Rhythm measures and dimensions of durational variation in speech[a)]

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(Dated: December 8, 2010)

[a)] Preliminary results obtained on part of the corpus were presented in "Rhythm measures with language-independent segmentation", Proceedings of Interspeech, Brighton, 2009, 1531-1534

Abstract

Patterns of durational variation were examined by applying fifteen previously published rhythm measures to a large corpus of speech from five languages. In order to achieve consistent segmentation across all languages, an automatic speech recognition system was developed to divide the waveforms into consonantal and vocalic regions. The resulting duration measurements rest strictly on acoustic criteria. Machine classification showed that rhythm measures could separate languages at rates above chance. Within-language variability in rhythm measures, however, was large and comparable to that between languages. Therefore, different languages could not be identified reliably from single paragraphs. In experiments separating pairs of languages, a rhythm measure that was relatively successful at separating one pair often performed very poorly on another pair: there was no broadly successful rhythm measure. Separation of all five languages at once required a combination of three rhythm measures. Many triplets were about equally effective, but the confusion patterns between languages varied with the choice of rhythm measures.

PACS numbers: 43.70.Kv, 43.70.Fq, 43.70.Jt, 43.72.Ar

This paper was submitted to the Journal of the Acoustical Society of America, December 2010. Until publication, it can be found at http://kochanski.org/gpk/papers/2010/classifier.pdf.

I. INTRODUCTION

There is a widespread intuition that languages differ in 'rhythmic structure'. Experimental studies suggest that the perception of rhythm rests on a combination of different acoustic properties that are not limited to duration. Barry *et al.* (2009), for example, showed that changes in F_0 influence the perceived strength of rhythmicity. In another study, rate of spectral change proved the most robust property for distinguishing spoken poetry from prose (Kochanski *et al.*, 2010). Furthermore, spectral properties (Tilsen and Johnson, 2008; Tilsen, 2008), intensity (Lee and Todd, 2004; Keane, 2006) and modelled auditory prominence (Lee and Todd, 2004) can help to determine rhythm in different languages.

Nevertheless, the acoustic parameter most frequently linked to perceived differences in rhythm remains duration. Perceptual studies show that both infants and adults can distinguish between languages when presented with resynthesized signals that primarily contain durational cues (for references see Ramus *et al.*, 1999; Nazzi and Ramus, 2003; Komatsu, 2007)[1]. Accordingly, numerous quantitative indices have been developed in attempts to capture the variation in duration that underpins both the intuition and the experimental findings. We follow Barry and Russo (2003) in calling these indices of durational variation 'rhythm measures' (RMs).

Rhythm measures have been widely used for comparisons between different languages and varieties (see, for example, White and Mattys, 2007a, for an overview). All these previous studies have used relatively small corpora of speech. Growing evidence, however, shows that RMs can vary greatly between speakers or texts (Lee and Todd, 2004; Keane, 2006; Arvaniti, 2009; Wiget *et al.*, 2010). A large speech corpus thereby becomes essential

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for an extensive rhythm study. The corpus should cover numerous speakers and many texts.

Much work has tried to determine which particular rhythm measures best separate languages and varieties (see White and Mattys, 2007a, for an overview). For example, White and Mattys (2007a) and White and Mattys (2007b) examined which RMs best differentiated speech from two languages or from native and non-native speakers of a single language. Very few studies, however, have compared languages on more than two measures at a time. Limited evidence intimates that this may be insufficient for covering cross-language distinctions in rhythm. Ramus *et al.* (1999) found that while just two measures distinguished groups of languages in their corpus, a third pulled Polish apart from English and Dutch. (They suggested that this third measure actually reflects phonological properties of the language and may be irrelevant to the perception of rhythm.) Recently, a discriminant analysis by Liss *et al.* (2009) indicated that several measures were necessary to distinguish dysarthric from normal speech. These various findings raise two questions. First, can just two measures truly encapsulate cross-language differences in rhythm? Second, can some particular, limited set of measures suffice to capture the differences in durational patterns between any two languages or varieties? Therefore, the many available measures should be examined systematically.

A. Purpose of experiment

To meet these requirements, we studied patterns of durational variation in speech from five languages by applying 15 previously published RMs. The corpus for each language was substantially larger than anything used in past rhythm studies. We used several automatic segmentation algorithms that split speech into consonant-like, vowel-like and silent regions. The algorithms offer uniform, language-independent treatment of acoustic signals, avoiding the inevitable inconsistencies introduced by human labelling and, very importantly, permitting computation of rhythm measures over our large corpora. Unless rhythm measures are defined in such a language-independent manner, they cannot be used to compare lan-

guages. Machine classification was essential for processing of the resulting extensive set of measurements.

Our principal aim was to examine rhythm from the acoustic point of view, without reference to phonological interpretation of a given language. Given this aim, three major issues were addressed. First, how well can machine classification identify the languages, using various combinations of the rhythm measures (RMs)? Second, how many RMs are needed to disentangle cross-linguistic variation in rhythm? Third, does the array of the most useful measures depend on the languages being identified?

II. METHOD

A. Speech data

Our corpus contained 2300 texts recorded from 50 speakers distributed across Southern British English (N=12), Standard Greek (N=9), Standard Russian (N=10), Standard French (N=9) and Taiwanese Mandarin (N=10). Each speaker read the same set of 42 texts (original or translated) in their own language[2]. Texts included extracts from "Harry Potter", fables, and the fairy tale Cinderella. On average, texts contained 217 syllables. Each speaker also read 4 nursery rhymes (75 syllables on average), matched across the languages for the number of syllables per line and, where possible, poetic meter.

Speakers were 20-32 years old, born to monolingual parents, and had grown up in their respective countries. At the time of the recording, all speakers were living in Oxford, UK. Non-English participants had lived outside their home country for less than 4 years (median length of residence 1 year)[3]. Recordings were made through a condenser microphone in a soundproof room in the Oxford University Phonetics Laboratory and saved direct to disc at a 16 kHz sampling rate. Texts were presented on a VDU screen in standard orthography for each language. Speakers could repeat any text if dissatisfied with their reading. Overall, 15% of the recordings were repeated, although the fraction varied greatly between speakers. In most cases the recordings were repeated after a brief false start. The recordings of each

speaker took place in two or three sessions on separate days.

B. Automatic segmentation

Before any interval-based rhythm measures can be calculated, a first crucial step is the language-independent segmentation of the speech signals into vocalic and intervocalic intervals. The definition of 'vocalic' and 'intervocalic' intervals must avoid any phonological interpretations and ignore syllable and foot boundaries unless they can be approximated in a language-independent way (cf. Ramus *et al.*, 1999).

Most studies on rhythm measures have employed manual segmentation. Its outcome, however, varies between the labellers and, more importantly, depends on their phonological knowledge. Even with the precautions suggested by Wiget *et al.* (2010), manual segmentation has serious shortcomings. For example, a labeller's ideas of 'acoustic criteria' often rest on the experience of segmenting English data. When applied to other languages, such ideas may produce counter-intuitive results, prompting re-evaluation (see, e.g., Barry and Russo, 2003; Grabe and Low, 2002; Lee and Todd, 2004). Crucially, variability in rhythm measures absolutely requires use of large corpora. Manual segmentation here would be virtually prohibitive.

Given the pitfalls of manual segmentation, interest has understandably developed in automatic segmentation based purely on acoustics (Galves *et al.*, 2002; Dellwo *et al.*, 2007). Wiget *et al.* (2010) in particular compared automatic and human segmentation of a small corpus. They first employed automatic forced alignment to match a transcription with the signal. Then they converted the transcription into a sequence of vocalic and consonantal intervals. Scores for traditional rhythm measures computed from the automatic segmentation were within or just outside the ranges produced by the human labellers.

