FOREIGN ACCENT CONVERSION THROUGH VOICE MORPHING

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ABSTRACT

We present a voice morphing strategy that can be used to generate a continuum of accent transformations between a foreign speaker and a native speaker. The approach performs a cepstral decomposition of speech into spectral slope and spectral detail. Accent conversions are then generated by combining the spectral slope of the foreign speaker with a morph of the spectral detail of the native speaker. Spectral morphing is achieved by representing the spectral detail through pulse density modulation and averaging pulses in a pair-wise fashion. The technique is validated on parallel recordings from two ARCTIC speakers using both objective and subjective measures of acoustic quality, speaker identity and foreign accent.

Index Terms— voice morphing, accent conversion.

1. INTRODUCTION

During the last two decades, a few studies have suggested that it would be beneficial for second language (L2) students to be able to listen to their own voices producing native-accented speech [1] The rationale behind this proposal is that removing information that is only related to the teacher's voice quality makes it easier for students to perceive differences between their accented utterances and their ideal accent-free counterparts. As a step towards this goal, we have recently developed techniques that can be used to synthesize native-accented utterances from their foreign-accented counterpart while preserving the speaker's voice quality [1-3].

Here, we propose a morphing technique that generates a continuum of accent-conversions between the learner's productions and those of the teacher. The technique works as follows. First, we decompose speech spectra into two components: (i) broad spectral features that capture speaker differences in glottal source spectra [4], and (ii) spectral details (i.e. formant positions) that capture linguistic content. Then, we generate accent morphs by combining the learner's broad spectra with a morph of the spectral detail of both speakers. Generating the morph requires that we establish correspondence between the two detailed spectra. This is achieved by encoding both spectra as a pulse density, and then averaging the position of corresponding pulses.

Morphing accent conversions may serve as a behavioral shaping strategy in computer assisted pronunciation training. In behavioral shaping, the teacher asks the student to compare their utterances against their "best" previous efforts rather than against a separate standard [5]. Using a normative reference can be detrimental early in training, when the student's utterances are very distant from the ideal pronunciation. Instead, by using a "floating" reference (i.e., one that adapts to the performance of the learner), the teacher can provide carefully graded evaluations of the learners' performance and guide them towards the ultimate goal. Likewise, morphing accent conversions during the early stages of learning may be used to produce utterances that have less ambitious prosodic and segmental goals, slowly improving the reference by incorporating the best pronunciation of the learner and higher degrees of morphing towards the teacher's productions.

2. RELATED WORK

Morphing has been extensively used for face perception, but is challenging when applied on speech. Whereas facial landmarks are well defined (eyes, mouth, jaw lines, etc.), spectral features in speech (i.e., formant frequencies) are difficult to measure and ill-defined in the case of unvoiced phones. Rather than use formant-tracking techniques, which are notoriously unreliable, various methods have been proposed to generate morphs directly from the spectra of two speakers. Slaney et al. [6] generate separate spectrograms for the pitch and broad spectral shape of a sound, and interpolate each channel separately using dynamic programming and harmonic alignment, respectively. Pfitzinger [7] also uses dynamic programming to find a frequency warp between two spectra, but in this case the warping is performed on the first-order derivative of the two LP spectral envelopes. Ezzat et al. [8] also use the derivative of the two (log magnitude) spectra but instead employ an optical-flow technique to find a correspondence between the two spectra. More recently, Shiga [9] has proposed a method where spectral envelopes are encoded as a distribution of pulses (see Fig 2). In this case, morphing can be performed by pairing individual pulses from the two spectra (according to their order) and then computing the weighted average of each pair. This results in significant time savings as compared to previous methods based on dynamic programming or optical flow. An added advantage of pulse density coding is that, unlike all-pole models such as LPC, it can model spectral zeros accurately. Also recently, Kawahara et al. [10] have developed an auditory morphing algorithm for STRAIGHT [11] that allows temporally-variable morphing rates; the method takes user-selected anchor points and maps the two spectrograms using a piecewise bilinear transform.

