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A fuzzy system for tone detection applications

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Abstract

In this paper we propose a computationally simple algorithm for the detection of a sinusoidal tone for applications in the field of telecommunication systems. More specifically, we have developed an algorithm based on fuzzy logic (FL) to disable an echo canceller in a telephone exchange. The Fuzzy Tone Detector (FTD) presented uses three simple time-domain parameters and a matching phase based on only three fuzzy rules, trained by a new hybrid learning tool. A fuzzy system called a Fuzzy Phase Reversal Detector (FPRD) was also trained for the detection of phase reversals. The new algorithm outperforms the traditional methods in terms of robustness to channel noise, working up to a signal to noise ratio (SNR) of 0 dB.

Keywords: Tone detection; Signal processing; Fuzzy logic

1. Introduction

In the last few years in the field of telecommunication systems there have been a increasing number of applications based on algorithms using alternatives to classical logic. For some time now more sophisticated methods based on Neural Networks (NNs) have been introduced for intelligent signal processing. Lately various applications of Fuzzy Logic (FL) in the field of telecommunications have also been developed [1]. These methodologies, which belong to a large subclass of Artificial Intelligence called Soft Computing [2], often give

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better performance levels than traditional methods. FL, for example, is a simple, robust technique developed to allow formal management of uncertainty and imprecision, which has proved to be a valid alternative in the field of robust signal classification as well [3–7].

In this paper we propose an algorithm based on SC for the detection of a voiceband sinusoidal tone. The human capacity to detect the presence of a tone even in the presence of strong noise is evident. In the paper we will give the results of a simple experiment showing the validity of this statement. On the basis of the results of this test we are persuaded that the problem of tone detection in the presence of noise falls into the class of applications for which a matching based on a non-linear technique like FL is more advantageous than a traditional linear or threshold approach. The problem of tone detection in fact is of simple solution when the signal-to-noise ratio (SNR) is quite high (up to 5 dB) [8–11], but it becomes complex in applications for which the SNR decreases up to 0 dB or below due to channel degradations. The goal of this work was therefore to develop a tone detector providing a good trade-off between the robustness to channel noise and the computational simplicity of some approaches present in literature. As is known, low computational complexity is one of the principal features of FL. In addition, FL offers, beside a linguistic representation, a great robustness to noise [12]. As we will see, this feature is evident in the results obtained.

It was also of particular interest to identify a new set of significant features extracted from the signal [13]. Further, although fuzzy rules are generally obtained manually according to heuristic criteria derived from knowledge of the problem, in this paper we have used a new fuzzy learning tool, called Fuzzy Genetic Neural System (FuGeNeSys) [14,15], based on Genetic Algorithms (GA) and NNs, which automatically extracts the fuzzy knowledge base in a supervised manner.

Although the method proposed has a generic validity in several tone detection applications [6,7], in this paper we present an algorithm, based on the new methodology, for the recognition of a 2100 Hz tone to disable an echo canceller in a telephone exchange. The Fuzzy Tone Detector (FTD) needs only three simple time-domain parameters and three fuzzy rules as the matching phase. It meets the requirements laid down by ITU-T Recommendation G.165 and outperforms the performance of a traditional solution based on Fisher discriminant analysis [16]. A fuzzy system called a Fuzzy Phase Reversal Detector (FPRD) was also trained for the detection of phase reversal. This system needs only two rules.

This paper is organized as follows. Section 2 presents a brief introduction to fuzzy inferencing, Section 3 reports the results of the above-mentioned experiment. In Section 4 we discuss the choice of the features, in Section 5 we present the FTD and FPRD. In the last section we draw our conclusions.

2. Fuzzy inferencing

A fuzzy set [17] is a set whose membership function can take all the values contained in the real closed interval $[0, 1] \subseteq \Re$. A fuzzy subset A of a generic set X, called the *Universe of Discourse*, features the following membership function

$$\mu_A : X \rightarrow [0, 1] \tag{1}$$

which associates with each element x of X a number $\mu_A(x)$ between 0 and 1 representing the degree of membership of x in A.