Unfortunately, forced alignment depends upon language-specific transcription, and therefore the resulting segmentation is not based on purely acoustic criteria. Similar acoustic signals could be assigned different labels in different languages, depending on their phonolog-

ical interpretation in each language. Forced alignment, moreover, is insensitive to variation in the realization of individual sounds. For example, it misses lenition and reduction or deletion of segments or syllabic consonants, unless they are reflected in the transcription. In theory, the transcription could be manually adjusted to reflect such connected speech processes, or a comprehensive dictionary of alternative realizations could be compiled. Either alternative would be expensive and would simply negate the benefits of automatic segmentation.

To avoid these difficulties, we used current methods of speech recognition to create cross-linguistic statistical models of vocalic and intervocalic regions. Then the models were embedded in segmentation algorithms (SAs). To investigate whether different models affect the findings, we compared the results from three different algorithms. One algorithm (SA1) employed the loudness of the signal and the regularity of its waveform. The other two algorithms (SA2a and SA2b) were developed through the standard HTK toolkit (Young *et al.*, 2006). Finally, all three algorithms and human labellers were compared on the analysis of a sub-corpus of our speech data. All SAs acted as recognizers. After the training stage, an SA had no access to transcriptions. It assigned labels according to acoustic properties of the signal. As an example, fig. 1 shows a waveform segmented by the three algorithms.

1. Segmentation algorithm SA1 based on loudness and aperiodicity

For algorithm SA1, we computed time series of specific loudness of the signal and aperiodicity of the waveform. Aperiodicity varies between zero for a perfectly periodic signal and 1 for random white noise. Loudness was computed from the signal using algorithms described in Kochanski *et al.* (2005) and Kochanski and Orphanidou (2008). These values were smoothed and then compared against thresholds to generate transitions from one segment to another (see fig. 2). The process operated with three types of segments: (1) vowel-like segments with a nearly periodic waveform; (2) segments with an aperiodic waveform which can include frication and/or regions with rapid changes in the waveform; and

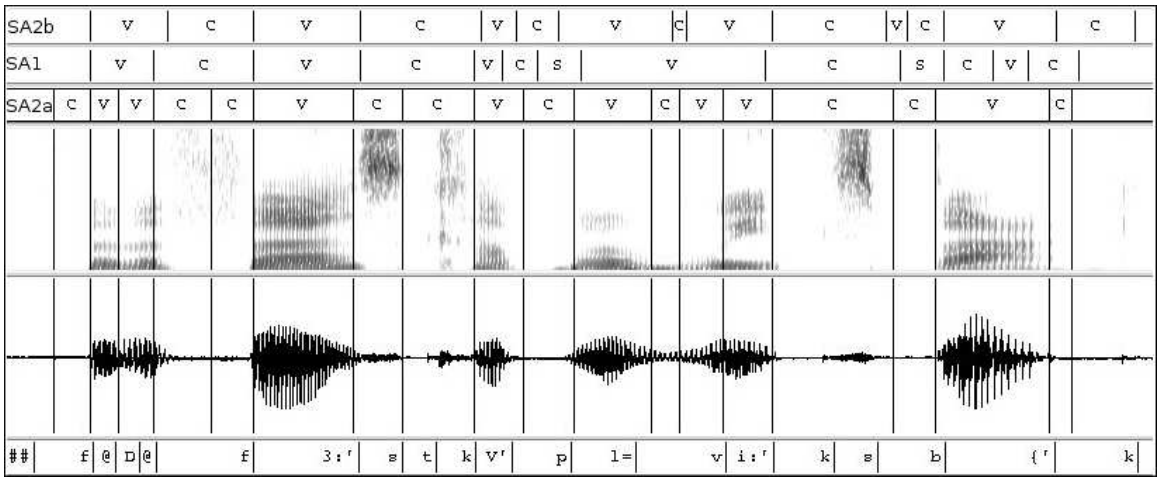

FIG. 1. The outcome of three segmentation algorithms for an English phrase 'For the first couple of weeks back'. The bottom pane shows X-Sampa labels assigned by one of the authors, the top three panes show the labels assigned by three automatic segmentations. The vertical lines correspond to the borders assigned by SA2a.

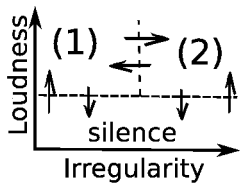

FIG. 2. Transitions between the three states

(3) silences. These three categories are broadly consistent with the specifications of most published rhythm measures, which are defined in terms of vocalic and intervocalic intervals. Five parameters controlled SA1: [a] a smoothing time constant for the loudness and aperiodicity time series (the smoothing process tends to suppress very short segments); [b] the normalised loudness of the silence-to-non-silence transition; [c] the normalised loudness of the opposite transition; [d and e] aperiodicity thresholds for the (2)→(1) and (1)→(2) transitions respectively. Two different thresholds were necessary to prevent small fluctuations in the data from generating a sequence of very short segments.

An optimization procedure set the parameters for SA1, using a sample of 7143 utterances

from the corpus. The sample contained data from 12 speakers, two per language but four for English. It included texts from our corpus as well as short sentences recorded by the same speakers for a larger study. The parameters were adjusted to minimize the mean-squared difference between the number of segments generated by SA1 and the number predicted from phoneme-level transcriptions of the utterances. The number of occurrences of segment type (1) produced by the SA1 was matched to the number of appearances of vowels and sonorants. The number of occurrences of segment type (2) was matched to that of the remaining phonemes. Silences (segment type (3)) were weakly constrained to appear about 10% as often as the other regions. After this optimization, the parameters were applied across the entire corpus.

2. HTK segmentation algorithms SA2a and SA2b

The HTK toolkit (Young *et al.*, 2006) underlay the other two segmentation algorithms, SA2a and SA2b. For SA2a speech was represented as a 26-dimensional standard Mel frequency cepstrum coefficient (MFCC) vector (see, for example, Davis and Mermelstein, 1980). For SA2b speech was represented as 41-dimensional Acoustic Description Vector (Kochanski *et al.*, 2010). The two algorithms also varied in numbers of states, minimal pause lengths, and ways of measuring phoneme duration (see Appendix A for further details). Standard speech recognition algorithms are usually trained on the data from a particular language which may result in different acoustic models for different languages. We trained the algorithms on human-segmented data containing a mixture of texts from all five languages and then applied the derived models to the whole corpus. As a result the same acoustic models were used to segment the data from all languages, thereby ensuring consistent language-independent segmentation.

C. Rhythm measures

Published rhythm measures differ in three respects. Firstly, they use differently determined intervals. Initially, rhythm metrics rested on the durations of vocalic or of consonantal intervals. Explanations of perceived differences in rhythm have also invoked phonological properties such as vowel reduction and syllable complexity (Dauer, 1983); these properties presumably would affect RMs that employ vocalic or consonantal durations. More recently, however, Barry *et al.* (2003) argued that treating consonants and vowels separately forces RMs to miss the combined effect of vocalic and consonantal structure. They proposed that RMs should be defined in terms of syllables or pseudo-syllables. Deterding (2001) had earlier suggested a similar approach. Liss *et al.* (2009) measured variation in the duration of VC sequences, arguing that these better represent the perception of syllable weight. Finally, Nolan and Asu (2009) recently suggested further modifications of RMs based on feet.