Our work is related to the problem of voice conversion [12-17]. However, voice conversion seeks to transform utterances from a speaker so they sound as if another speaker had produced them, whereas accent conversion seeks to transform only those features of an utterance that contribute to accent while maintaining those that carry the identity of the speaker. Only a handful of studies have been published on the subject of accent conversion. Yan et al. [18] proposed an accent-synthesis method based on formant warping. First, the authors developed a formant tracker based on HMMs and LPC, and applied it to a corpus containing several regional English accents (British, Australian, and American). Analysis of the formant trajectories revealed systematic differences in the vowel formant space for the three regional accents. Second, the authors re-synthesized utterances by warping formants from a foreign accent onto the formants of a native accent; pitch-scale and time-scale modifications were also applied. An ABX test showed that 75% of the re-synthesized utterances were perceived as having the native accent. Huckvale and Yanagisawa [19] used an English TTS system to simulate English-accented Japanese utterances by transcribing Japanese phonemes with their closest English counterparts. The authors then evaluated the intelligibility of a Japanese TTS against the English TTS, and against several prosodic and segmental transformations of the English TTS. Their results showed that both segmental and prosodic transformations are required to improve significantly the intelligibility of English-accented Japanese utterances.

Our work differs from Yan et al. [18] in two ways. First, we use pulse coding to represent speech spectra, which makes our method more robust than formant tracking, particularly for unvoiced segments. Second, we evaluate not only the accentedness of the re-synthesized speech but also the perceived identity of the resulting speaker. The latter is critical because accent conversion should preserve the identity of the foreign-accented speaker. In contrast with Huckvale and Yanagisawa [19], our study is performed on natural speech, and focuses on accentedness and identity rather than on intelligibility; as noted by Munro and Derwing [20], a strong foreign accent does not necessarily limit the speaker's intelligibility. Finally, unlike these previous methods and our own prior work [1-3], the work presented here allows us to achieve different degrees of accent conversion by virtue of a morphing coefficient, as described next.

3. METHODS

3.1. Voice morphing through pulse density modulation

Our approach is based on the pulse density modulation (PDM) technique of Shiga [9]. PDM employs a delta-sigma modulator to convert a log spectral envelope $x(n)$, where n denotes frequency, into a pulse sequence $y(n) = PDM[x(n)]$ as follows:

$$e(n) = x(n) - v_c\, y(n-1) \tag{1}$$

$$r(n) = e(n) - r(n-1) \tag{2}$$

$$y(n) = sign\big(r(n)\big) \tag{3}$$

with initial conditions $r(1) = e(1) = x(1)$ and $y(n) = 0$; the term v_c represents the feedback gain of the delta-sigma modulator: $v_c = max(x)$. In turn, the pulse sequence $y(n)$ can be decoded back into a log spectral envelope $\hat{x}(n) = PDM^{-1}[y(n)]$ through the discrete cosine transform (DCT) as:

$$c(n) = DCT[y(n)] \tag{4}$$

$$c(n) = 0 \quad \forall\ n > k \tag{5}$$

$$\hat{x}(n) = DCT^{-1}[c(n)] \times v_c \tag{6}$$

which essentially acts as a low-pass filter by truncating the DCT expansion with an appropriate cutoff k ($k = 100$ in our implementation.) Thus, given a pair of spectral envelopes $x_1(n)$ and $x_2(n)$, a morphed spectral envelope can be computed by averaging the position of corresponding pulses in the two spectra:

$$x_m(n) = PDM^{-1}\big[(1-\alpha)PDM[x_1(n)] + \alpha PDM[x_2(n)]\big] \tag{7}$$

where the morphing coefficient α $(0 \le \alpha \le 1)$ can be used to generate a continuum of morphs between the two spectral envelopes $x_1(n)$ and $x_2(n)$.

