

1993-01

Evaluation of Speaker Normalization Methods for Vowel Recognition Using Fuzzy ARTMAP and K-NN

<https://hdl.handle.net/2144/1990>

"Downloaded from OpenBU. Boston University's institutional repository."

EVALUATION OF SPEAKER NORMALIZATION
METHODS FOR VOWEL RECOGNITION
USING FUZZY ARTMAP AND K-NN

Gail A. Carpenter and Krishna Govindarajan

January 1993

Technical Report CAS/CNS-93-013

Proceedings of the world congress on neural networks,
Portland, III, 10-15. Hillsdale, NJ: Erlbaum Associates.

Permission to copy without fee all or part of this material is granted provided that: 1. the copies are not made or distributed for direct commercial advantage, 2. the report title, author, document number, and release date appear, and notice is given that copying is by permission of the BOSTON UNIVERSITY CENTER FOR ADAPTIVE SYSTEMS AND DEPARTMENT OF COGNITIVE AND NEURAL SYSTEMS. To copy otherwise, or to republish, requires a fee and/or special permission.

Copyright © 1993

Boston University Center for Adaptive Systems and
Department of Cognitive and Neural Systems
111 Cummington Street
Boston, MA 02215

Evaluation of speaker normalization methods for vowel recognition using fuzzy ARTMAP and K-NN

Gail A. Carpenter * and Krishna K. Govindarajan †

Center for Adaptive Systems and Department of Cognitive and Neural Systems
Boston University, 111 Cummington Street, Boston, MA 02215

Abstract

A procedure that uses fuzzy ARTMAP and K-Nearest Neighbor (K-NN) categorizers to evaluate intrinsic and extrinsic speaker normalization methods is described. Each classifier is trained on preprocessed, or normalized, vowel tokens from about 30% of the speakers of the Peterson-Barney database, then tested on data from the remaining speakers. Intrinsic normalization methods included one nonscaled, four psychophysical scales (bark, bark with end-correction, mel, ERB), and three log scales, each tested on four different combinations of the fundamental (F_0) and the formants (F_1, F_2, F_3). For each scale and frequency combination, four extrinsic speaker adaptation schemes were tested: centroid subtraction across all frequencies (CS), centroid subtraction for each frequency (CSi), linear scale (LS), and linear transformation (LT). A total of 32 intrinsic and 128 extrinsic methods were thus compared. Fuzzy ARTMAP and K-NN showed similar trends, with K-NN performing somewhat better and fuzzy ARTMAP requiring about 1/10 as much memory. The optimal intrinsic normalization method was bark scale, or bark with end-correction, using the differences between all frequencies (Diff All). The order of performance for the extrinsic methods was LT, CSi, LS, and CS, with fuzzy ARTMAP performing best using bark scale with Diff All; and K-NN choosing psychophysical measures for all except CSi.

Speaker Normalization

Human listeners are able to identify as a single phoneme a wide variety of speech signals produced by different speakers in different contexts. For example, the vowel /æ/ is recognized despite the fact that the average F_1 formant frequency is 660 Hz for males and 1010 Hz for children [15]. *Speaker normalization* is a general term used to describe the process whereby a listener compensates for individual characteristics of a speech signal in order to extract invariant features needed to identify the sound.

This paper describes a procedure that can be used to make systematic comparisons of the many speaker normalization schemes that have been proposed in recent decades. To evaluate a given normalization method, the 1520 vowel token vectors of the Peterson and Barney (1952) database are preprocessed using that method. Normalized inputs from about 30% of the speakers are used to train three different classifiers, a neural network (fuzzy ARTMAP [4]) and two K-nearest neighbor systems[5]. The remaining test data set is then presented to each classifier, which tries to identify each as one of ten vowel sounds. The normalization scheme in question is evaluated in terms of the number of correct test set identifications made by each of the classifiers. Speaker independence is required since the test set inputs and the training set inputs are generated by disjoint sets

We would like to thank R. Watrous for providing the Peterson-Barney database and for useful discussions on the linear transformation extrinsic method; and Ah-Hwee Tan for help with the fuzzy ARTMAP code.

*Supported in part by British Petroleum (BP-89-A-1204), DARPA (AFOSR-90-0083 and ONR-N00014-92-J-4015), the National Science Foundation (NSF-IRI-90-00530), and the Office of Naval Research (ONR-N00014-91-J-4100).