The second difference between rhythm measures is whether they assume 'global' or 'local' forms. Global RMs capture variation in the duration of particular intervals over an entire utterance. Local measures focus on differences between two immediately consecutive intervals and then average those differences over the utterance. Local measures supposedly differentiate better between various patterns of successive long and short intervals, thereby capturing auditory impressions of rhythm (see Barry *et al.*, 2003).

Thirdly, some measures include a normalization step, while others keep raw durations. Measures based on raw durations are more vulnerable to changes in speech tempo. Normalized measures, however, may level out cross-linguistic differences. Many studies have used a combination of both. For example, Grabe and Low (2002) normalized their vocalic index but used raw values for the consonantal index. In another study, Wiget *et al.* (2010) found that normalized measures of variability of vocalic intervals discriminated best between languages and were most stable under changes in articulation rate. They recommended using a combination of at least two measures that were robust to segmentation procedures and to speech rate.

Using each of the three segmentation algorithms described above, we computed the 15 rhythm measures (RMs) listed in Table I on each of the 2300 spoken texts in our corpus (see II.A). Although the conventional labels V and C appear in the table, they really refer to the labels assigned by the segmentation algorithms. Our labels reflect the acoustic properties of spoken speech and may not correspond perfectly to phonologically transcribed vowels and consonants. For rhythm measures based on phonological syllables, we used sequences of consecutive consonantal and vocalic intervals. We did not use measures based on VC sequences, which Liss *et al.* (2009) suggested for dealing with syllable weight, since most languages in our corpus do not contrast light and heavy syllables. We also excluded measures based on feet, since the definition of foot is language specific.

Previous studies of RMs have treated pauses and pre-pausal syllables in different ways. To evaluate the importance of such different treatments, we computed each RM in three different ways. First, we calculated the scores for each inter-pause stretch (IPS) then averaged over all IPSs within a text. The average was weighted by the duration of each IPS. Second, we made the same calculation after omitting the final 'syllable'. For each IPS that ended in a vocalic interval, we omitted the final sequence of consonantal and vocalic intervals (CV). For each IPS that ended in a consonantal interval, we omitted the two final consonantal intervals and the intervening final vocalic interval (CVC). Third and finally, scores were simply computed across the whole text, including intervals spanning a pause.

D. Classifiers

To quantify variation in RMs between languages, we applied classifier techniques (cf. Kochanski and Orphanidou, 2008). A classifier is an algorithm that decides which language was most likely to have produced an utterance, given one or more observed RMs. We used linear discriminant classifiers and a Bayesian forest approach (see Appendix B). Insofar as the RMs capture the rhythmic differences between the languages, success corresponds roughly to the probability that a listener could identify the language from its rhythm after

hearing a single spoken paragraph.

Our classifiers assume that the log likelihood ratio between the probabilities of any two languages is a linear function of the input rhythm measures. The classification boundaries for each language then form a convex polygonal region in the space of the observed RMs.

To obtain reliable error bars on our classification probabilities, we used a combination of Bootstrap resampling (Efron, 1982) and Monte Carlo sampling. To do this, classifiers were built with 12 different combinations of non-overlapping training and test sets. These sets came from a typical 3-to-1 split of the dataset, respectively. The algorithm produced 20 different Monte Carlo samples of classifiers that were consistent with that training set. We report averages of the resulting 240 (12*20) individual runs on each dataset. The variation in performance of a classifier from one instance to another was used to determine whether differences in performance are statistically significant. To prevent classifiers from learning patterns of individual speakers, data from a given speaker never appeared in both the training and the test set for a given run.

For each segmentation algorithm and pause condition, we ran 15 classifiers based on single RMs, 105 based on all possible combinations of two RMs, and 455 classifiers based on all possible combinations of three RMs. Finally, one classifier used all 15 RMs, for a grand total of 576 classifiers. For each of the three segmentation algorithms (SAs), then, there were 1728 runs that included different pause conditions. Similarly, each pause condition was represented in 1728 runs that included the different SAs. We first applied all classifiers to pairwise identification of all 10 pairs of languages in our corpus. We then repeated the analysis for the whole corpus at once, testing how well the classifiers separated all five languages.

Our results are based on the probability of correctly identifying the language of a paragraph. If this is large (i.e. near 1.0), it means that the data from the various languages can be separated into distinct groups by straight lines[4]. One can think of this as a test of the hypothesis that RMs for different languages form separable clumps. An identification probability near chance happens if the data from different languages are intermingled.

We defined our chance level conservatively, to be the best possible performance of a classifier that knows the relative frequencies of the classes, but not the RM value(s) for a particular paragraph. The chance level is then the proportion of passages from the most frequent language in the training set. This varies from experiment to experiment, and even for the different classifier instances within a forest, since the training sets do not have exactly the same composition.

To allow simple comparisons, we report both the proportions of correct identifications, $P(\mathrm{C})$ and a figure of merit designated K. This is computed as $K = \frac{P(\mathrm{C})-chance}{1.00-chance}$, where 1.00 represents perfect performance. Thus, K varies between 0 for classifiers that perform at chance and 1 for perfect classifiers. We used z-tests to assess both the significance of differences between $P(\mathrm{C})$ and chance for each classifier and the significance of differences in $P(\mathrm{C})$ between classifiers. Since we foresaw a large number of tests, we set the significance level of the tests (α) conservatively at .01.

III. RESULTS

A. The effect of segmentation and computation method

The three methods of handling pauses in the computation of rhythm measures did not affect classifier performance. For classifiers using identical RMs, differences in $P(\mathrm{C})$ between pause conditions were significant in less than 1% of all 5184 (3*1728) possible pairwise comparisons. This outcome is at chance. Segmentation algorithm did not influence the performance of classifiers that treated all five languages in one run. Classifiers using identical RMs yielded significantly different values of $P(\mathrm{C})$ between two SAs in less than 1% of the 5184 possible comparisons. This again is at chance.

In contrast, for classifiers that sorted just a pair of languages, significant differences in $P(\mathrm{C})$ appeared between SAs in about 2% of the 51840 cases. (Each of the 10 possible pairs underwent 5184 comparisons across SAs.) Across all pairs, the differences mainly occurred between SA1 as against the two HTK-based algorithms, SA2a and SA2b. Generally, SA1

performed worse than the other two. The $P(\mathrm{C})$ was higher for SA2a than for SA1 in 70% of significantly different comparisons. Where $P(\mathrm{C})$ differed significantly between SA2b and SA1, the former performed better 93% of the time.

In short, computation procedure had no effect on the accuracy of language identification. Segmentation algorithm had only a small effect. Accordingly, the classifier results presented below rest on algorithm SA2a and on RM computations that omit the final sequence of consonantal and vocalic intervals (CV or CVC) in each IPS.

B. The effect of repetition

As described in section II.A, speakers could stop the recording and start from the beginning, if they were dissatisfied with their reading. As a result about 15% of the texts were recorded on a second or third attempt. To estimate any effect of such repetition on rhythm measures, we ran multiple regressions with RMs as dependent variables. For each RM, we compared the r^2 obtained with both 'speaker' and 'repetition' as independent variables against the r^2 obtained with 'speaker' alone. We did a similar analysis for mean syllable duration for each text. Mean difference in r^2 for all RMs and speech rate was .0005. Repetition clearly did not affect the values of RMs.

C. Classifiers for pairs of languages

Most behavioral language identification experiments have used pairs of languages. Therefore, we took the 576 classifiers using all possible combinations of 1, 2, 3 and 15 RMs and applied them to the 10 possible pairs of languages in our corpus. Languages in all pairs could be separated above chance, but $P(\mathrm{C})$ never reached unity (perfect identification). That occurred because all pairs of languages showed substantial overlaps in RM values. Fig. 3 shows the distribution of values for a randomly selected pair of measures and pair of languages.