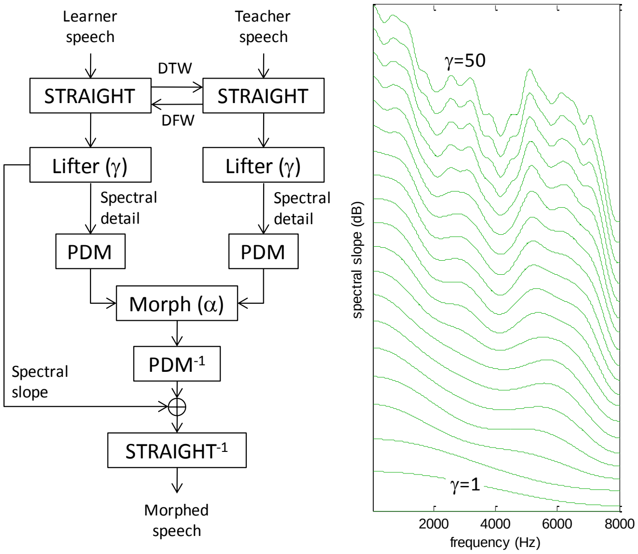

Fig 1. *(a) Morphing accent conversion strategy. (DTW/DFW: dynamic time/frequency warping). (b) Spectral slope $x^L(n)$ as a function of liftering cutoff $\gamma \in \{1,2,3 \dots 9,10,12 \dots 20,25 \dots 50\}$. Individual spectra have been shifted vertically for visualization purposes.*

3.2. Accent conversion through voice morphing

Given parallel recordings from the learner $x_1(n)$ and the teacher $x_2(n)$, eq. (7) produces a morph of *both* the identity and the accent of the two speakers. In accent conversion, however, we seek to morph only the accent while preserving the learner's identity. For this purpose, prior to the PDM encoding in eq. (1-3), each spectra $x_i(n)$ is separated into two components, $x_i^L(n)$ carrying the broad spectral features (i.e. shape of the glottal source spectra [4]), and $x_i^H(n)$ carrying the spectral detail (i.e. formant positions). This, again, is performed by liftering in the DCT domain as:

$$x_i^H(n) = DCT^{-1}\big[DCT\big(x(n)\big) \times l(n)\big] \tag{8}$$

$$x_i^L(n) = DCT^{-1}\big[DCT\big(x(n)\big) \times \big(1 - l(n)\big)\big] \tag{9}$$

where $l(n)$ are the liftering coefficients, defined by:

$$l(n) = \begin{cases} n/\gamma & 1 \le n \le \gamma \\ 1 & n > \gamma \end{cases} \tag{10}$$

An accent morph $x_m(n)$ is then produced by combining the learner's broad spectra $x_1^L(n)$ with a morph of the spectral detail of both speakers $x_m^H(n)$:

$$x_m(n) = x_1^L(n) + x_m^H(n) \tag{11}$$

$$x_m^H(n) = PDM^{-1}\Big[\alpha PDM[x_1^H(n)] + (1-\alpha)PDM[x_2^H(n)]\Big] \tag{12}$$

Larger values of the liftering coefficient γ in (10) ensure that increasing spectral detail is preserved in the learner's broad envelope $x_1^L(n)$ and that, likewise, equivalent spectral detail is discarded from the teacher's spectral detail $x_2^H(n)$. The overall accent-conversion process and liftering results for different values of γ are illustrated in Fig 1.

