TABLE I. Results of the fixed-effect predictors in the generalized linear mixed model (binomial logit). The reference category of the response variable LANG is group E. The β -coefficient estimates the change of logit per unit change in the predictor. The exponentiated β -coefficient estimates the odds ratio. The likelihood-ratio (LR) χ^2 test compares a predictor-reduced model to the full model.

Predictors	β	Std. err.	Wald z	Odds ratio (e^β)	95% CI of odds ratio	LR χ^2 (with 1 DoF)
CENTROID	-1.05	0.21	-5.05***	0.35	0.23 – 0.52	25.53***
SPREAD	-2.15	0.40	-5.41***	0.12	0.05 – 0.25	29.22***
ROLLOFF	0.13	0.16	0.79•	1.13	0.83 – 1.55	0.62•
FLATNESS	0.40	0.17	2.38*	1.49	1.07 – 2.06	5.67*
ENTROPY	0.26	0.03	7.82***	1.30	1.22 – 1.39	61.17***

*** $0 < p < 0.001$; * $0.01 < p < 0.05$; • $0.05 < p < 1$

(a)

(b)

More subplots are on the following page

(c)

(d)

One more subplot is on the following page

(e)

FIG. 3. (Color online). Predictor effects plots of (a) CENTROID, (b) SPREAD, (c) ROLLOFF, (d) FLATNESS, and (e) ENTROPY. The vertical axes of the plots were drawn in the logit scale, but the tick marks were labeled in the probability scale. 95% confidence bands were drawn with fitted lines. The horizontal dashed lines indicate 0.5 in the probability scale ($\cong 0$ in the logit scale).

FIG. 4. Plot of fitted probabilities arranged in ascending order. Points with fitted probabilities smaller than 0.50 were predicted as a member in group E, and those with fitted probabilities higher than 0.50, in group M. The actual categories are color-coded: red for group E and blue for group M.

IV. DISCUSSION

This paper investigated the rhythmic characteristics of both L1 and L2 English from the perspective of the rhythmic *frame*, combining the temporal envelope and the mouth opening-closing function using the spectral coherence. Variables capturing the spectral shape in the coherence were computed and analyzed as numeric predictors in a binomial logistic model. Except for the spectral ROLLOFF, all other variables were significant in discriminating native and non-native sentences.

Overall, the binomial logistic model was effective in predicting native- and non-nativeness in the sentences ($\mathcal{A}' = 0.71$, also see Fig. 4), suggesting that the L2 English speakers who speak Mandarin

as the L1 (group M) exhibit systematic differences in their rhythmic *frames*. A slight prediction bias towards native speakers (group E) was observed ($B''_D = -0.06$), which is obvious in Fig. 4: there were cases in group M that have reached extremely low fitted probabilities (thus predicted as typical sentences in the reference group E), yet no cases in group E were seen to have bled into the high fitted probability region, where cases predicted as typical group M members would reside. The reason for the slight bias may be because some speakers in group M have attained sufficient proficiency in English speaking skills (speakers in group M were living in the United States, possibly attending higher education at the time of corpus construction), thus exhibiting near native rhythmic *frame* patterns for some utterances. The results for each variable are discussed below:

(i) The L2 speakers (group M) in general showed lower CENTROID frequencies in the ENV- O_m coherence (see Table I: $\beta = -1.05$ and $e^{\beta} = 0.35$ with $p < 0.001$; also see Fig. 3a). This finding conforms to the expectation. Non-native speech typically exhibits a slower speech rate,¹¹⁵ realized by slower articulatory movements. As a result, the rhythmic *frame* sizes are stretched, and the recurring frequencies extracted from the rhythmic *frame* become smaller, thus the centroid frequencies in the ENV- O_m coherence are smaller in L2 speech compared with those in the L1.