For nine of the pairs of languages, maximum $P(\mathrm{C})$ could be achieved using only one RM

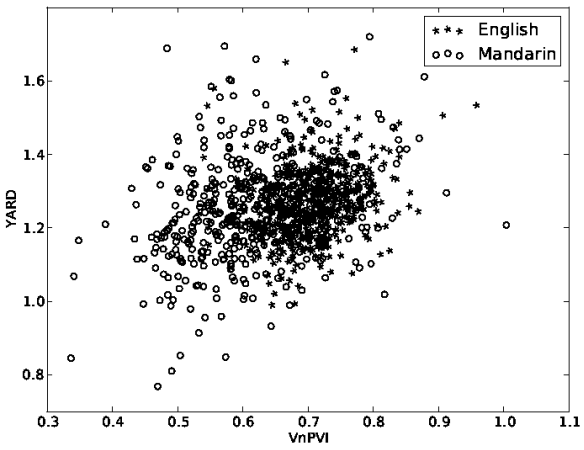

FIG. 3. The values of of VnPVI and YARD in English and Mandarin data (K=.46, P(C)=.76, chance=.54)

(see Table II); adding further RMs gave no significant gain in P(C). The one exceptional case was identification of Russian vs Greek, where three RMs were needed to maximize P(C). Table II shows that the most successful single RM (or successful set of RMs) depended on the language pair. For example, a single consonantal measure allowed the best possible separation of Mandarin from English, but no consonantal measure could separate Mandarin from French above the chance level.

Not all pairs of languages showed the same degree of confusion. Mandarin was identified most readily: across all four language pairs that included Mandarin, the best classifiers gave an average K of .53 and average P(C) of .78 (average chance .53). In contrast, across all six pairs of European languages, the best classifiers yielded an average K of .30 with an average P(C) of .68 (average chance .54). The difference in P(C) between any two pairs of European languages was not significant.

D. Identification of all five languages

1. The success of individual RMs

Only eight of the 15 RMs performed above chance in correctly sorting all five languages in our corpus. These were the two ratio measures, all normalized vocalic measures and all normalized CV-based measures (see Table I). Their average P(C) was .33 (chance=.23, K=.12). No significant differences appeared amongst these eight classifiers.

2. Classifiers based on several RMs

As reported above, the RM that maximized observed P(C) for a pair of languages differed between pairs. As these results imply, classifiers required a combination of RMs to maximize P(C) for all five languages. Given a single CV or V measure, adding two more measures from the V, CV, or ratio types raised P(C) to an average of .44 (K=.27). For classifiers based on a single ratio measure, significant improvement required adding three V or CV measures. Average P(C) for classifiers using four such RMs then reached .46 (K=.30). Finally, although no classifier using a single consonantal measure had performed above chance on all five languages, a combination of C-based measures improved matters significantly. Fifteen classifiers based on pairs or triads of local and global C-based measures achieved an average P(C) of .36 (K=.17).

Beyond this, adding more RMs to the classifiers yielded no further gains. No combination of classifiers correctly identified the five languages all the time. Indeed, classifiers based on all 15 rhythm measures gave a *P(C)* around .55 (K=.41). This does not differ significantly from the rates achieved by virtually all classifiers that used just three vocalic or syllabic measures. In short, within the 15 RMs studied here, maximum accuracy in identifying our five languages required a combination of just three of the right types of measures. Moreover, many sets of three RMs performed similarly well.

E. Relations between RMs

Many of the 15 RMs rely on similar calculations and therefore are highly correlated. To estimate the minimum number of RMs needed to cover the variation between our five languages, we performed multidimensional scaling (MDS) with PROXSCAL. To create a dissimilarity measure, RMs were intercorrelated within each language. Then 1-r^2, where r is a correlation, gave an ordinal dissimilarity measure between two RMs, ranging from 0 to 1. Languages were treated as separate sources for PROXSCAL.

The dissimilarities between the 15 RMs gave rise to a 5-dimensional solution (stress=.008). The dimensions seemed to represent distinctions between subgroups of RMs due to type of interval (C, CV, ratio, V) and to presence or absence of normalization. No grouping appeared that reflected scope (local or global). Languages differed modestly in their weights on the different dimensions.

At first sight, this seems to disagree with the fact that more than 3 RMs did not significantly improve *P(C)* for classification of five languages. The MDS solution, however, addresses language identification only indirectly: it shows that with just 5 RMs one can accurately predict any of the other ten. This sets a maximum on the number of RMs that could be used to identify languages. The success of 3-RM classifiers readily fits with this: there are 5 independent RMs, but languages in our corpus only differ in three of them. Notice that the criterion of "statistically significant improvement" used in this study is conservative: a fourth RM might yield some small gain that only an extremely large experiment could detect.

F. Relative location of languages

Although classification of all five languages using different combination of RMs can yield comparable values of P(C), the confusion patterns depend on the types of RMs. To demonstrate this, we created two 5 X 5 asymmetric matrices containing proportions of confusion between pairs of languages. One matrix held the results for all significant 3-RM

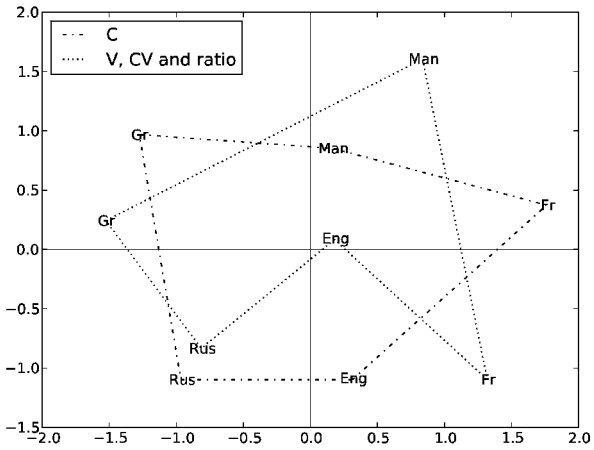

FIG. 4. The location of the 5 languages on MDS map computed using classifiers based on C-only measures or V/CV/ratio measures (V: stress=.18, R^2=.9, C: stress=.18, R^2=.9)

classifiers based on on CV, V and ratio only measures. The other was constructed from the results of all significant 3-RM classifiers using C measures only. Fig. 4 shows the two MDS maps produced by ALSCAL from these matrices. The two maps reveal different confusion patterns. Classifiers based on V/CV/ratio measures separated Mandarin from the European languages but often confused those four. Classifiers using consonantal measures exclusively put Russian and English in one MDS region and French, Greek and Mandarin in another. This agrees with the finding that consonantal measures separate Mandarin pairwise from Russian or English but not from Greek or French. Both matrices, however, displayed substantial confusion between each pair of languages.

G. Comparison between automatic and manual segmentation

Our automatic segmentation algorithms were designed to avoid the language-specific aspects of human segmentation of speech. Human segmentation inevitably reflects knowledge of the language being labelled. Furthermore, automatic segmentation is inherently consistent and reproducible, while human segmentation is not. Thus automatic and human

segmentation will never agree entirely.

Manual segmentation of our large corpus is impractical. Nevertheless, an important theoretical question remains: Does human segmentation agree well enough with automatic segmentation so that it would yield our basic findings on RMs and on identification of different languages? A segmentation algorithm suitable for quantifying rhythm should agree well with human labels on longer vowels and obstruents, but it might well disagree on less clear-cut cases such as sonorants or short vowels.

