

On Automatic Plosive Identification Using Fuzziness in Property Sets

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Abstract—The present paper is a continuation of our previous work [1] in vowel and speaker recognition and is an attempt to demonstrate the effectiveness of fuzzy algorithms developed for computer recognition of unaspirated plosives in CVC context. The maximum recognition score for voiced ranges from 60 percent for dentals to 85 percent for bilabials when the on-glide formant transitional data alone were considered as input. Variation in recognition score due to multiple applications of the operators CON, DIL, and INT is about 20–25 percent and becomes insignificant after optimum fuzziness is achieved.

1. INTRODUCTION

The present study is a continuation of that in our previous correspondence [1] on fuzzy sets and decisionmaking approaches in vowel and speaker recognition where the decisional algorithms were based on the maximum values of membership function and magnitude of similarity vectors among the fuzzy property sets of a pattern. Two constant parameters which appeared in the exponent and denominator of the expressions for membership-value and property-value played the role of fuzzy generators. The object of the present correspondence is to demonstrate the effectiveness of using fuzziness in property sets as a classificatory method and

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also the formant transitional data alone as characteristic features to automatic recognition of initial unaspirated plosives in CVC context. The function of the fuzzy operators CON, DIL, and INT [2], [3] was implemented by changing the value of the exponential fuzzy generators. Their effect on plosive accuracy rate is also investigated.

The information regarding the place of articulation of stop consonants is now believed to be present in both the burst spectra and the transition of vowel formants [4]-[6]. The listening experiment conducted by LaRiviere *et al.* [7] with segmented and gated speech and ten native undergraduate listeners revealed that the highest score was obtained when aperiodic and vocalic transition of the CV syllables were presented to the listeners. The aperiodic spectra portion included the burst spectra. The result for recognition of /p/, /t/, and /k/ with target vowels /i/, /a/, and /u/ using aperiodic plus vocalic transition is much improved from that obtained with vocalic transition alone. A recent experiment for Telugu unaspirated plosives [8], using a maximum likelihood ratio as a test of classification, supported the above findings and showed the characterizing behavior of formant transitional data for consonant recognition. To examine the above claim, the acoustic features in the present experiment for classification of consonants were considered to be the on-glide transition (ΔF), the duration (Δt), and rate of transition ($\Delta F/\Delta t$) from the point of transient release of stop closure to the steady state of formants. In the present experiment only the first two formants were considered for selection of the transitional features. These had been extracted from spectrum analysis of a set of Telugu vocabulary containing about 600 commonly used speech units in CVC combination and uttered by three informants. Results are furnished through confusion matrices and plotting curves.

II. FUZZY SETS AND OPERATORS

A fuzzy set (A) with its finite number of supports x_1, x_2, \dots, x_n in the universe of discourse U is defined as

$$A = \{\mu_A(x_i), x_i\}, \quad i = 1, 2, \dots, n \quad (1)$$

where the membership function $\mu_A(x_i)$ having positive value in the interval [0,1] denotes the degree to which an event x_i may be a member of or belong to A . This characteristic function can be viewed as a weighting coefficient which reflects the ambiguity in a set. As it approaches unity, the grade of membership of an event in A becomes higher.

The operations which effectively generate a fuzzy set A are summarized here.

- i) Concentration of A (CON (A)):

$$\Rightarrow \mu_{\text{CON}(A)}(x) = [\mu_A(x)]^2, \quad \text{for all } x. \quad (2a)$$

- ii) Dilation of A (DIL (A)):

$$\Rightarrow \mu_{\text{DIL}(A)}(x) = [\mu_A(x)]^{0.5}, \quad \text{for all } x. \quad (2b)$$

- iii) Contrast intensification of A (INT (A)):

$$\Rightarrow \mu_{\text{INT}(A)}(x) = \begin{cases} 2[\mu_A(x)]^2, & 0 \leq \mu_A(x) \leq 0.5 \\ [1 - 2(1 - \mu_A(x))^2], & 0.5 \leq \mu_A(x) \leq 1.0. \end{cases} \quad (2c)$$

All these operations have the effect of altering the fuzziness of a set. The effect of DIL (A) is opposite to that of concentration, which reduces the magnitude of $\mu_A(x)$ by a relatively smaller amount for those x having higher membership value in A compared to those with low μ_A values. Contrast intensification, as its name applies, reduces the fuzziness of A by increasing the values of $\mu_A(x)$ which are above 0.5 and decreasing those which are below it.