†Supported in part by the Air Force Office of Scientific Research (AFOSR-F49620-92-J-0225), DARPA (AFOSR-90-0083), and the National Science Foundation (NSF-IRI-90-00530).

of speakers (men, women, and children). Comparative evaluations of 160 different normalization schemes were carried out using this method.

The two main classes of normalization methods are *intrinsic* and *extrinsic* [1, 14]. Intrinsic normalization uses only the information present in each vowel token. Extrinsic normalization uses information from several vowel tokens of a given speaker. Intrinsic normalization methods include psychophysical measures, such as bark differences [16], logarithm measures [2, 9, 10, 11, 13], and logarithms of formant ratios [10, 13]. Extrinsic methods include centroid subtraction across all frequencies (CS) [2, 11, 13, 14], centroid subtraction for each frequency (CSi) [2, 13, 14], linear scale (LS) [7], and linear transformation (LT) [8, 19, 21].

Fuzzy ARTMAP and K-Nearest Neighbor Algorithms

Fuzzy ARTMAP [4] is a supervised neural network algorithm that learns to map (transformed) frequency vectors to vowel categories. ARTMAP clusters frequency vectors on-line in one module (ART_a) and vowel categories in a second module (ART_b). An intervening map field (F^{ab}) adaptively associates frequency categories to vowel categories. Performance was compared with that of K-nearest neighbor (K-NN) algorithms [5], using both city block (L_1) and Euclidean (L_2) metrics. The K-NN algorithm chooses a vowel category based on the K training points that lie nearest to a test point. Preliminary simulations on different normalization methods were used to choose parameters for the two different recognition methods. Fuzzy ARTMAP parameters for all the simulations were: $\bar{\rho}_a = 0.0$, $\alpha = 0.1$, and $\beta = 1.0$. For the K-NN systems, the number of neighbors (K) was fixed at 10 throughout.

Peterson-Barney Vowel Database

The Peterson-Barney database specifies the fundamental frequency (F_0) and the first three formants (F_1, F_2, F_3) from the steady-state portion of 10 vowels spoken twice by 33 males, 28 females, and 15 children, yielding a total of 1520 vowel tokens (76 speakers x 10 vowels x 2 repetitions) [15, 18]. In evaluating different normalization methods, the database was split into a training set, consisting of 480 vowels spoken by approximately 30% of the speakers (10 males, 9 females, and 5 children); and a test set consisting of the remaining speakers' 1040 vowel tokens.

Intrinsic Normalization Methods

For the intrinsic normalization schemes, eight normalization scales were compared: one nontransformed (N) scale; four psychophysical scales: bark scale (B) [22], bark scale with end-correction (Be) [17], mel scale (Mel) [6], and equivalent rectangular bandwidth scale (ERB) [12]; and three log measures: a semitone scale ($\log_{1.06}$), natural log scale (\log_e), and log base 10 scale (\log_{10}).

The bark scale, thought to correspond to critical bands or auditory bandpass filters, transforms $F_0 \dots F_3$ to $F'_0 \dots F'_3$ according to the equation:

$$F'_i = 13.0 * \arctan(0.76 * F_i/1000) + 3.5 * \arctan(F_i/7500)^2, \quad (1)$$

where F_i is the i^{th} frequency, in Hz. Bark scale with end-correction (Be) adjusts the low frequencies before converting to them to bark scale. Frequencies below 150 Hz are increased to 150 Hz; frequencies between 150 and 200 Hz are reduced to $0.8F_i + 30$; and frequencies between 200 and 250 Hz are increased to $1.2F_i - 50$. The mel scale (Mel) corresponds to the transformation:

$$F'_i = 2595 \log_{10}(1 + F_i/700). \quad (2)$$

Finally, the equivalent rectangular bandwidth (ERB) scale is calculated by:

$$F'_i = 11.17 * \log_e((F_i + 312)/(F_i + 14675)) + 43. \quad (3)$$

The three logarithmic measures consist of the semitone scale:

$$F'_i = \log_{1.06}(F_i), \quad (4)$$

the natural logarithm scale:

$$F'_i = \log_e(F_i), \quad (5)$$

and the log base 10 scale:

$$F'_i = \log_{10}(F_i). \quad (6)$$

Each of the eight normalization scales was tested with four different combinations: only the first two formants (F'_1, F'_2); the fundamental and all three formants (F'_0, F'_1, F'_2, F'_3); the three differences $F'_1 - F'_0, F'_2 - F'_1, F'_3 - F'_2$ (Diff Subset); and all six difference combinations $F'_1 - F'_0, F'_2 - F'_0, F'_3 - F'_0, F'_2 - F'_1, F'_3 - F'_1, F'_3 - F'_2$ (Diff All). The Diff Subset method, using the bark scale with end correction, is the method proposed by Syrdal and Gopal [16]. The differences between the frequencies correspond to the ratios of the frequencies in the log scales; thus they correspond to the methods proposed by Nearey and colleagues [2, 13, 14] and Miller and colleagues [10, 11]. Combining the 8 vowel space scales and the 4 frequency combinations, 32 intrinsic methods were tested.

Extrinsic Normalization Methods

For the extrinsic methods, adaptation to a speaker was superimposed on each of the 32 intrinsic normalization methods. Four types of extrinsic normalization were tested: centroid subtraction across frequencies (CS), centroid subtraction for each frequency (CSi), linear scale (LS), and linear transformation (LT). The CS method finds the mean frequency value (\bar{F}) across all transformed frequencies of all the vowels of a given speaker and subtracts this value from F'_i :

$$F''_i = F'_i - \bar{F}. \quad (7)$$

The CS method was proposed by Miller and colleagues [10, 11] and Nearey and colleagues [2, 14].

The CSi method extends the CS method by computing the centroid (\bar{F}_i) for each transformed frequency and subtracting this value from F'_i :

$$F''_i = F'_i - \bar{F}_i. \quad (8)$$

The CLIH2 method [13], and CLIH3 method [2] are functionally equivalent to the CSi method in a log vowel space.

The linear scale (LS) approach [7] finds the minimum and maximum frequency values for each F'_i across all vowels of a given speaker, then rescales each frequency to the range [0,999]:

$$F''_i = 999 * (F'_i - F_i^{min'}) / (F_i^{max'} - F_i^{min'}). \quad (9)$$

In the LT method [8, 19, 21], a linear transformation matrix \mathcal{A} is obtained which transforms each speaker's frequencies into some prototypical frequency values. New frequencies are linear combinations of the original transformed frequencies:

$$F'_i = \sum_{k=0}^3 \alpha_{ik} F'_k + \beta_i. \quad (10)$$

The matrix \mathcal{A} is derived using the LMS algorithm [20] to minimize the mean squared error between a given speaker's fundamental and formant frequencies and the mean fundamental and formant frequencies across all speakers for each vowel.

In all, 128 extrinsic normalization schemes were tested: 4 speaker adaptations x 4 frequency combinations x 8 scales.

Comparative Evaluation of Normalization Methods

The three pattern recognition systems (fuzzy ARTMAP, L_1 K-NN, and L_2 K-NN) generally agreed on which normalization methods gave better predictive performance on test set data. K-NN tended to outperform fuzzy ARTMAP by a few percent (Figure 1). However, improved performance achieved by K-NN comes at a cost of storing all 480 training vectors. Fuzzy ARTMAP coded between 22 and 135 F_2^g nodes, which provides a compression of 3.5 to 21.8 compared to the storage requirements of K-NN. Table 1 and Figure 1 show fuzzy ARTMAP and K-NN performance on the 32 intrinsic normalization methods. Similar analysis of the four extrinsic schemes has also been carried out [3].

