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DEEP LEARNING AND VOICE COMPARISON : PHONETICALLY-MOTIVATED VS. AUTOMATICALLY-LEARNED FEATURES

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ABSTRACT

Broadband spectrograms of French vowels /ɑ̃/, /a/, /ɛ/, /e/, /i/, /ə/, and /ɔ/ extracted from radio broadcast corpora were used to recognize 45 speakers with a deep convolutional neural network (CNN). The same network was also trained with 62 phonetic parameters to i) see if the resulting confusions were identical to those made by the CNN trained with spectrograms, and ii) understand which acoustic parameters were used by the network. The two networks had identical discrimination results 68% of the time. In 22% of the data, the network trained with spectrograms achieved successful discrimination while the network trained with phonetic parameters failed, and the reverse was found in 10% of the data. We display the relevant phonetic parameters with raw values and values relative to the speakers' means and show cases favouring bad discrimination results. When the network trained with spectrograms failed to discriminate between some tokens, parameters related to f0 proved significant.

Keywords: deep learning, voice comparison, forensic phonetics, vowels, phonetic parameters.

1. INTRODUCTION

Traditional phonetic analyses tend to focus on production features – realizations of specific phonemes or prosodic units – that are relatively stable across speakers, and individual strategies are frequently overlooked. In contrast, speaker recognition and forensic voice comparison seek to select phonetic features that display maximal between-speaker variation. In the present work we aim at identifying phonetic invariants that are helpful for speaker characterization, be it for phoneticians willing to better understand the articulatory habits that are representative of speakers, or for automatic speaker recognition systems in small datasets, for example [6]. This experiment is thus closer to a voice comparison task rather than true speaker identification. Recently, deep neural networks (DNNs) have been highly successful in speaker classification tasks when used as feature extractors with so-called bottleneck features [10] and embeddings [15]. Linear predictive cepstral coefficients or Mel frequency cepstral coefficients are usually well-suited for these systems. However, these parameters turn out to be quite frustrating for phoneticians since, contrary to e.g. formants, they are not interpretable in articulatory terms [1, 11].

As a preliminary step towards interpreting what DNNs predict, we ran two experiments involving a deep convolutional neural network (CNN). Firstly, speaker classification was performed with speech excerpts comprised of productions of French vowels /ɑ̃/, /a/, /ɛ/, /e/, /i/, /ə/, and /ɔ/ by 45 speakers. The CNN was provided with broadband spectrograms (SPECTR model hereafter). Secondly, the same model architecture was trained and tested on the same vowels, but this time providing the model with acoustic measurements traditionally used by phoneticians (PHONET model henceforth) rather than spectrograms.

The SPECTR model was expected to achieve better scores than PHONET because contrary to the latter, SPECTR had the opportunity to learn its own phonetic representations, and also, it was trained with a higher-dimensional space. Our prediction was borne out, and it is precisely the comparison between the two models and how they allow us to infer relevant phonetic features for speaker classification that constitutes the aim of the current work.

2. SPEECH MATERIAL AND METHOD

2.1. Vowel extractions

The vowels were extracted from the ESTER Corpus [3], a radio broadcast corpus characterized by prepared speech [4]. *France Inter*, *France Info* and

Radio France International were the three sources and some speakers had occurrences over different radio stations. We used the phonetic alignment provided with the corpus by the IRISA (*Institut de Recherche en Informatique et Systèmes Aléatoires*) through the AFCP (*Association Francophone de la Communication Parlée*) website (http://www.afcp-parole.org/camp_eval_systemes_transcription/). Automatic alignment was used to extract vowels with a rectangular window shape and without their phonetic context, the latter being neither controlled nor provided to the network. Vowels were extracted from 35 male speakers and 10 female speakers.

2.2. Spectrograms

Based on Praat default values, we chose to use 5.0625 ms frames and 0.5 ms hop size for spectrograms with a 16 kHz sampling rate. The speech segments were element-wise multiplied by a Hamming window and padded to obtain 512-sample segments on which FFT was applied. No pre-emphasis was performed and the dynamic amplitude range was normalized to 70 dB to make sure that dynamics did not bias discrimination. Vowels whose duration was greater than 250 ms were left out; the shortest vowels were 30 ms long. Spectrograms of vowels shorter than 250 ms were padded with zeros in order for all spectrograms to have equal width. They then were converted to 8-bit grayscale images and resized to 224×224 pixels, where a pixel was equal to 1.15 ms in the time dimension and 35.71 Hz in terms of frequency. The conversion to 8 bits was performed so that GPU memory would handle mini-batches of sufficient size.