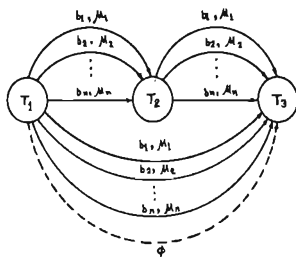


Fig. 1. Generalized fuzzy recognition model.

III. FUZZY RECOGNITION SYSTEM

The theory of fuzzy sets provides a suitable algorithm for classification of imprecisely defined patterns, particularly, in problems having a small number of samples where statistical interdependency can not be assumed (nonparametric learning).

Fig. 1 shows a state transition diagram of a fuzzy recognition model where $B = (b_1, b_2, \dots, b_n)$ is the possible output symbol for each input, $\mu_1, \mu_2, \dots, \mu_n$ are the membership functions corresponding to the output associated with each of the outgoing transitions. Null transitions \emptyset having no output are shown by dotted lines between initial state T_1 and final state T_3 . These are called deletions. Other transitions described as $T_1 \rightarrow T_3$ represent substitutions, and transitions for $T_1 \rightarrow T_2 \rightarrow T_3$, which produce two outputs due to wrong segmentation of the input symbol, denote insertions. If the segmentations are perfect (supervized) deletion and insertion errors will not be present, but error due to misclassification may occur. Let us now describe in brief the multicategory fuzzy classifier on the basis of properties extracted from a pattern where the error is present only due to misrecognition of patterns. The property p defined on an event x is a function $p(x)$ which can have values only in the interval [0,1]. A set of these functions $p(x)$, which assigns the degree of possession of some property p by an event x , constitutes what is called a property set. For example, p_n may denote the property that the outer boundary of a pattern is a circular or straight line or that a person is blonde, tall, etc. Such a classifier is shown in Fig. 2 where the input pattern and decision (output) of the categorizer is deterministic, but the process of classification is fuzzy.

The problem of feature extraction is to select a map of the form $X = f(Y)$, where $Y = (y_1, y_2, \dots, y_p, \dots, y_P)$ is a P -dimensional measurement vector derived from a pattern and $X = (x_1, x_2, \dots, x_n, \dots, x_N)$ is an N -dimensional feature vector. The number of features are usually less than the measurements, and the feature vector X should adequately characterize the particular class into which the pattern is to be allocated.

The preprocessed N -dimensional pattern X is then applied to a fuzzy processor consisting of fuzzy property matrices $P_i^j = [p_i^j]$ for the i th prototype in a category C_j , where p_i^j denotes the degree to which property p_i is possessed by the i th prototype in C_j . Since the output of the processor $S_i^j(X) = [s_i^j]$ represents an N -dimensional fuzzy similarity vector, the nonfuzzy output $\eta S_i^j(X)$ may be obtained from either of the following two equations:

$$\eta S_i^j(X) = \max_{i,j} \min_{i,j} \{s_i^j\} \quad (3a)$$

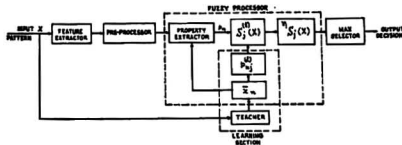


Fig. 2. Structure of fuzzy multicategorizer.

and

$$\eta S_j(X) = \min_i |S_j^0(X)|. \quad (3b)$$

Then it is decided that the pattern X is from the k th class if

$$\eta S_k(X) = \max_j \eta S_j(X), \quad k, j = 1, 2, \dots, m, \quad l = 1, 2, \dots, h.$$

The numerical value of S_j^0 in the foregoing represents the grade of similarity between the n th property of X and that of the l th prototype in C_j , m and h denote the number of pattern classes and number of prototype vectors in each class, respectively.

The learning behavior is reflected by using the effect of a fuzzy generator in property matrices whose elements are redefined by the following equations [1]:

$$p_{ik} = \left[1 + \left| \frac{x_{ik} - x_{ik}^{(t-1)}}{F_k} \right| \right]^{-F_k} \quad (4)$$

and

$$\bar{x}_{ik} = \max_j E[x] = \max_j \frac{1}{M_j} \sum_{l=1}^{M_j} x_{ikl}, \quad i = 1, 2, \dots, M_j \quad (5)$$

where M_j is the total number of features x_{ikl} representing the n th components of training samples associated with class C_j , $E[x]$ denotes the expected value of x , and F_k and F_k are, respectively, the exponential and denominational fuzzy generators. For $F_k > 1$, the p_{ik} value reduces by a relatively smaller amount for those features having higher property values compared to those with low p_{ik} value. With further increase of F_k , such reduction of the degree of property increases by a relatively smaller (higher) amount for those events with higher (lower) property values. The reverse is true for values of $F_k < 1$.