In order to get some grasp on this question, we selected a new test set of 30 spoken paragraphs from our corpus, covering all five languages (each paragraph on average contained 258 syllables). They were segmented by trained phoneticians in the same way as the set originally used to train the SAs (see Appendix A). One author segmented 2 paragraphs. The remaining 28 were segmented by seven other phoneticians, each from a different institution.

To compare SAs against the phoneticians, we applied each of our three segmentation algorithms to the test sub-corpus. We divided the human labels into four broad categories: vowels, voiced obstruents, voiceless obstruents and sonorants. At each 10 ms epoch of speech, we recorded both the broad human label and the automatic label of 'V', 'C' or 'S'. Then for each language, we computed the percentage of co-occurrences of 'V', 'C' or 'S' within each broad human label.

We first present detailed results for the comparison with SA2a, and then we consider differences between SA2a and the other two algorithms. Algorithm SA2a treated human labels for vowels or consonants as 'S' on less than 1 per cent of all occasions. This mainly arose from differences in placement of phrase-final and phrase-initial boundaries and from occasional differences in segmentation of voiceless plosives. Otherwise, agreement on identification of silences was almost perfect. We therefore dropped silences from further analysis.

Table III gives the percentages of 'V' and 'C' labels assigned to each of the four broad human labels. Of the epochs labelled as vowels by the phoneticians, 88%- 93% were tagged automatically as 'V', depending on the language. The bulk of the disagreements concerned the high vowels [i], [u], and [y] and the unstressed [ə]. Less than 85% of these cases were

tagged by SA2a as 'V'.

Voiceless obstruents were treated by SA2a as 'C' in 83-89% of the samples. More serious disagreement appeared on the English [h], with a 61% tagging as 'V'. (This agrees with the view that in English, and possibly in other languages, [h] is acoustically closer to approximants than to other fricatives (cf. Ladefoged and Maddieson, 1996, p. 326)). As expected, agreement between human and automatic segmentation was worse for sonorants and voiced obstruents than for voiceless obstruents. Sonorants were generally recognized as 'V' (77-91%). Voiced obstruents showed the greatest discrepancies, with the voiced fricatives [v], [ð], [ɣ] often recognized as vowels.

In short, segmentation algorithm SA2a successfully identified most unreduced vowels as 'V' and most voiceless obstruents as 'C'. It had learned the difference between more and less sonorous segments, and it apparently applied criteria similar to those used by phoneticians.

Algorithm SA2b used feature vectors rather than the MFCC vectors implemented in SA2a. The former consistently tagged vowels and voiceless obstruents as 'V' (90-94%) and as 'C' (79-89 %), respectively. Likewise, sonorants were mainly marked as 'V' (78-88%). Voiced obstruents showed the most variation, with patterns of tagging similar to those for SA2a.

Algorithm SA1 employed simple acoustic criteria. It mapped automatic labels onto the four human categories slightly less consistently than its two more complex partners. Only 79-88% of vowels labelled by humans were marked as 'V', while 79-89% of voiceless obstruents were tagged as 'C'. A noticeable difference appeared in the tagging of voiced stops as 'C' between Russian, Greek and French versus English (20-30% vs 63-79%). This reflects differences in the acoustic correlates of phonological voicing.

Finally, we recoded the labels assigned by the phoneticians into three categories of Vowel, Consonant, and Silence. The sonorants were coded as vowels. We treated labels at each 10 ms epoch as separate observations, giving 4000-7000 observations for each test paragraph. We excluded initial and final silences where they were labelled by both sources. Cohen's kappa was then used to compare the automatic tags of 'V', 'C', and 'S' against the

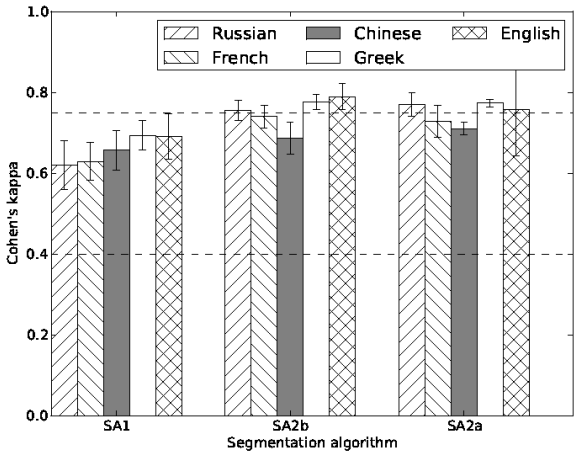

FIG. 5. Average values of Cohen's kappa between automatic and manual segmentation for all five languages. The automatic labels for each paragraphs in the test set were compared to manual labels for these paragraphs. The whiskers indicate standard deviation. The Kappa values between .4 and .75 (dashed lines) are interpreted as 'fair to good' agreement, the Kappa values above .75 are interpreted as 'excellent' agreement'.

three recoded categories of human labels. This statistic measures overall agreement between automatic and manual segmentations.

The box plots in Fig. 5 display the values of kappa for agreement between each segmentation algorithm and the phoneticians for each of the five language in our corpus. The median kappa value for both SA2b and SA2a is about .75. This is interpreted as 'excellent agreement beyond chance'. The median kappa of .65 for SA1 suggests fair to good agreement (see Banerjee *et al.*, 1999, for further discussion of the use of kappa). There was no consistent difference in recognition rates between the languages.

IV. DISCUSSION

In order to study the nature and complexity of patterns of durational variation as reflected by rhythm measures, we analyzed a large corpus of speech from five languages. Automatic segmentation and machine classification were necessary to do this. We obtained three major findings.

First, our procedures showed as expected that languages have different durational patterns. Within-language variation is so high, however, that it would appear impossible to identify one language reliably from rhythm measures based on single paragraphs. This conclusion agrees with results on human language identification. Numerous studies show that when listeners confront a processed signal lacking segmental information, they cannot identify the originating language with perfect accuracy. The exact success rate depends on experimental conditions and on the languages. In studies with low-pass filtering of speech from two languages, $P(\mathrm{C})$ for identification is around .63-.68, above chance of .50 (see Komatsu, 2007, for references). Our classifiers were at least as accurate as that in identifying two languages.

Our second main finding is that no one RM or set of RMs was the best for identifying all pairs of languages. The most effective choice differed from one language-pair to another. In agreement with results reported by White and Mattys (2007a) and Wiget *et al.* (2010), normalized vocalic measures were generally more successful than consonantal or non-normalized measures. Yet there was no consistent, clear way to rank RMs. Specifically, no particular RMs consistently outperform the others. Our results imply that searching for the 'best' RMs for separating all languages is fruitless.

Indeed, it is hardly surprising that different measures are optimal for identifying the members of different pairs of languages. Variation in duration is a product of many factors; among them are stress, syllable complexity, realization of individual sounds, and differences in sentence prosody, in speech tempo and in subject-specific patterns. One or two relatively simple measures would seem very inadequate for capturing all possible differences in rhythm

between all languages. Even if the measures were fine-tuned to capture one specific contrast, such as temporal stress (cf. Wiget *et al.*, 2010), other factors would still vary across other pairs of languages/varieties. Moreover, our results suggest that the correlation between the sort of information that is captured and the resulting classification performance of a given RM is generally weak and complicated.

Our third main finding is that three measures were necessary to achieve optimal identification of all our five languages at once. Given that no single measure provided optimal separation across all pairs of languages, it is only logical that several measures should prove necessary to achieve maximum identification of more than two languages. Furthermore, the number of measures necessary to separate the members of a given corpus might depend on the languages represented. There were many RMs and combinations of RMs that were nearly equally good at classifying our five languages, and almost any RM could be part of a good combination. The average P(C) of .46 achieved by classifiers using four RMs to identify five languages is comparable to human performance. For example, Navrátil (2001) reported a P(C) of .49 (chance=.20) for identifying German, English, French, Japanese and Chinese.