2.3. Measurements of phonetic parameters

Phonetic parameters were collected with Praat [2] and VoiceSauce software [13]. VoiceSauce is a Matlab toolbox that provides automated voice measurements from audio recordings. Most parameters gathered within VoiceSauce are measured using several software programs, thus providing several values for the same phonetic parameter.

We used the full selection of measurements, that is f0, formants F1-F4 center frequencies and bandwidths, energy, cepstral peak prominence (CPP), harmonic to noise ratios (HNR), subharmonic to harmonic ratio (SHR), strength of excitation (SOE) for the *uncorrected* parameters. All other parameters measured by VoiceSauce are H1 (amplitude of harmonic 1), H2, H4, A1 (amplitude of formant 1), A2, A3, 2K (amplitude of the harmonic at 2kHz), 5K, H1-H2, H2-H4, H1-A1, H1-A2, H1-A3, H4-2K, 2K-5K. These are provided as *corrected* (c) relative to the measured formants (except for 5K), but also *uncorrected* (u), see [13] and [8] for more information on the parameters. The 62 parameters were measured every millisecond.

These parameters are considered to be good descriptors of voice quality, which is an important aspect in voice comparison [12], and they have been used in the relevant literature [8]. Measurements of spectral moments: center of gravity (COG), kurtosis, skewness, and standard deviation (SD) were extracted with Praat. All values were normalized per vowel for all speakers on a 0-255 scale, in order to match the quantization of our spectrograms, and resized to 224×224 to conform to the fixed input size of our model. For the descriptive phonetic analysis we carried out after running the DNNs, values were taken at 25, 50 and 75 % temporal points and were averaged here for the sake of legibility. The spectral variation within each vowel will have to be accounted for in a follow-up study.

2.4. Model training and testing

We used VGG16 [14], which is a popular CNN in image recognition. In bith experiments the model was re-trained from scratch with randomly initialized weights. The models were trained using an NVIDIA GTX 1080 GPU with the Adam optimizer [7], with a gradient decay factor of 0.900, and a squared gradient decay factor of 0.999. The initial learn rate was 0.0001 and the mini-batches contained 56 spectrograms. For each vowel and each speaker, 140 tokens were used for training (70 %), 20 for validation (10 %), and 40 for test (20 %). One SPECTR model and one PHONET model were trained for each of the 7 vowels in our dataset.

3. RESULTS

3.1. Classification rates

The results presented in Table 1 show that features learned from spectrograms (SPECTR) score on average 10-15 points above the acoustic features. The highest scores, above 69% accuracy, are highlighted in bold. For our descriptive analysis the results were split into 5 categories:

- cat. 1: PHONET was successful.
- cat. 2: SPECTR successful.
- cat. 3: PHONET successful; SPECTR failed.
- cat. 4: PHONET failed; SPECTR successful.
- cat. 5: PHONET and SPECTR failed.

The two networks showed identical classification results for 68.0 % of the test vowels, whether

Table 1: Classification rates (%) for each vowel according to the two methods (P for PHONET and S for SPECTR).

cat.	ɑ̃	a	ɛ	e	i	ə	ɔ
cat. 1	**71.2**	**69.3**	63.6	64.8	53.1	57.9	63.2
cat. 2	**86.7**	**77.1**	**75.4**	**76.0**	**69.8**	**71.5**	**74.5**
cat. 3	5.8	10.5	10.3	9.7	10.5	10.1	11.6
cat. 4	21.3	18.3	22.1	20.9	27.3	21.4	25.2
cat. 5	7.4	12.4	14.3	14.3	19.7	25.2	16.9

correct: 53.5 % or incorrect: 14.5 %. 22.0 % of the vowels were correctly classified with SPECTR while PHONET misclassified them, and the reverse was found in 10.0 % of the vowels. For both methods, /ɑ̃/ had the best discrimination results. Table 1 also shows that with SPECTR, the difference is more important between /ɑ̃/ and the other vowels.