IV. IMPLEMENTATION TO PLOSIVE RECOGNITION

The test material was prepared from the Telugu vocabulary containing a set of discrete phonetically balanced (PB) speech units in CV context. Out of these words, the velars k, g , the alveolar t, d , the dentals h, j , and the bilabials p, b in combination with ten vowels $/a, \bar{a}, i, \bar{i}, e, \bar{e}, u, \bar{u}, /a', /e', /i', /o', /o', /a', /e', /i', /o', /o'/$ including shorter and longer categories had been selected. The experimental setup for recording and measurement of these words, including nature of speakers and measurement process, is described in our previous communication [1].

The manual extraction of features from spectrograms consisted of the following steps:

a) Extrapolate the transition of the formants to the instant of the release of stop closure, and measure the frequency at that point (beginning of transition) from the base line of the spectrogram.

b) Trace the central line of the formant bands where the formant is parallel to base line (steady state), and measure the formant value from the base line.

c) Measure the duration of transition from the point of release of stop closure up to the instant the formant reaches a reasonable steady state.

The recognition parameters selected for classification of consonants in CV context are the amount of on-glide transitions of the first two formants ($\Delta F_1, \Delta F_2$), their duration (Δt), and rate of transitions ($\Delta F_1/\Delta t, \Delta F_2/\Delta t$). The number of transitions is obtained by subtracting the F values at the steady state from those at the beginning of on-glide transitions, and transition rates are computed by dividing the number of transitions by their duration. The total number of samples obtained after processing the spectrograms is only 594. The respective parameters thus constitute a five-dimensional pattern vector space Ω_2 , where each point associates five measured parameters of a CV context uttered by one of the three informants.

Prototype points chosen for recognition are the averages of the coordinate values corresponding to entire set of samples in a particular class. Properties corresponding to each of the five parameters were computed with $F_k = 100$, m (number of pattern classes) = 4, $N = 5$, and h (number of prototypes in each class) = 1. The effect of fuzzy generation on the cognitive system was incorporated by changing only the values of F_k . F_k is kept constant at a value of 100 since it creates less ambiguity than F_k . Various values considered for F_k in the experiment are 4, 2, 1, $\frac{1}{2}$, $\frac{1}{4}$, $\frac{1}{8}$, and $\frac{1}{16}$ such that $F_k = 2$ represents the operator CON, $F_k = 4$ represents CON(CON), $F_k = \frac{1}{2}$ represents DIL, $F_k = \frac{1}{4}$ represents DIL(DIL), etc. In other words, the fuzzy hedges "very," "slightly," and their multiple operations are being implemented with these constants. Besides these values of F_k , fuzziness in property sets was also introduced by applying the function INT.

With the above information, the fuzzy similarity matrices were formed, which denote the degree of similarity of the pattern with the four classes for a specified value of F_k . The method of evaluating the similarity matrices has already been reported [1], where the reciprocal of the standard deviation of a component was used as its weighting coefficient so that the features with increasing variance have a decreasing weighting coefficient. Again, in a few cases, where the standard deviation of the coordinate values in a class was zero, the corresponding coefficient was set at unity. This is logical since an attribute occurring in identical magnitudes in all members of a set is an important feature of the set. Hence, its contribution to the similarity measurement need not be reduced. To assign a proper class to an unknown pattern, the nonfuzzy decision was adopted by the machine by measuring the maximum closeness on the basis of the magnitudes of the similarity vectors. For instance, the property values of an event corresponding to $F_k = 0.5$ indicate its degree of "slightly having" the properties, and the components in the fuzzy similarity vectors denote its corresponding grades of membership of "slightly belonging" to the respective classes, etc. The class possessing maximum nonfuzzy

TABLE I
TYPICAL FEATURE VALUES OF PLOSIVES FOR TARGET VOWEL /u/

| PLoSIVES | ΔF_1 (Hz) | ΔF_2 (Hz) | Δt (ms) |
|----------|-------------------|-------------------|-----------------|
| /k/ | 0 | -150 | 60 |
| /k̄/ | 50 | 100 | 50 |
| /g/ | 100 | 825 | 48 |
| /p/ | 0 | 100 | 60 |
| /p̄/ | -50 | -150 | 45 |
| /t̄/ | 50 | 200 | 53 |
| /t/ | 0 | 850 | 45 |
| /d/ | 50 | 100 | 54 |

output as measured with (3b) is then decided to be the proper class of that event for the hedge "slightly."