A fuzzy conditional rule is generally made up of a premise and a conclusion

$$\text{IF premise THEN conclusion.} \tag{2}$$

The premise is made up of a number of fuzzy predicates (henceforward also called antecedents) of the general form (Tom IS fast) that are eventually negated or combined by different operators such as AND or OR computed with *t-norms* or *t-conorms* (which, according to Zadeh, are minimum and maximum operations, respectively).

In the latter example Tom is the value of the linguistic variable defined in the Universe of the Discourse of men and *fast* is one of the names of the term set of the linguistic variable (for example *slow*, *normal*, fast).

The following is an example of a fuzzy conditional rule using such operators

$$\text{IF } P_1 \text{ AND } P_2 \text{ OR } P_3 \text{ THEN } P_4, \tag{3}$$

where, for example,

P_1 = (car IS light),

P_2 = (power IS intermediate),

P_3 = (power IS high),

P_4 = (car IS fast).

To apply an inference method to the conclusion, it is first necessary to asses the degree of membership θ of the premise, through assessment of the degrees of membership α_i of each predicate $P_i = (X_i \text{ IS } A_i)$ in the premise. The membership degree α_i is calculated by assessing the degree of membership of a generic value of X_i in the fuzzy set A_i. If X_i is made up of a fuzzy set, its degree of membership α_i is determined by making an intersection between the fuzzy value of X_i and the fuzzy set A_i and choosing the maximum value of membership; if X_i is a crisp value, its degree of membership in the fuzzy set A_i is made up of the value the membership function of A assumes corresponding to X_i. The degree of membership, θ, of the premise can thus be calculated by assessing the fuzzy operations on the predicates.

Once the value of θ is known, an inference method can be applied to assess the conclusion. This conclusion derives from assessment of all the rules concerning the same output variable.

Lastly, once the fuzzy output set is obtained, it is defuzzified to transform the fuzzy information into numerical information [14,15].

Recently defuzzification methods have been introduced which simplify calculation of the output value in that a single operation is sufficient to aggregate the rules and defuzzify, bypassing calculation of the fuzzy output set [14,15].

Below we give the equations used to calculate the fuzzy inference we trained:

$$\alpha_{ir} = \exp\left(-\frac{(x_1 - c_{ir})^2}{2x\sigma_{ir}^2}\right), \tag{4}$$

$$\theta_r = \min_{i=1}^{I}(\alpha_{ir}), \tag{5}$$

$$y = \frac{\sum_{r=1}^{R} \theta_r \sigma_r c_r}{\sum_{r=1}^{R} \theta_r \sigma_r}, \tag{6}$$

where:

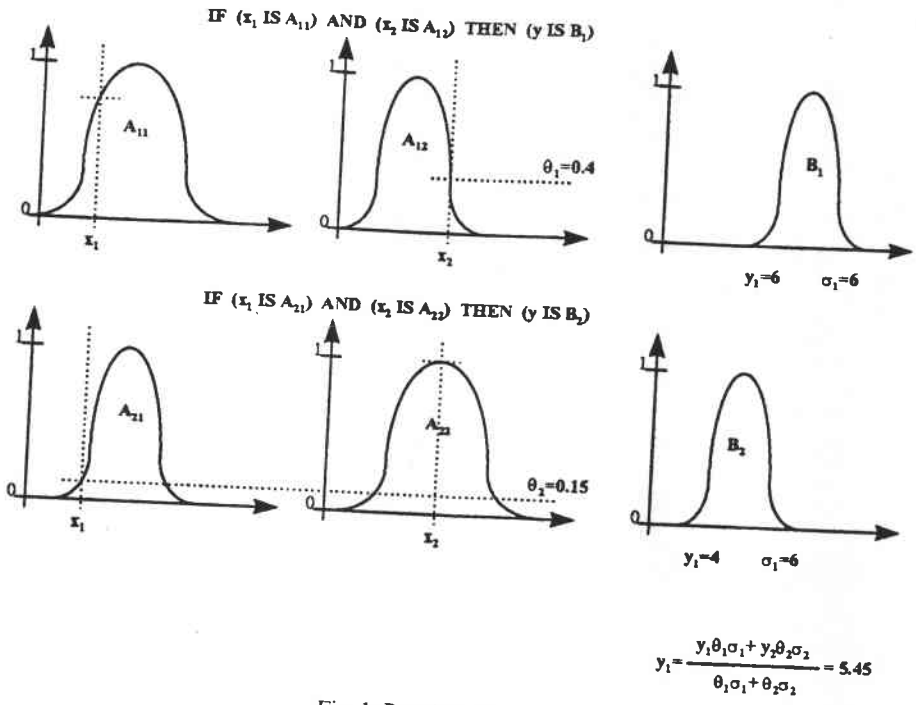
- y is the fuzzy output;
- x_i is the ith crisp input;
- R is the number of rules;
- I is the number of antecedents per rule;
- θ_r is degree of truth of the premise of the rth rule;
- α_{ir} is the degree of membership of the ith input to the jth fuzzy set;
- y_r and σ_r are, respectively, the rth rule output and weight;
- σ_{ir} and c_{ir} are the two parameters of the ith input membership function of the rth rule.