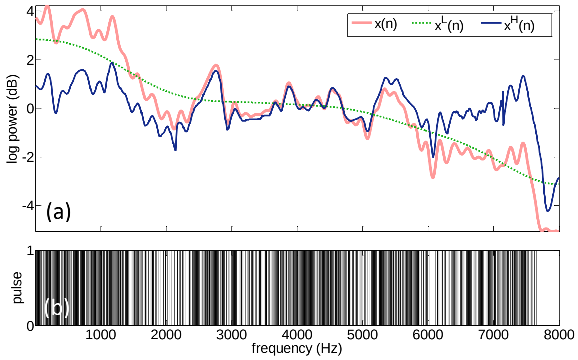

Fig 2. *(a) Decomposition of the spectral envelope $x(n)$ into global shape $x^L(n)$ and spectral detail $x^H(n)$. (b) Encoding of spectral detail $x^H(n)$ through pulse density modulation.*

4. EXPERIMENTAL VALIDATION

The proposed method was evaluated on two speakers from the ARCTIC corpus [21]: *ksp_indianmale*, who was treated as the foreign-accented learner, and *rms_usmale2*, who was treated as the native-accented teacher. The STRAIGHT vocoder [11] was used to generate smooth spectrograms and resynthesize the resulting voice morphs. Prior to performing the morphing accent conversions, learner utterances were time-aligned at the frame level (80ms windows, 1ms shift; default frame shift in STRAIGHT) to those of the teacher using dynamic time warping (DTW) and a conventional 39-dimensional feature vector (13 MFCCs, delta and delta-delta features) computed from the STRAIGHT spectrum. To account for differences in vocal tract length, teacher utterances were then frequency warped to those of the target; a global warping function was obtained by applying DTW in the frequency domain [22] to 100 sentences in ARCTIC's "B" set. Finally, utterances were resynthesized using the teacher's pitch contour shifted to the baseline of the learner. As a result of these steps, all subsequent morphs conformed to the timing and pitch dynamics of the teacher, but had the global frequency warp and pitch range of the learner.

Morphing accent conversions were generated for parameter values $\gamma \in \{1,2,3 \dots 9,10,12,14 \dots 20,25,30 \dots 50\}$ and $\alpha \in \{0, 0.1, 0.2 \dots 1\}$. One hundred sentences from ARCTIC's "A" set were synthesized for each of these 11×21 combinations, and analyzed in terms of their acoustic quality, speaker identity and foreign accentedness. Three objective measures shown in our earlier work [2] to correlate with listening tests were used for this purpose. Namely, acoustic quality was estimated through the ITU-T recommendation P.563, speaker identity was estimated from a linear discriminant analysis (LDA) of natural utterances from the learner and the teacher, and foreign accent was assessed by the forced-alignment score (log-likelihood) of acoustic models trained on North American speakers using HTK; see [2]. These objective ratings were also verified through subjective listening tests on a subset of the 11×21 combinations.

5. RESULTS

5.1. Objective measures

Fig 3 shows the average performance of the morphing accent conversion in terms of the three objective measures. Acoustic quality improves for higher values of the liftering cutoff γ and low values of the morphing parameter α. This result can be explained as follows. As the value of γ increases, additional spectral structure is retained for the learner's broad envelope $x_1^L(n)$. As a result, the spectral detail $x_i^H(n)$ becomes flatter for large γ, which improves the PDM encoding (i.e., for a spectrum with a significant spectral slope most of the pulses will be placed at the lower frequencies). Overall, however, the result in Fig 3(a) shows that the acoustic quality of the morphed accent conversions remains at an estimated mean-opinion-score (MOS) above 4.7, which in our earlier study [2] corresponds to a perceived MOS of 4.1.

Results from the speaker identity scores are shown in Fig 3(b) in terms of the ratio:

$$ID = \frac{\sum_u \sum_i \left[d\left(y_{u,i}, \mu_L\right)/\sigma_L - d\left(y_{u,i}, \mu_T\right)/\sigma_T \right]}{d(\mu_L, \mu_T)/(\sigma_L + \sigma_T)/2} \qquad (13)$$

where $d(\cdot)$ is the Euclidean metric, $y_{u,i}$ is the projection of acoustic frame i in utterance u onto the LDA solution for the two speakers, μ_L, μ_T are the average LDA projection for learner and teacher utterances, respectively, and σ_L, σ_T are their standard deviations. Thus, ID values greater than 0 indicate that the morph is closer to the learner than to the teacher, and vice versa. As shown in Fig 3(b), the morphed accent conversions remain closer to the learner except for a small number of parameter combinations (large α and small γ); the dashed line indicates the maximum-likelihood decision boundary between both speakers. These results are to be expected since for large α the morph is dominated by the target speaker (the teacher) and for small γ only the overall spectral slope of the source speaker (the learner) is preserved.