V. RESULTS

Typical values of the acoustic features for all unaspirated plosives with target nucleus /u/ are shown in Table I. The percentages of recognition of plosives for different target vowels when F_e is set at a value of $\frac{1}{2}$ are given in Table II. Fig. 3 illustrates the variation of the recognition score for unvoiced and voiced counterparts with different values of the exponential fuzziifier. Scores plotted are the average values of the results obtained for all target vowels. The rate of correct decisions rendered by machine in the recognition of a consonant is found to increase with a decrease in the magnitude of F_e . Variation in recognition is about 20-25 percent (except for velars) as F_e changes from $\frac{1}{2}$ to 8. With further reduction of the value of F_e beyond 0.5, the error rate does not deteriorate significantly. The s_{ij} values of an event corresponding to $F_e \rightarrow 0.5$ indicate its degree of "slightly belonging" to the respective classes. It could therefore be stated that after an optimum value of the exponential fuzziifier is achieved, the ambiguity in property sets is not much altered, and the variation of machine's performance with fuzziification becomes insignificant. For higher values of F_e , the property degree for samples having low property value is reduced by a larger amount than the samples having high property value. As a result, the magnitudes of fuzzy similarity components are decreased for the samples in a common class.

Voiced stops are seen to be differentiated better than the unvoiced parts. The increase in maximum score for voiced over unvoiced is about 15 percent for /p, b/ and /t, d/ pairs and about 7 percent for the /k, g/ pair. For the /t, d/ pair, the variation is reversed at higher values of F_e . These results agree well with those

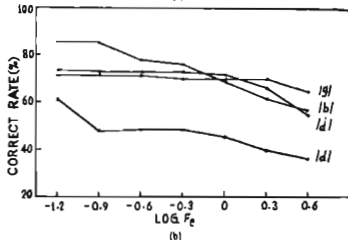
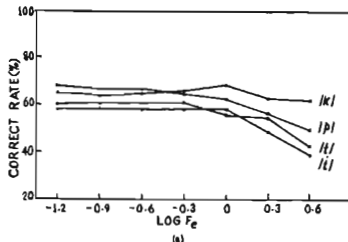


Fig. 3. Variation of overall recognition score (averaged over all target vowels) for plosives with fuzziiness in property sets. (a) Unvoiced. (b) Voiced.

of an earlier experiment [8]. The larger formant spreads for voiced stops indicate a larger extent of coarticulation with the vowels that follow them. This larger coarticulation is expected to be responsible for better discrimination of the place of articulation for voiced stops once the target vowel is known a priori.

The overall percentages of correctness with different target vowels and their variation with fuzziiness are sketched in Fig. 4 for unvoiced and voiced plosives. Table III explains how the confusion made by machine in taking correct decision changes for different amount of fuzziiness introduced in property sets. For brevity, only the results of voiced plosives for the target vowel /u/ are mentioned. The figures represent the number of instances in which the same decision was made by machine, and diagonal elements therefore indicate the number of events correctly identified. Confusion tends to be minimum as F_e approaches a

TABLE II
PERCENTAGE OF CORRECT CLASSIFICATION OF PLOSIVES ($F_e = \frac{1}{2}$)

| Target Vowel | /k/ | /k̄/ | /g/ | /p/ | /p̄/ | /t/ | /t̄/ | /d/ | /d̄/ |
|--------------|--------|-------|-------|--------|--------|--------|--------|--------|------|
| /b/ | 51.58 | 88.89 | 38.10 | 100.00 | 33.34 | 50.00 | 83.34 | 100.00 | |
| /g/ | 48.14 | 60.00 | 37.50 | 100.00 | 38.46 | 76.92 | 40.00 | 100.00 | |
| /k/ | 100.00 | 75.00 | 75.00 | 22.23 | 100.00 | 85.71 | 80.00 | 40.00 | |
| /p/ | 100.00 | 62.50 | 72.73 | 100.00 | 100.00 | 100.00 | 100.00 | 65.67 | |
| /t/ | 100.00 | 66.67 | 88.89 | 90.90 | 100.00 | 58.82 | 25.00 | 33.75 | |
| /d/ | 91.67 | 25.00 | 70.00 | 11.12 | 100.00 | 64.70 | 13.34 | 66.67 | |