Classification results according to speaker sex were better for male speakers (67.6 %) compared to female speakers (62.0 %) with PHONET, while they were very similar with SPECTR (74.5 % vs. 76.4 %). As could be expected due to f0 and spectral similarity, discrimination errors were more frequent within the same sex but more so for male speakers compared to female speakers: 92.0 % vs. 70.0 % on average for both models. While, as is well known, some PHONET parameters (e.g. formants) are sensitive to differences between men and women, CNNs trained with spectrograms may be more immune to such differences – and therefore constitute effective normalization tools – because they are translation invariant [5].

3.2. Relevance of phonetic features

A MANOVA for each vowel was conducted with all phonetic parameters as dependent variables and speaker identity as independent variable. In order to test the post-hoc relevance of phonetic parameters, we also calculated the eta-squared values for univariate ANOVAs with speaker as independent variable. Only eta-squared values higher than 10 for all vowels are considered here (see Table 2). Measurements containing more than 25 % of undefined values were discarded: pB4, SOE, pF4, epoch, & SHR.

We then calculated a linear discriminant analysis, so that we could infer the weight of each acoustic parameter as well as their degree of collinearity since collinearity is expected considering some measurements are identical phonetic parameters provided by several software. Parameters that did not show any collinearity for more than one vowel were kept for the following sections, and among parameters that

Table 2: Eta squares for each vowel for main phonetic parameters (values above 30 % in bold).

P	ɑ̃	a	ɛ	e	i	ə	ɔ
H1c	**61**	**55**	**47**	**50**	**33**	**47**	**47**
H2c	**43**	**39**	**38**	**44**	23	**36**	**40**
H4c	17	25	20	19	15	20	25
H1H2c	**48**	**51**	**51**	20	**52**	**51**	**48**
A1c	20	22	16	15	8	13	16
H1A1c	**47**	**54**	**47**	**42**	12	**36**	**38**
CPP	13	14	11	13	11	10	11
energy	**54**	**58**	**52**	**50**	**45**	**53**	**50**
sF1	9	7	17	17	8	10	7
sF2	18	18	29	37	25	9	11
sB1	12	11	13	11	7	7	9
sB2	14	9	10	9	6	11	8
COG	27	27	24	26	13	6	19
skewness	20	22	27	30	25	36	20
kurtosis	15	17	12	24	15	35	19
SD	14	24	28	21	17	11	25
HNR35	**35**	**34**	**38**	**36**	**34**	**38**	**37**
pF0	**47**	**40**	**38**	**39**	**37**	**36**	**34**

showed collinearity, the one with the highest weight was chosen, that is HNR35, energy, H1u, H1H2u, H1H2c, H1A1u, skewness, COG, pF0, H2KH5Kc, A2u, and A3u.

Figure 1: Mean values of H1A1c for /ɑ̃/ reordered by speaker's mean.

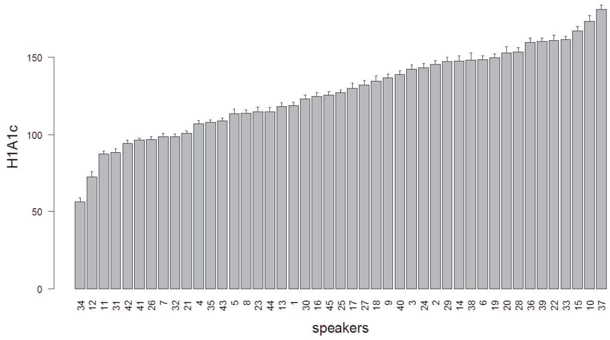


Fig. 1 illustrates that H1A1c values display consistent between-speaker variation. Phonetic parameters with a higher eta-squared value thus imply a steeper slope between speakers.

3.3. Comparing correct and incorrect classification

By computing the mean per speaker for each phonetic feature and for each vowel, as shown in Fig. 1 for H1A1c and /ɑ̃/, we calculated the difference for each occurrence between its actual value and its mean for each speaker and analyzed its distance to the mean. If the value was too far away from the mean value, then it was expected to be less typical of the speaker. Within-speaker variation therefore stands out as a plausible reason for incorrect classification.

Figure 2: Mean values of H1c for all vowels according to classification results.