Different patterns of grouping occurred among our five languages, depending on the choice of rhythm measures. The debate around RMs has often been linked to the concept of rhythm class, to the distinction between stress-timed and syllable-timed languages and to the question of whether languages form discrete classes or a continuum. The historical background of this debate and the arguments on both sides have been widely discussed (see for example Ramus, 2002; Keane, 2006). The 'rhythm class' concept predicts that languages within the same class will overlap on rhythm measures. We observed such overlap. The concept, however, also requires constant grouping patterns: languages from the same rhythm class should always show greater confusion than languages from different classes. We found no such constancy of confusions within our five languages. Although Mandarin was identified more readily from other European languages based on vocalic measures, consonantal measures demonstrated no such pattern. Different combinations of measures produced different

patterns of confusion between particular languages or particular subgroups of languages.

This absence of a consistent confusion pattern fits with the fact that the single RM yielding maximum identification for two particular languages depended on the pair of languages. Furthermore, two languages that showed similar values on some RMs could still be separated on others. The pattern of effective and ineffective RMs varied across pairs. Claims about the similarity of two varieties based solely on rhythm measures seem to depend largely on the choice of measures and on the expectations of the researcher (cf. also Arvaniti, 2009, for similar remarks).

Perceptual studies have been offered as evidence for the rhythm class concept. The listener's native language, however, seriously influences the results of such studies, just as it plays a crucial role in speech segmentation (cf. Murty *et al.*, 2007; Tyler and Cutler, 2009, and references therein).[5] Experiments with processed signals reveal that both infants and adults are generally better at distinguishing their native language from a foreign language than at distinguishing between two foreign languages. For example, 5-month-old American infants discriminated languages traditionally assigned to different rhythm classes such as Italian and Japanese. They also discriminated languages traditionally assigned to the same rhythm class if one language was English but not when both languages were foreign (Nazzi *et al.*, 2000). Ramus *et al.* (2003) found that French students could only discriminate at chance between processed Spanish and Catalan stimuli. In contrast, Bosch and Sebastian-Galles (1997) reported that 4-month-old Spanish and Catalan infants discriminated low-pass filtered versions of speech from the two languages. Similarly, Szakay (2008) found that listeners who were highly integrated into either of two ethnic communities were better at discriminating processed signals representing the two ethnolects than were less integrated listeners.

Altogether, these studies provide little evidence for grouping into internally consistent rhythm classes (cf. also Arvaniti and Ross, 2010, for critical review of other studies). Listeners apparently use different acoustic cues to discriminate between languages, and the cues depend on the listener's native language or familiarity with the languages being tested. This

undermines the use of perceptual results to buttress any particular grouping of languages into classes. The reality of such classes becomes questionable.

Besides our main study with automatic segmentation and identification of languages, we compared automatic and manual segmentation of the same (necessarily limited) set of texts. Excellent but not perfect agreement was found between the labels from the two sources. The results have two important consequences. First, they once again show that segments placed by a human labeller in the same phonological category may be assigned automatically to different categories on the basis of purely on acoustic properties. Human labellers apparently base their decisions not only on the acoustic properties of the signal but also on their knowledge of the phonological structure of the text being segmented. Consequently, the segmentation rules may differ from language to language, and rhythm measures based on manual labelling may suffer from the influence of language-specific phonological interpretations. Second, our comparison of human and automatic labelling suggests that perception experiments using substitution of segments (for example, substituting [s] for all consonants and [a] for all vowels) reflect the investigator's own prior phonological interpretations. Future experiments should employ signals with gradient transitions between more and less sonorous synthetic segments.

V. CONCLUSIONS

On average, the languages that we studied with a language-independent segmentation procedure proved to have their own particular patterns of durational variation ("rhythm"). However, there is substantial variation within each language on every RM. Because of this variation, one cannot reliably identify a language or determine its properties from published duration measures computed from a single paragraph.

The differences between the five languages in our corpus cannot be captured by only one rhythm measure. While most pairs of languages could be separated fairly well with a classifier based on just one carefully-chosen RM, different pairs needed different RMs. This

suggests that languages differ rhythmically in a variety of ways.

Combinations of three RMs were needed to reach the highest correct identification rate for all five languages at once. These findings and multidimensional scaling show that linguistic rhythm is a multidimensional system. However, there are many different combinations of three RMs that are nearly equally effective. Overall, our machine classifier results are as accurate as human identification of languages in perception experiments.

Our results are not consistent with the traditional rhythm class hypothesis that would put our languages into two (or three) sharply-defined classes. The rhythm class hypothesis implies that many combinations of RMs would give the same groupings of languages. Our data show that languages group differently, depending upon which rhythm measures are used to classify them. Plausibly, each rhythm measure captures different language properties.

Finally, human segmentation of a small sub-corpus of speech agreed well with the labels produced by applying our segmentation algorithms to that sub-corpus. There were systematic differences, however, showing that manual labelling of speech depends on phonological interpretations. Therefore, experiments that compare manually-obtained durations across two or more languages have an intrinsic confound: they simply cannot distinguish differences between languages from language-dependent differences in the segmentation process.

Acknowledgments

This project is supported by the Economic and Social Research Council (UK) via RES-062-23-1323. The authors would like to thank John Coleman for useful discussions and three anonymous reviewers for their comments and suggestions which greatly improved the paper. We acknowledge the National Science Foundation for providing support to Dr. Shih via IIS-0623805 and IIS-0534133. We also thank Speech Technology Center Ltd. (St.-Petersburg, Russia) and Institute for Speech and Language Processing (Athens, Greece) for their help with automatic transcription of the data. Finally, we thank all speakers and transcribers for their help with this study.

APPENDIX A: HTK-BASED SEGMENTATIONS

Segmentation algorithms SA2a and SA2b were developed using the standard HTK toolkit. Segmentation algorithm SA2a uses three labels, Consonant, Vowel, and Silence, that correspond to spoken consonants, vowels, and silences, respectively. The Silence label captures silences at the end of each utterance and between phrases. As a final step in the processing, the algorithm merges runs of consonants and of vowels into consonantal and vocalic regions, respectively.

The acoustic model for Consonant contains four alternative, mutually independent sub-models, each roughly representing a major group of spoken phones. Each sub-model is a 3-state sequence, with looping allowed. Thus, consonants are a minimum of 30 milliseconds long. A state corresponds to a relatively steady part of the phone: for example, it might detect the moment of closure of a variety of stop consonants. All consonant states share the same diagonal variance. The Consonant model was trained on individual consonants, so when it met a consonant cluster, it often recognized several consonants in sequence.

The Vowel model uses six 3-state sub-models. It also has another 36 sub-models designed to identify diphthongs. A diphthong sub-model consists of the initial and middle states of one vowel sub-model, then the middle and final states of another. It therefore is four states long and shares states with the vowel sub-models. Finally, the Silence model is at least 100 milliseconds long. This prevents it from responding to short closures that may occur in stop consonants. One hundred milliseconds corresponds roughly to the boundary between short silences that often go unnoticed by listeners and longer ones that are explicitly interpreted as pauses. The Silence model is constructed from two 3-state and two 4-state sub-models that can follow each other in any order, so trajectories pass through multiples of ten states.