TABLE III
CONFUSION MATRICES OF VOICED PLOSIVES WITH TARGET VOWEL /u/ FOR DIFFERENT VALUES OF F_e

| Observed Class | Actual Class | | | | Observed Class | Actual Class | | | |
|------------------|--------------|-----|-----|-----|------------------------|--------------|-----|-----|-----|
| | /k/ | /g/ | /k/ | /ŋ/ | | /k/ | /g/ | /k/ | /ŋ/ |
| /k/ | 26 | | 1 | | /k/ | 26 | | | |
| /g/ | | 10 | 5 | 1 | /g/ | | 10 | 6 | 1 |
| /k/ | | 5 | 2 | | /k/ | | 5 | 2 | |
| /ŋ/ | | 2 | | 12 | /ŋ/ | | 2 | | 12 |
| (a) $F_e = 1/16$ | | | | | (b) $F_e = 1/8$ | | | | |
| Observed Class | Actual Class | | | | Observed Class | Actual Class | | | |
| | /k/ | /g/ | /k/ | /ŋ/ | | /k/ | /g/ | /k/ | /ŋ/ |
| /k/ | 26 | | 1 | | /k/ | 25 | | | |
| /g/ | | 11 | 6 | 4 | /g/ | | 11 | 6 | 5 |
| /k/ | | 5 | 2 | | /k/ | | 5 | 2 | |
| /ŋ/ | | 2 | | 12 | /ŋ/ | | 1 | | 11 |
| (c) $F_e = 1/4$ | | | | | (d) $F_e = 1/2$ | | | | |
| Observed Class | Actual Class | | | | Observed Class | Actual Class | | | |
| | /k/ | /g/ | /k/ | /ŋ/ | | /k/ | /g/ | /k/ | /ŋ/ |
| /k/ | 25 | | 1 | | /k/ | 25 | | | |
| /g/ | | 11 | 6 | 9 | /g/ | | 11 | 6 | 10 |
| /k/ | | 5 | 2 | | /k/ | | 4 | 2 | |
| /ŋ/ | | 2 | | 7 | /ŋ/ | | 1 | | 6 |
| (e) $F_e = 1$ | | | | | (f) $F_e = 2$ | | | | |
| Observed Class | Actual Class | | | | Observed Class | Actual Class | | | |
| | /k/ | /g/ | /k/ | /ŋ/ | | /k/ | /g/ | /k/ | /ŋ/ |
| /k/ | 25 | | 1 | | /k/ | 22 | | | |
| /g/ | | 8 | 5 | 6 | /g/ | | 16 | 7 | 11 |
| /k/ | | 8 | 3 | 5 | /k/ | | 5 | 1 | |
| /ŋ/ | | 1 | | 5 | /ŋ/ | | | | 5 |
| (g) $F_e = 4$ | | | | | (h) $F_e = \text{DIP}$ | | | | |

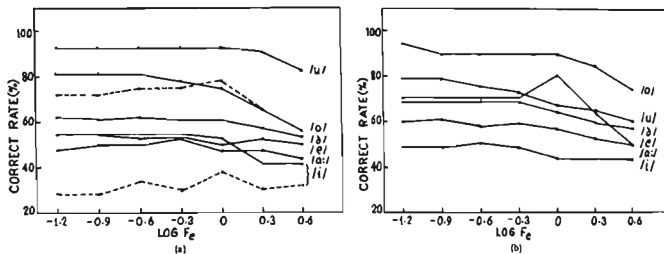


Fig. 4. Variation of overall recognition score of plosives (for different target vowels) with fuzziness in property sets. (a) Unvoiced. (b) Voiced.

value of λ . Plosives in initial positions with back target vowels are better identified than other target vowels.