(ii) The L2 speakers (group M) in general showed a narrower spectral SPREAD in the ENV- O_m coherence (see Table I: $\beta = -2.15$ and $e^{\beta} = 0.12$ with $p < 0.001$; also see Fig. 3b), suggesting that the oscillations in the rhythmic *frame* were more regular around the centroid. The L2 speakers may have transferred the rhythmic pattern of Mandarin to the production of English. The rhythmic *frame* of Mandarin is characterized as being more regular. In particular, the jaw cycles only exhibit large displacements at the utterance ends, but remained stabler elsewhere, though local perturbations were also observed at phrasal junctures and grammatically auxiliary parts.⁷⁵ Whereas for English, the jaw displacements in an utterance are more variable, possibly because stress is a conspicuous prosodic device in English phonology,⁷³ as a result the rhythmic *frame* appears more variable. It has been

demonstrated that speakers of different languages would transfer the jaw oscillation patterns of their L1s to the rhythm production in L2 English, resulting in a more regular rhythmic *frame* compared with L1 English.⁹⁴⁻⁹⁶ From the acoustics perspective, L2 English by Mandarin speakers and Mandarin showed smaller intensity and sonority variabilities compared with L1 English,^{90, 116} further supporting a more regular rhythmic *frame* in L2 English. As a consequence, smaller spreads in ENV- O_m coherences were observed for L2 English speech.

(iii) The difference in the spectral ROLLOFF in the ENV- O_m coherence was not significant between L1 and L2 speakers (see Table I: β and the associated e^{β} did not reach the α -level of 0.05; also see Fig. 3c). This finding suggests that the right-skewness in the coherence was similar for both groups. Although both groups differ in the frequency spread around the centroid, their speech productions of English sentences were within some common constraint of the rhythmic *frame* which may be around 2–7 Hz as reported in Chandrasekaran et al.⁸¹ As Fig. 3c shows, rolloff frequencies rarely exceed 5 Hz.

(iv) The L2 speakers (group M) in general showed greater FLATNESS (see Table I: $\beta = 0.40$ and $e^{\beta} = 0.12$ with $p < 0.05$; also see Fig. 3d) and higher ENTROPY (see Table I: $\beta = 0.26$ and $e^{\beta} = 1.30$ with $p < 0.001$; also see Fig. 3e) in the ENV- O_m coherence. These findings suggest that unpredictability is more pervasive in the rhythmic *frame* of L2 speech, whose coherence is more complex. Such complexity in the rhythmic *frame* may be because the L2 speakers were in general less fluent than the native speakers. Glitches were not uncommon in their speech production. Local *ritardandi* were observed in L2 speech when the sentences contained unfamiliar words and topics, or when the grammatical structure was more complex. Some speakers also hurried up after a *ritardando* possibly to compensate for the time loss. Higher frequency components in the rhythmic *frame* were thus introduced. Although these higher frequency components may not be so prominent as to substantially push the centroid towards higher frequencies or increase the spread, the disorder

introduced by them in the L2 coherence has been effectively captured by both spectral FLATNESS and ENTROPY. In fact, L2 speakers showed a slight tendency of possessing greater right-skewness in the coherence as captured by the spectral ROLLOFF (see Fig. 3c); this tendency did not reach significance, nevertheless.

It is plausible that for L2 learners with more limited proficiency, the FLATNESS and ENTROPY are even greater due to high frequency components introduced by the disfluency, which in turn significantly shifts the ROLLOFF towards higher frequencies and expands the SPREAD. The CENTROID will be even smaller due to slower speech tempo. This hypothesis warrants further research. As a major weakness of this study, the L2 English speakers did not produce a comparable set of sentences in Mandarin for a full comparison. Filling the lacuna will be left for further studies. Yet, it is expected that Mandarin would exhibit a narrower SPREAD, lower ROLLOFF, and smaller FLATNESS and ENTROPY, due to its more regular rhythmic frames.⁷⁵ CENTROID is difficult to foretell, though, because the balancing point in the coherence is affected holistically by the whole frequency range in addition to the averaged size of rhythmic frames largely influenced by speech tempo.

These results have two major implications for L2 acquisition and teaching:

(i) The importance of the *frame* aspect in the rhythm acquisition is highlighted. The rhythmic characteristics in an L2 may not be adequately addressed from the traditional *content*-based perspective alone. Sometimes, durational variability of different phonetic intervals even failed to capture differences between L1 and L2.^{88,89} From the coherence between the mouth opening-closing alternations and the temporal envelope, rich information about L2 rhythm can be revealed, including the speech tempo, degrees of regularity, and how chaotic the rhythmic *frame* appears. Such measurements may be valuable to L2 teachers and researchers to spot weaknesses in the L2 speech and develop strategies to help learners improve in speech rhythm.