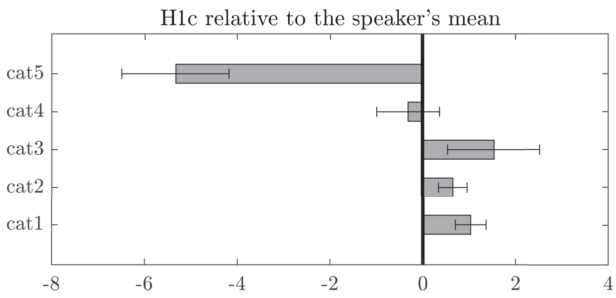


Fig. 2 shows occurrences where discrimination was successful (cat. 1 & 2) compared to occurrences where discrimination had failed for both PHONET and SPECTR (cat. 5), and for all vowels a significant difference was found:

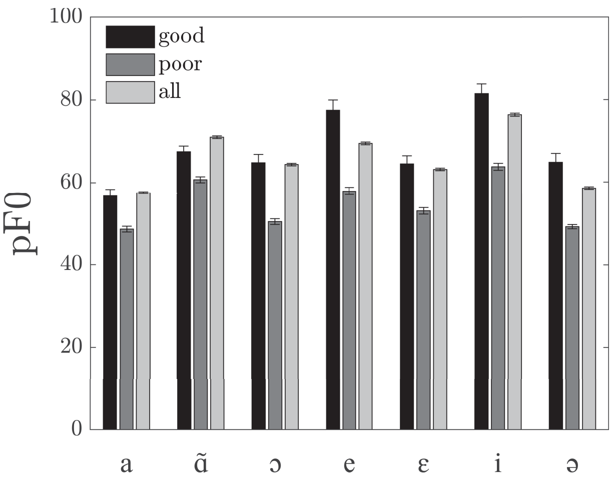
- incorrect classification showed higher values than the speaker's mean for pf0, HNR35, skewness, and H1A1u.
- correct classifications showed higher values for energy, H1u, H1H2u, H1H2c, H2KH5Kc, CPP, A2u, and A3u.

When comparing the complementarity of PHONET and SPECTR – that is when PHONET yielded correct classification while SPECTR had misclassifications (cat. 3 from Table 1), and vice-versa (cat. 4) – results were mostly inconsistent.

3.4. Comparing *good* speakers and *poor* speakers

In order to understand the differences between speakers who show the best results (*good speakers*) and those with the worst results (*poor speakers*), we analyzed the four male speakers with the best classification results, together with the four male speakers with the worst results, and who were common to both methods. The four *good* speakers represent 13.7 % (SPECTR) and 14.8 % (PHONET) of the successful predictions, while the four *poor* speakers represent 17.1 % (SPECTR) and 16.1 % (PHONET) of the mistakes. We used raw values this time as we only compared a few speakers with supposedly different characteristics. We considered a third category for better comparison, the mean of all the 45 speakers. We only mention here results that are stable for all vowels. As can be seen in Fig. 3, the 4 speakers with the worst discrimination rates are characterized by a lower f0 compared to the mean and compared to speakers with high discrimination rates. The same was found for H1H2u, H1H2c, and COG. They were however characterized by higher values of H1u, Energy, H1A1u, HNR35, and skewness.

Figure 3: F0 mean values for /ɑ̃/ according to the classification result quality.



4. DISCUSSION AND CONCLUSION

The vowel for which the best results were achieved was the nasal vowel /ɑ̃/. It has been argued that it was better than other vowels for speaker discrimination [1] as the opening of the nasal cavity in these phonemes adds relevant acoustic information. Nasal vowels are also longer than oral vowels (100 ms vs 60 ms on average) and thus naturally bring more acoustic information. These results emphasize the difficulty phoneticians encounter in the acoustic analysis of specific phonemes, like nasal vowels due to the presence of anti-formants in their spectrum [9], or high vowel /i/, acoustic information about the first harmonics is often biased by the presence of the first formant. Formants 1 to 2 and their bandwidths were poor indicators of speakers' characteristics, which was expected as they are known to be good descriptors of vowel category, especially for oral vowels. We found that F4 was characterized by high eta-squared values but with many missing values, this point will have to be further investigated.

Phonetic parameters like f0, energy, H1, HNR, and skweness were useful to recognize speakers, and the SPECTR model did not seem to fully take them into account. Future work will explore early/late fusion strategies to measure how phonetic features identified here as relevant might enhance performance when used in conjunction with spectrograms.

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