Algorithm SA2a was trained on 19 human-segmented spoken paragraphs. Four professional phoneticians, including three of the authors, independently labelled data in their native language or in a language in which they were reasonably fluent. They used broad phonetic transcriptions and were only given standard guidelines. The labels assigned by

phoneticians were recoded into three categories of Vowels, Consonants and Silences. The sonorants were recoded into vowels. The final training data contained 9793 segments (61% English, 18% French, 10% Greek, 9% Russian, 2% Mandarin) that included sufficient admixtures of each language to allow construction of a single set of Gaussian mixtures for Vowels, Consonants and Silences for all five languages in the corpus[6].

The SA2a algorithm was trained to establish a rough system using one mixture per state. Then the middle state of each Consonant submodel was extended to include a second mixture, and the model was retrained. Adding the extra mixtures brought the complexity of the consonant models closer to that of the vowel models. The retrained SA2a was used as a recognizer on entire corpus of speech data exclusive of the training data. The same acoustic models were used to recognize the data from all languages. Speech was represented as standard MFCC feature vectors. A grammar put two constraints on recognition: first, the sequence of phones that represent an utterance must start and end in a silence; and second, two immediately successive silences are prohibited.

Segmentation algorithm SA2b generally follows SA2a but with several changes. Sequences marked by the phoneticians as entirely of consonants were mapped into a single segment before training. Likewise pure sequences of vowels in the training utterances were mapped first into a single vocalic segment. For Consonant and for Vowel, SA2b has only two sub-models each, and each of these has three states. The Silence model has a minimum length of 130 milliseconds. It consists of a single sub-model that allows backward steps of 20 ms to 80 ms. It thereby can avoid confusion by substantial, complex repetitive structures within a silence, such as breathing noises and lip smacks.

Like SA2a, the SA2b algorithm was trained once on the human-segmented spoken paragraphs to establish a rough model. Then the middle state of each Consonant and Vowel submodel was modified to include four mixtures. Four selected states in the silence model were also enhanced to four mixtures. After these alterations, SA2b was re-trained and finally used as a segment recognizer on the corpus of speech. Audio processing for SA2b employed a 41-dimensional Acoustic Description Vector as against the 26-dimensional MFCC+derivatives

used in SA2a. The former larger vector gives somewhat more emphasis to spectral shape and uses only 5 components of derivative information.

The grammar for SA2b requires an alternation between C and V segments, with occasional silences. So the algorithm must try to model a complex consonant cluster with a single phone. In contrast, SA2a can use several Consonants in sequence to represent a consonant cluster. This is a substantial difference. It forces SA2b to represent a potentially very complex consonant cluster with a single model limited to three states. Unlike algorithm SA2a, SA2b needed no final stage to merge repeated pairs of consonants or repeated vowel pairs. It also was subjected to the same two constraints on treatment of silences as was S2a.

APPENDIX B: BAYESIAN FORESTS OF LINEAR DISCRIMINANT CLASSIFIERS

Each "classifier" used in this paper is actually a group of 240 closely related instances. This is a classifier forest approach, inspired by Ho (1998). When applied to small data sets, a forest has the advantage of reporting partial success as well as reporting an item as correctly or wrongly classified. Partial success occurs when some classifiers in the forest identify the item correctly while others treat it incorrectly; this reduces statistical noise compared to using a single classifier.

More importantly, a forest provides a better assessment of how accurately the classifier boundaries are known. Conventional classifiers often report class boundaries, half-way between the outliers of each class, as if they were precisely known. A Bayesian forest samples all plausibly good classifiers. Hence, the variation in boundary positions reflects the true uncertainty about the underlying boundaries. Finally, the various classifier instances can be combined into a ensemble classifier that potentially generalizes to new data more reliably than a single classifier (cf. Tumer and Ghosh, 1996).

The classifier forest is generated in two steps. First, the data are randomly split into a training and a test set. Successive splits are anti-correlated, making the number of times each item is chosen for a test set more uniform than expected from independent random splitting.

Second, for each test-set/training-set split, a bootstrap Markov Chain Monte Carlo (BMCMC) optimizer and sampler (Kochanski and Rosner, 2010) generates linear discriminant classifiers that individually separate the data into N classes as well as possible. Each classifier is a sample from the distribution of all classifiers that are consistent with the training set. (The BMCMC routine is implemented in the `stepper` class in `mcmc_helper.py` and `BootStepper` in `mcmc.py`; these are available to download at Kochanski (2010b).)

In a linear discriminant classifier, each class i has an associated likelihood function:

$$L_i(\vec{c}) = \vec{c_i} \cdot \vec{v} + \alpha_i, \tag{B1}$$

where $\vec{v}$ is the position at which evaluation is occurring, $\vec{c_i}$ are coefficients that describe the class, and α_i relates to the overall preference for class i. (Class i is a particular language in our case.) The probability of assigning a given datum to class i is

$$P_i(\vec{c_i}) = L_i(\vec{c_i}) / \sum_i L_i(\vec{c_i}). \tag{B2}$$

(The final α_i and $\vec{c_i}$ can be both set to zero without loss of generality, which we do.)

The probability density of sampling a particular $\vec{C}$, where C represents complete classifier forest, is the Bayesian posterior probability, given the training data:

$$P(\vec{C}) \propto \prod_j P_d(\vec{c_j}). \tag{B3}$$

Here, j runs over all the training data, and d is the index of the correct class for each datum. In this algorithm, we use a prior that assigns equal probability to each class, and all the measurements are assumed to be mutually independent.

This is a model that does not have sharp class boundaries. Rather, at each point, there are probabilities that the datum could be a member of any of the classes, and these probabilities change smoothly. (Though the model can represent cases with sharp class boundaries by making the change very rapid.)

The BMCMC sampler uses a bootstrap version of the Metropolis algorithm (Metropolis *et al.*, 1953). The algorithm keeps track of the current value of $\vec{C}$ and attempts to change it at each step. A change that increases $P(\vec{C})$ is accepted, and $\vec{C}$ is moved to the new position. A change that decreases $P(\vec{C})$ is accepted with probability $P(\vec{C}_{\rm new})/P(\vec{C}_{\rm old})$. Equation B3 is written as a proportionality, because the denominator of Bayes' Theorem is an impractical multidimensional integral that (fortunately) is independent of $\vec{C}$; this independence allows computation of the step acceptance probability without the need to integrate.

The BMCMC algorithm generates changes by making steps proportional to differences amongst an archive of its previous positions. It is described more fully in Kochanski and Rosner (2010); it has been used in prior work, notably Alvey *et al.* (2008) and Braun *et al.* (2006), and is available for download (Kochanski, 2010b). It is first run to convergence

(via `stepper.run_to_bottom` in `mcmc_helper.py`) and then run to generate (in this instance) 20 samples of $\vec{C}$ from the distribution of classifiers for each test/training split. (via `stepper.run_to_ergodic` in `mcmc_helper.py`). These samples are chosen with a probability that reflects how well Equation B3 matches the available data; thus most samples will come from the vicinity of the maximum likelihood classifier.

One can define confidence regions from these samples. In particular, if the actual data are generated from Equation B2, there is a 95% chance that the underlying parameters used to generate the data will lie within a confidence region that contains 95% of the generated samples.

The classifications that the algorithm produces (and the class boundaries) are simply the class that gives the largest probability in Equation B2, or (equivalently) the maximum likelihood class (Equation B1). Class boundaries are convenient for visual display. More importantly,a "hard" classification is useful because it leads to a good (and easily understandable) measure of the classifier performance: the probability of correct classification.

The work here used the `qd_classifier` program with the `-L` flag to produce linear discriminant classifier forests. The `-group` flag was used to extract the speaker identification, making the classifier group data by speakers. The classifier code is available for download (Kochanski, 2010a). Related code, `l_classifier`, is also available and recommended for items that are nearly independent.