Results from the accented measure are shown in Fig 3(c) in terms of the HTK forced-alignment score:

$$ACC = \frac{\sum_u \sum_p \left(s_{u,p} - s_{u,sil}\right)}{N_u N_p} \qquad (14)$$

where $s_{u,p}$ is the score (log-likelihood) of phone p on utterance u, N_u is the number of test utterances and N_p is the size of the phone set $\left(N_u = 100;\ N_p = 39 + sil\right)$. Subtraction of the silence score $s_{u,sil}$ compensates for misalignment errors. As may be expected, large values of the morphing parameter α reduce the foreign accentedness. In addition, the more information about the learner that is preserved in the spectral slope (i.e., by increasing the liftering cutoff γ), the larger the morphing value will have to be in order to achieve a given accent score. Comparison of Fig 3(b) and Fig 3(c) shows that the accent measure improves (i.e., morphs become more native) faster than the identity measure degrades (i.e., morphs become more like the teacher), which suggests that there is a "sweet spot" where foreign accent reduction can be achieved while preserving the identity of the learner.

5.2. Subjective measures

To verify these objective measures, we ran additional subjective studies on the five selected (α, γ) pairs shown in Table 1 and Fig 3, which represent intermediate degrees of morphing: V1 and V5 being nearest to the learner and the teacher, respectively. For each condition, we transformed the same 10 sentences. Participants performed the following tests through Amazon's Mechanical Turk:

- *Accent* – 10 subjects rated the degree of accent for 50 utterances (5 conditions, 10 sentences) using a 7-point scale (0=not at all accented; 2=slightly; 4=quite a bit; 6=extremely). Subjects had to qualify for this test by passing an American dialect identification test, which only native speakers of American English are likely to complete.

- *Quality* – 10 subjects rated the quality of the same 50 utterances using a 5-point MOS (1=bad, 2=poor, 3=fair, 4=good, 5=excellent).
- *Identity* – 10 subjects participated in a forced choice test. They listened to two pairs of utterances; each pair consisted of V1 or V5, a separating beep, and one of the intermediate voices (V2-V4). Subjects were asked to select the pair whose voices were more different from each other. The order of presentation was random, and utterances were time-reversed so subjects focused on the physiological components of the voices [2]. Identity scores were calculated as the fraction of times that a given voice was perceived to be closer to V1.

Subjective ratings were consistent with the corresponding objective measures. Accent ratings decrease monotonically through the sequence (V1-V5) and the perceived accent drops suddenly at V3 near a similar drop-off in Fig 3. Quality tended to decrease with γ, as predicted by the objective measure. Due to the design of the test, no identity score is available for V1 or V5. The intermediate voices were considered closer to the learner than to the teacher, and the order of similarity agrees with the objective measures. Original and morphed utterances for ARTIC sentence "*We have plenty of capital ourselves, and yet we want more*" (a0364) for the five conditions in the listening tests are available at http://research.cs.tamu.edu/prism/publications/interspeech2013.zip.

6. DISCUSSION

We have presented a method for foreign accent conversion that combines a cepstral decomposition of the spectral envelope and a voice morphing technique through pulse density modulation. Given parallel recordings from a native speaker and a foreign speaker, we decompose the spectral envelope into its overall shape, which captures speaker-dependent cues (i.e. spectral slope), and its spectral detail, which captures linguistic content. The critical step in the morphing process is matching peaks across two spectra. We address this issue by representing the spectral detail as a distribution of a large number of pulses. In this manner, morphing two spectra is equivalent to averaging the position of their pulses in a pair-wise fashion. The overall procedure contains two parameters: a liftering cutoff γ that determines the amount of information to be preserved in the foreign speaker's spectral slope, and a morphing coefficient α that determines the degree of morphing between the spectral detail of both speakers.