(ii) The rhythmic *frame* may be implemented in computer-assisted language learning systems. Mouth movements can be captured using either the built-in camera or an external device ⁹⁷; the temporal envelope can be easily extracted from audio input. Differences in either mouth cycles or the envelope patterns between a learner's utterance and a native exemplar can be visualized. This will help the learner better understand the task to achieve near-native speech rhythm. Such explicit awareness in the learning task has generally been shown to play a positive role in L2 speech learning. ¹¹⁷ Similar research using visualizations of jaw movements has already shown promising results. ⁹⁵

V. GENERAL DISCUSSION

In general, this paper demonstrated that characteristics in the rhythmic *frame* can be effectively operationalized by calculating the spectral coherence between mouth opening-closing cycles and the temporal envelope. The mouth opening-closing cycles constitute the articulatory basis for the rhythmicity in speech production, which are purported to have its root in language evolution. ^{1, 54, 57} The mouth opening-closing movements modulate the vocal tract geometry and hence its transfer function at a rate that can be revealed in the temporal envelope of the speech signal (in particular in the frequency band containing mostly the vocalic energy). The coherence capturing the shared periodicities in the two domains of signals can thus become a natural basis for the empirical analysis of the *frame* aspect of speech rhythm. By nature, the coherence is a power spectrum, and is analyzable using various spectral tools, including but not limited to the ones reported in this paper. Additionally, coherence analysis can be carried out between the mouth opening-closing movements and other physical quantities in the speech signal, such as f_0 . According to Jun, ⁵⁰ the f_0 excursion (also referred to as the macro- or tonal rhythm) carries important information about prosodic typology. The f_0 coexists with the sonorant portions of the speech signal, and the sonority and

obstruency alternations typically follow the opening-closing movements of the mouth, which constitutes the core of the frame-content theory.¹ Further research on the relationship between mouth cycles and the tonal rhythm may yield insightful findings about the rhythmicity in speech. However, f_0 typically exists as a piecewise function, and the treatment of the obstruent gaps requires careful decisions.

From the neuropsychological perspective, the rhythmic *frame* affords the entrainment of cortical oscillations for speech processing and comprehension,⁶⁵⁻⁶⁹ which was claimed to have its root in evolution.^{55,56} Disrupting the expected rhythmic *frame*, such as compressions in the time-scale, severely hinders entrainment and comprehension.¹¹⁸ The ENV- O_m coherence as a physical realization of the rhythmic *frame* may become a very useful tool to predict the comprehensibility of an utterance from the angle of rhythmicity, and at least partially explain why, given the same signal condition, listeners prefer some utterances to others.¹¹⁹

From the linguistic perspective, the existence of speech rhythm has been debated because of (a) the opacity between rhythm and linguistic function, (b) the lack of precise clock-timing in speech, and (c) between-language disparities in making use of stress and prominence.¹²⁰ With regard to (a), it would be overambitious to discuss in any depth here (see Schlüter,¹²¹ though, for a treatise on grammatical changes under the rhythmic principle). With regard to (b) and (c), the ENV- O_m coherence may offer a fresh perspective to contemplate the conundrum of speech rhythm. First, the lack of precise clock-timing *per se* does not uphold the lack of rhythm in speech. Deviations from strict clock-timing is extremely common even in western music (an epitome of rhythmicity), where *ritardandi*, *accelerandi*, and *fermate* all push the music signal away from the expected timing as prescribed by the meter signature; nonetheless, music has rarely been questioned about its rhythmicity. In a similar vein, strict clock-timing (corresponding to a single peak in the ENV- O_m coherence) is rare in ecologically produced speech, and spectral analysis of the rhythmic *frame* (in

terms of the ENV- O_m coherence) can reveal different levels of regularity irrespective of how stress and prominence is employed in phonology. This idea is fundamentally akin to Nolan and Jeon's¹²⁰ view of speech rhythm as a metaphor. An aerial view of a crop field can be likened to a chessboard, although a field is seldom as regular as a chessboard. Similarly, speech timing almost always deviates from metronome beats, yet different structures of regularities are revealed in the ENV- O_m coherence. The spectral composition in the ENV- O_m coherence may contain rich information on, for example, language design, talker idiosyncrasy, pathological traits, and emotion, in addition to the nativeness of an utterance that the present study aimed to explore.