In `qd_classifier`, the data are split into test and training sets via the `bluedata_groups` class in `data_splitter.py`. (We use 12 splits in this work.) This splitting is a two-pass algorithm and is a stratified sampling scheme. First, we assign a group (a subject in our case) to either the test or the training set. This assignment is anti-correlated with previous assignments. For example, if in previous splits, subject D3 has not yet been assigned to the test set, D3 is more likely to be assigned this time.

This procedure insures that data from a given speaker never appear in both the training and test set. A classifier's success rate therefore does not measure its ability to learn the quirks of any individual speaker. Rather, it measures only the properties shared by the

entire sample of speakers.

In the second pass the algorithm samples (without replacement) from each speaker, so that the test and training sets have nearly the same fraction of items from each class. This sampling is also done in an anti-correlated fashion, so that all items will be in the test set nearly the same number of times.

Our hybrid scheme of using multiple training/test-set splits combined with a Bayesian sampling of classifiers with each training set is well-behaved even in cases where there are only a few groups. For instance, in a data set with only four groups (e.g. four experimental subjects), there are only four ways to make a split into a training set and a test set that hold 75% and 25% of the data, respectively. If more than four samples are needed, e.g. to compute error bars for the probability of correct classification, the Bayesian procedure can still generate multiple samples from each training set.

Multiple test-set/training-set splits are valuable, because real data are probably not generated from Equation B2 and utterances are generally not independent. Properties of utterances can be correlated with each other for many reasons, but the most common and often the most important one is that the same person generates them. If each individual has a different voice or style of speech, inter-speaker variation can be much larger than the variation within an individual's utterances. In such a case (as here), two utterances from the same speaker are not independent because one can use the properties of the first to predict the properties of the second.

If utterances are not independent, samples drawn from a BMCMC sampler based on Equation B3 will give an overly narrow distribution of $\vec{C}$, because Equation B3 falsely assumes independence. In an extreme case where inter-speaker variation dominates and there are many utterances per speaker ($N_{\mathrm{ups}} \gg 1$), error bars would be underestimated by a factor of ${N_{\mathrm{ups}}}^{1/2}$, causing false significances in hypothesis tests.

This problem is germane to all work where statistical tests do not account for inter-speaker variation; many published papers suffer from it, not just Markov chain Monte Carlo samplers. Our solution is to compute a new group of BMCMC samples for each test/training-

set split. Each split is approximately a bootstrap (Efron, 1982) sample of speakers, thereby capturing the inter-speaker variation. Within each split, the BMCMC sampler reflects intra-speaker variation, and the overall result reflects the full variability of speech.

ENDNOTES

1. Ramus *et al.* (1999) suggested that infants perceive speech as a succession of vowels alternating with periods of unanalyzed noise. Gerhardt *et al.* (1990) measured the intrauterine acoustic environment of fetal sheep. They found that high frequencies are somewhat attenuated, but with only a single-pole filter. As a result enough high frequency information remains so a fetus could potentially discriminate among the consonants or among the vowels.

2. Read speech was preferred as it allows better control over the segmental content. The extent to which our results apply to spontaneous conversational speech remains an open question.

3. Previous studies have reported changes in speech of long-term migrants or even proficient speakers (see De Leeuw *et al.*, 2009, for references). However, all these studies concerned immigrants who lived abroad for a considerably longer period of time – at least a decade but usually more than 25 years – than had our non-native speakers. There is no evidence of substantial changes to L1 after only several years of living abroad. Furthermore, research on language attrition shows that the susceptibility to L1 attrition decreases after puberty (see Bylund, 2009, for review). The mean age of arrival into the UK for our non-English speakers is 24 years. Therefore even if our non-native speakers showed any adaptation to English rhythm it is unlikely to substantially affect the results of this study.

4. More generally, by N-1 dimensional hyperplanes for a N-dimensional classifier.

5. The effect of native language on the perception of rhythm even extends beyond the

domain of speech. In their study of the perception of rhythmic grouping of nonlinguistic stimuli by English and Japanese listeners, Iversen *et al.* (2008) showed that language experience can shape the the results.

6. The asymmetry of the training set does not disturb the main point of the procedure: it is a strictly language-independent segmentation, since the same models are applied to all languages. Use of a symmetrical dataset would be unlikely to have any major effect on the results of this paper. The comparison between the HTK-based segmentation algorithms and a substantially different, simpler algorithm (SA1) revealed only a small effect of segmentation on the classification results.

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TABLE I. Rhythm measures used in this study classified by type of intervals, scope, and normalization.

RM	Description	Type of interval	Scope	Normalization	Reference
%V	Percentage of vocalic intervals	Ratio	Global	Yes	Ramus *et al.* (1999)
Vdur/Cdur	Ratio of vowels duration to consonant duration	Ratio	Global	Yes	Barry and Russo (2003)
ΔV	Standard deviation of vocalic intervals	V	Global	No	Ramus *et al.* (1999)
VarcoΔV	ΔV/mean vocalic duration	V	Global	Yes	Dellwo (2006)
VnPVI	Normalised pairwise variability index (PVI) of vocalic intervals	V	Local	Yes	Grabe and Low (2002)
medVnPVI	VnPVI computed using median value	V	Local	Yes	Ferragne and Pellegrino (2004)
ΔC	Standard deviation of consonantal intervals	C	Global	No	Ramus *et al.* (1999)
VarcoΔC	ΔC/mean vocalic duration	C	Global	Yes	Dellwo (2006)
CrPVI	Raw PVI of consonantal intervals	C	Local	No	Grabe and Low (2002)
CnPVI	Normalised PVI of consonantal intervals	C	Local	Yes	Grabe and Low (2002)
medCrPVI	CrPVI computed using median value	C	Local	No	Ferragne and Pellegrino (2004)
PVI-CV	PVI of consonant+vowels groups	CV	Local	No	Barry *et al.* (2003)
VI	Variability index of syllable durations	CV	Local	Yes	Deterding (2001)
YARD	Variability of syllable durations	CV	Local	Yes	Wagner and Dellwo (2004)
nCVPVI	Normalised PVI of consonant+vowel groups	CV	Local	Yes	Asu and Nolan (2005)

TABLE II. The smallest number of RMs, the best performing measures or types of measures for optimal separation of pairs of languages and average K values for the best performing measures or combinations of measures (The 'best performing' measures or combinations of measures are those for which K value was not significantly different from the maximum value achieved for a given pair of languages). The best performing RMs depend on the language pair.

Language pair	Min N of RMs	Best RMs	K
Russian-Mandarin	1	ratio, VarcoΔV, ΔC, %V	0.56
English-Mandarin	1	ratio, C	0.52
French-Mandarin	1	VarcoΔV, %V	0.47
Greek-Mandarin	1	ratio, normalized V and CV	0.58
Russian-Greek	3	V and CV	0.37
English-Greek	1	VarcoΔV, medCrPVI	0.37
English-Russian	1	VarcoΔV	0.33
English-French	1	VarcoΔV	0.26
French-Greek	1	VnPVI	0.27
French-Russian	1	medVnPVI	0.21

TABLE III. Percentage of times that SA2a assigned 'C' or 'V' labels to voiceless obstruents, voiced obstruents, vowels and consonants within languages.

	Voiceless obstr.		Voiced obstr.		Sonorant		Vowel	
	'C'	'V'	'C'	'V'	'C'	'V'	'C'	'V'
Russian	88	10	55	45	9	91	7	92
Greek	83	11	54	46	17	83	8	91
French	89	8	56	43	18	80	12	87
Chinese	86	11	41	59	22	77	10	89
English	84	11	75	22	15	83	11	88

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