The procedure was evaluated on two speakers in the ARCTIC corpus using objective and subjective measures of acoustic quality, speaker identity and foreign accent. The results indicate that there is a trade-off between quality, identity and accent. Higher quality and identity scores are obtained by retaining as much of the learner's spectral information as possible (large γ and small α) at the expense of reducing accent scores. However, our results also show a region in parameter space where significant reductions in accent are obtained while preserving cues to the learner's identity.

Our approach preserves the pitch range and overall vocal tract length of the learner, and assumes that speaker-dependent and linguistic cues in the spectral envelope can be separated through cepstral decomposition (i.e., spectral slope vs. spectral detail, respectively). While F0, vocal tract length and spectral slope are known to be good discriminator among speakers [23], additional acoustic cues from the learner's voice could be captured and preserved before the morphing stage. As an example, jitter and shimmer (cycle-to-cycle variations in $F0$ and amplitude, respectively) have been used to characterize various voice qualities [24], as well as fine structure in the speech signal [25]. Other features from the speaker recognition literature (see [26] for a recent review) may also be investigated while considering that our goal is synthesis rather than recognition. Future work may also investigate filtering techniques (i.e., head-related transfer functions) to reduce differences between speakers' perception of self-produced speech and their speech recordings [27], which may become important in computer assisted pronunciation training.

7. ACKNOWLEDGEMENTS

This work was supported by NSF award 0713205 and a DoD SMART scholarship. We are grateful to Prof. Steve Renals and the Scottish Informatics and Computer Science Alliance (SICSA) for their support during RGO's sabbatical stay at the Center for Speech Technology Research (Univ. Edinburgh). We are also grateful to Prof. Hideki Kawahara for permission to use the STRAIGHT analysis-synthesis method.

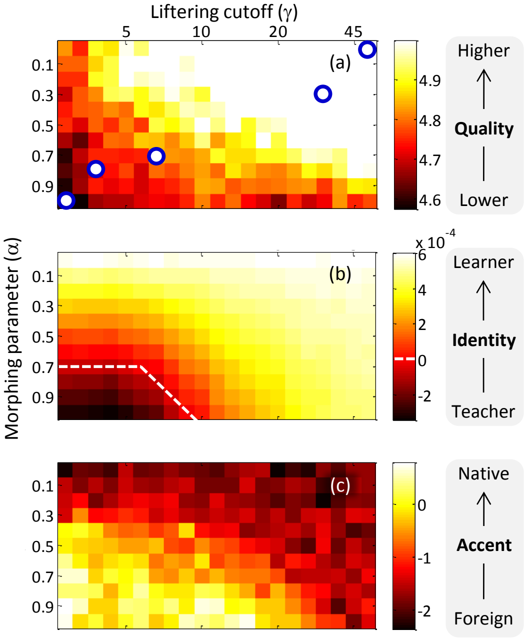

Fig 3. *(a) Quality, (b) identity, and (c) accentedness of the morphing accent conversions as a function of the liftering cutoff γ and morphing coefficient α. Lighter color denotes desirable effects (e.g., high quality, learner identity, and native accent). Dashed line in (b) represents the maximum-likelihood boundary between both speakers, as measured in the LDA subspace. Circles in (a) indicate the five conditions used in the listening tests.*

Table 1. *Subjective ratings of accent, quality and identity.*

(α, γ)	Accent	Quality	Learner's ID score
V1 (0,50)	2.94	3.38	n/a
V2 (0.3,30)	2.61	3.41	74%
V3 (0.7,7)	0.40	3.26	69%
V4 (0.8,3)	0.26	3.07	64%
V5 (1,1)	0.14	2.56	n/a

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