Vowel Space	$[F_1, F_2]$			$[F_0, F_1, F_2, F_3]$			Diff Subset			Diff All		
	Fuzzy ARTMAP											
	Id	%	F_2^g	Id	%	F_2^g	Id	%	F_2^g	Id	%	F_2^g
N	1	66.4	123.1	9	78.4	63.5	17	80.4	55.8	25	80.7	57.5
B	2	66.0	123.7	10	79.1	61.6	18	81.4	56.3	26	83.1	43.9
Be	3	65.8	123.1	11	78.6	63.9	19	80.8	54.8	27	83.1	43.4
Mel	4	65.5	124.3	12	79.0	62.2	20	79.8	57.1	28	81.6	46.3
ERB	5	64.9	124.8	13	79.1	62.3	21	77.7	66.1	29	79.4	49.4
$\log_{1.06}$	6	65.4	122.0	14	79.4	60.7	22	72.1	73.2	30	74.2	58.9
\log_e	7	65.5	121.9	15	79.4	60.6	23	72.3	72.5	31	74.0	58.8
\log_{10}	8	65.5	122.1	16	79.4	60.8	24	71.9	73.9	32	74.2	58.9
Vowel Space	K-NN											
	Id	L_1 %	L_2 %	Id	L_1 %	L_2 %	Id	L_1 %	L_2 %	Id	L_1 %	L_2 %
N	1	75.2	75.2	9	76.8	75.1	17	78.9	77.1	25	76.8	76.3
B	2	74.3	75.1	10	82.6	82.6	18	83.7	84.5	26	85.5	85.5
Be	3	74.3	75.1	11	81.4	83.1	19	84.1	84.0	27	85.4	85.8
Mel	4	74.6	75.3	12	82.0	82.4	20	83.4	83.0	28	82.9	82.5
ERB	5	73.8	74.9	13	83.5	82.7	21	82.1	81.4	29	82.1	81.9
$\log_{1.06}$	6	74.5	74.8	14	82.0	82.5	22	76.1	76.1	30	77.2	77.1
\log_e	7	74.5	74.8	15	82.0	82.5	23	76.0	76.3	31	77.3	77.1
\log_{10}	8	74.5	74.8	16	82.1	82.5	24	76.0	76.0	32	77.2	77.1

Table 1: Fuzzy ARTMAP and K-NN test set performance with intrinsic normalization.

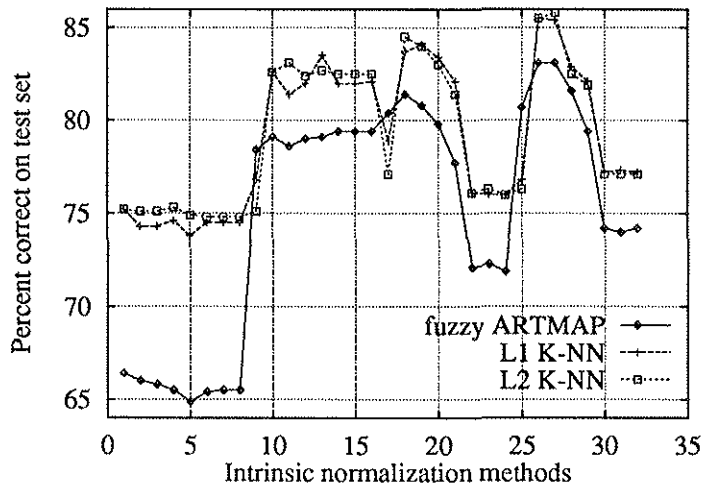


Figure 1: Test set performance of fuzzy ARTMAP and K-NN for intrinsic normalization methods # 1-32, which are identified in Table 1.

The psychophysical measures (B, Be, Mel, ERB) outperformed the log measures in most cases. For all the intrinsic and extrinsic methods, fuzzy ARTMAP performed best using bark, or bark with end correction, Diff All (Table 1). Although K-NN optimal performance varied more, these classifiers also chose the psychophysical measures in all cases except for the extrinsic scheme CSi. For the intrinsic and LS extrinsic method, K-NN chose the bark Diff All method. For the CS extrinsic method, K-NN chose ERB $[F_0, F_1, F_2, F_3]$. For the LT method, L_1/L_2 K-NN performed best with Mel/ERB $[F_0, F_1, F_2, F_3]$. Finally, for the CSi method, K-NN chose the log scales $[F_0, F_1, F_2, F_3]$.

While the LT method has the best performance, it requires vowels that are labeled *a priori* to obtain the transformation matrix \mathcal{A} . Thus, for speaker-independent machine vowel recognition, LT requires the user to say an initial specified utterance containing the requisite vowels. The other three extrinsic methods do not require these vowels to be labeled. Thus, the second best method (CSi) may be the best candidate for prototype human and machine perception systems, since CSi does not require as much *a priori* knowledge as LT, its computational demands are less, and its performance is almost as good.