The dotted curves in Fig. 4(a) indicate the scores when similarity components were computed with a unity weighting coefficient. This was done for only one each of the front and back vowels. It therefore appears that fixation of appropriate phase weights ensures correct representation of feature importance in classification, and the percentage of accuracy is much improved. Again it is interesting to note that the discrimination between the scores obtained with and without weighting coefficients decreases

with an increase in the value of F_e . When the operation INT is used to provide significant reduction in fuzziness among properties, the effect becomes predominant, as seen in Fig. 5, where the correct rates without weighting coefficients are seen to exceed (except for the target vowel /s/) those with weighting coefficients. It was revealed on investigation that these fuzzy generators provide transformation in such a way that the weighting coefficients do not ensure proper representation of the importance to the modified features, rather, over-importances are given to them. In other words, the property components corresponding to those

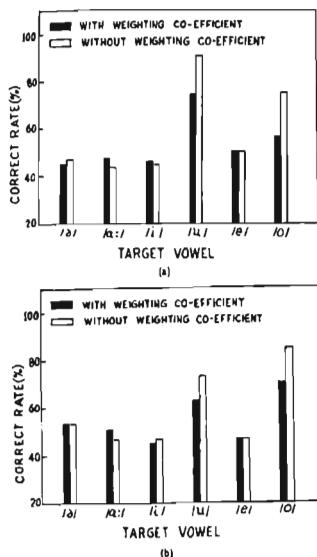


Fig. 5. Overall recognition score of plosives for different target vowels when consonant identification is dependent on property sets. (a) Unvoiced. (b) Voiced.

fuzzifiers themselves represent the proper importances to the characterizing features, and no additional factor is required for appropriate classification of patterns.

VI. DISCUSSION AND CONCLUSIONS

Fuzziness in property sets has been implemented in order to study the variation of the machine's performance for recognition of initial unaspirated plosives in CVC context. The on-glide transitional data can be used to identify the place of articulation of the voiced and unvoiced stop consonants with the *a priori* knowledge of target vowels. It should be mentioned here that the machine was found to recognize vowels with an 82 percent [1], [9] accuracy rate using the first three formants. Present results of machine recognition compares well with human perception as obtained in the listening experiments conducted with segmented and gated speech with ten native undergraduate listeners [7] and with several band pass filters and seven postgraduate male listeners [10]. The results of consonant recognition as conducted by LaRiviere *et al.* [7] with aperiodic and vocalic transition for the target vowels /b/, /k/, and /t/ are found to be 0.98, 1.0, 0.81 for /p/, 1.0, 1.0, 0.13 for /t/, and 0.63, 0.83, 0.95 for /d/. In a recent statistical study [8] using transitional data and the maximum likelihood ratio, the overall recognition scores for the unaspirated plosives were 0.65, 0.69, 0.45, 0.9, 0.95, and 0.72 for unvoiced and 0.58, 0.65, 0.73, 0.85, 0.85, and 0.53 for voiced with target vowels /b/, /k:/, /t:/, /d:/, /t:/, and /d/.

The corresponding figures obtained in our experiment are comparable. Although the results do not differ much, the

classification algorithm as compared to the reported methods is simpler, than available ones, less time consuming, and does not require much previous information over the distribution of the events in a class. The results do agree well with those of other recent studies [11]–[13] showing the conceptual and practical advantages of fuzzy algorithms over the probabilistic approach in demonstrating ill-defined patterns where pattern indeterminacy is due to inherent vagueness rather than randomness of events and especially when the sample size is small. In addition the method is more significant from the following viewpoints.

- The burst spectra, an important cue, particularly the anifor-manisms, were not included as recognition features.
- The CV syllables in the experiment were taken from normally spoken words, and therefore, coarticulation from distant vowels and consonants is likely to affect the transitions.
- The minimum duration of vowels (250 ms) for arriving at the perfect steady state could not be achieved in these utterances.

The role played by the exponential fuzzy generator is found to be satisfactory in altering the fuzziness within property sets. The fuzzy hedge "slightly," corresponding to the DIL operation as expected, results in better classification than that of the hedge "very" ($F_s = 2.0$). But successive application of the DIL operation does not ensure an increase in recognition score. In other words, after an optimum value of the exponential fuzzy generator is achieved, the fuzziness in property sets is not much altered. Hence, the variation of the score becomes insignificant. A wide variation of about 20–25 percent (excepting the velars) in accuracy rate is achieved with different values of F_s ranging from 8 to $\frac{1}{2}$.

The reciprocal of the standard deviation provides appropriate phase weights in measuring the importance of the features. This supports the findings in our previous communications [1], [9]. This characteristic is also found to be significant for the property sets having higher degrees of fuzziness. The recognition score is likely to be further improved by the inclusion of the transitional data of a third formant and the data of the burst spectra. Since this work is purposely restricted to show only the effectiveness of formant transitional data as a recognition parameter and the fuzzy-set theoretic approach as a decisional algorithm for automatic consonant recognition, these parameters were excluded.

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