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APPENDIX A

PRAAT and MATLAB scripts performing the main signal processing functions are listed below with respective URLs to the OSF research repository (<https://osf.io/>):

1. temporal_env.praat (<https://osf.io/vuskw/>)

This PRAAT script extracts the temporal envelope from a speech signal as described in Sec. II.B.1.

2. mouth_opening_area.mlx (<https://osf.io/qjh6p/>)

This MATLAB script calculates the mouth opening-closing movements from an electromagnetic articulographic datafile as described in Sec. II.B.2.

3. tukey_window.praat (<https://osf.io/6wfq9/>)

This PRAAT script creates the Tukey taper to smooth the signal edges as described in Sec. II.B.4.

4. spectral_coherence.praat (<https://osf.io/vm6qk/>)

This PRAAT script calculates the spectral coherence between the temporal envelope and the mouth opening-closing function as described in Sec. II.B.4.

5. spectral_centroid_spread.praat (<https://osf.io/8rjta/>)

This PRAAT script calculates the spectral centroid and spread from the ENV- O_m coherence as described in Sec. II.B.5.a and Sec. II.B.5.b.

6. spectral_rolloff.praat (<https://osf.io/q9tdk/>)

This PRAAT script calculates the spectral rolloff from the ENV- O_m coherence as described in Sec. II.B.5.c.

7. spectral_flatness.praat (<https://osf.io/tb8jw/>)

This PRAAT script calculates the spectral flatness from the ENV- O_m coherence as described in Sec. II.B.5.d.

8. spectral_entropy.praat (<https://osf.io/awzmf/>)

This PRAAT script calculates the spectral entropy from the ENV- O_m coherence as described in Sec. II.B.5.e.

APPENDIX B

This appendix presents the calculation details in evaluating the model prediction performance. First, the confusion matrix (**CM**) was established based on the logistic model built in Sec. III:

$$\mathbf{CM} = \begin{matrix} & \begin{matrix} \text{predicted } E & \text{predicted } M \end{matrix} \\ \begin{matrix} \text{actual } E \\ \text{actual } M \end{matrix} & \begin{bmatrix} 720 & 392 \\ 426 & 691 \end{bmatrix} \end{matrix} \quad (\text{B1})$$

The percentage correct (%Correct) was calculated as:

1

2

$$\%Correct = \frac{tr(\mathbf{CM})}{\Sigma\Sigma\mathbf{CM}} = \frac{720+691}{720+392+426+691} = 63.30\% \quad (B2)$$

3

4

Then, the sensitivity or hit rate (*hit*), and the specificity or false alarm rate (*fa*) were calculated as:

5

6

$$\text{sensitivity } (hit) = \frac{\mathbf{CM}_{(1,1)}}{\mathbf{CM}_{(1,1)}+\mathbf{CM}_{(1,2)}} = \frac{720}{720+392} = 64.75\% \quad (B3)$$

7

8

$$\text{specificity } (fa) = \frac{\mathbf{CM}_{(2,1)}}{\mathbf{CM}_{(2,1)}+\mathbf{CM}_{(2,2)}} = \frac{426}{426+691} = 38.14\% \quad (B4)$$

9

10

The discriminability ($\mathcal{A}'$) and prediction bias (B''_D) were calculated based on formulas (B3) and (B4):

11

12

$$\mathcal{A}' = \frac{1}{2} + \frac{(hit-fa) \times (1+hit-fa)}{4 \times hit \times (1-fa)} = 0.71 \quad (B5)$$

13

14

$$B''_D = \frac{(1-hit) \times (1-fa) - hit \times fa}{(1-hit) \times (1-fa) + hit \times fa} = -0.06 \quad (B6)$$

15

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