References

- [1] Ainsworth, W. A. (1975). "Intrinsic and extrinsic factors in vowel judgements," in *Auditory Analysis and Perception of Speech*, edited by G. Fant and M. Tatham (Academic Press, London), pp. 103–113.
- [2] Assmann, P. F., Nearey, T. M., and Hogan, J. T. (1982). "Vowel identification: Orthographic, perceptual and acoustic aspects," *J. Acoust. Soc. Am.* **71**, 975–989.
- [3] Carpenter, G. A. and Govindarajan, K. K. (1993). "Speaker normalization methods for vowel recognition: Comparative analysis using neural network and nearest neighbor classifiers," CAS/CNS Technical Report, Boston University, Boston, MA.

- [4] Carpenter, G. A., Grossberg, S., Markuzon, N., Reynolds, J. R., and Rosen, D. B. (1992). "Fuzzy ARTMAP: A neural network architecture for incremental supervised learning of analog multidimensional maps," *IEEE Trans. on Neural Networks* **3**, 698–713.
- [5] Dasarathy, B. V. (1991). *Nearest Neighbor (NN) Norms: NN Pattern Classification Techniques* (IEEE Computer Society Press, Los Alamitos, CA).
- [6] Fant, G. (1973). *Speech Sounds and Features* (MIT Press, Cambridge, MA).
- [7] Gerstman, L. J. (1968). "Classification of self-normalized vowels," *IEEE Trans. on Audio and Electroacoustics* **AU-16**, 78–80.
- [8] Hindle, D. (1978). "Approached to vowel normalization in the study of natural speech," in *Linguistic Variation Models and Methods*, edited by D. Sankoff (Academic Press, New York), pp. 161–171.
- [9] Joos, M. (1948). "Acoustic phonetics," *Lang. Suppl.* **24**, 1–36.
- [10] Miller, J. D. (1989). "Auditory-perceptual interpretation of the vowel," *J. Acoust. Soc. Am.* **85**, 2114–2134.
- [11] Miller, J. D., Engebretson, A. M., and Vemula, N. R. (1980). "Vowel normalization: Differences between vowels spoken by children, women, and men," *J. Acoust. Soc. Am. Suppl.* **1 68**, S33.
- [12] Moore, B. C. J. and Glasberg, B. R. (1983). "Suggested formulae for calculating auditory-filter bandwidths and excitation patterns," *J. Acoust. Soc. Am.* **74**, 750–753.
- [13] Nearey, T. M. (1978). *Phonetic Feature Systems for Vowels* (Indiana University Linguistics Club, Bloomington, IN).
- [14] Nearey, T. M. (1989). "Static, dynamic, and relational properties in vowel perception," *J. Acoust. Soc. Am.* **85**, 2088–2113.
- [15] Peterson, G. and Barney, H. L. (1952). "Control methods used in a study of the vowels," *J. Acoust. Soc. Am.* **24**, 175–184.
- [16] Syrdal, A. K. and Gopal, H. S. (1986). "A perceptual model of vowel recognition based on the auditory representation of American English vowels," *J. Acoust. Soc. Am.* **79**, 1086–1100.
- [17] Traunmüller, H. (1981). "Perceptual dimension of openness in vowels," *J. Acoust. Soc. Am.* **69**, 1465–1475.
- [18] Watrous, R. L. (1991). "Current status of Peterson-Barney vowel formant data," *J. Acoust. Soc. Am.* **89**, 2459–2460.
- [19] Watrous, R. L. (1992). "Speaker normalization and adaptation using second-order connectionist networks," *IEEE Trans. on Neural Networks*, in press.
- [20] Widrow, B. and Stearns, S. D. (1985). *Adaptive Signal Processing* (Prentice Hall, Englewood Cliffs, NJ).
- [21] Zahorian, S. A. and Jagharghi, A. J. (1991). "Speaker normalization of static and dynamic vowel spectral features," *J. Acoust. Soc. Am.* **90**, 67–75.
- [22] Zwicker, E. and Terhardt, E. (1980). "Analytical expression for critical-band rate and critical bandwidth as a function of frequency," *J. Acoust. Soc. Am.* **68**, 1523–1525.