As can be seen from the equations, we used crisp inputs (x_i) and Gaussian input membership functions (α_{ir}). In calculation of the premise (θ_r) we chose to use the minimum of the various degrees of membership of the antecedents (α_{ir}), i.e. the fuzzy connector AND, calculated according to Zadeh, was used with the various antecedents. For defuzzification we used a weighted mean method [2].

Fig. 1 gives a practical example of calculation of a fuzzy inference made up of two rules, using Eqs. (4)–(6).

2.1. Fuzzy inference complexity

We can show that the computational load is very low. For software implementations of FL it is possible to compute the degrees of truth of premises simply through look-up tables. Therefore, using R rules of I inputs and O outputs, to compute the degree of truth of a premise, we need RI memory accesses and R minimum operations among I values. For the defuzzification process we need $2RO$ products and $2RO$ sums.



$$y_1 = \frac{y_1\theta_1\sigma_1 + y_2\theta_2\sigma_2}{\theta_1\sigma_1 + \theta_2\sigma_2} = 5.45$$

Fig. 1. Practical inferencing.

2.2. The learning tool used

The rules governing a fuzzy system are often written using linguistic expressions which formalize the empirical rules by means of which a human operator is able to describe the process in question using his own experience. Fuzzy rules are therefore generally obtained manually according to heuristic criteria derived from knowledge of the problem. This approach, however, may have great drawbacks when no a priori knowledge is available about the input–output link the fuzzy system has to provide, or when it is highly complex or non-linear. In addition it requires a long refinement phase in the definition of the term sets of each input variable which optimize the system. In this paper we have used FuGeNeSys [14,15], a new fuzzy learning tool based on GAs and NNs which obtains the fuzzy rules in a supervised manner. The advantage of this is that the fuzzy knowledge base is created automatically. The tool also makes it possible to obtain the minimum set of fuzzy rules for optimization of the problem, discarding any rules that are of no use. The main features of FuGeNeSys are:

- It permits fuzzy modeling from input–output data.
- The number of rules needed for learning is always very low. In the various

applications developed the number has always been below ten.

- The learning error is comparable to, if not better than, that of other techniques described in literature.
- Simplified fuzzy knowledge bases can be generated, i.e. the tool is capable of eliminating the unnecessary antecedents in any rule.
- Significant features are correctly identified.
- The tool can be used in both classification and interpolation problems.

3. Humans can easily learn to solve tone detection problems

Before starting the work we carried out a simple experiment. Its aim was to show that a human being is capable of recognizing tones quite easily and with experience can discriminate between them correctly without being negatively affected by the level of noise.

The experiment consisted of randomly generating three tones at three different frequencies: 1900, 2100 and 2350 Hz. We then added Gaussian noise to these tones with SNRs in the range of [−5, +5] dB, with a mean level of about −1.5 dB.

We chose three listeners, only one of whom had a slight knowledge of music.

First we had the subjects listen to the 2100 Hz tone with no noise and then one of the randomly generated ones. The listener simply had to say whether the tone was the same or not.

At the first 25 attempts we had the following success rate: 64%, 72% and 60%, with an average of 65.3%. The highest percentage referred to the listener who had some knowledge of music. In the next 25 examples there was a significant improvement – 72%, 96% and 72%, with an average of 80.0%. Here again, the highest percentage referred to the listener who had some knowledge of music.

We observed that the results were practically unaffected by the level of noise. Slight differences were noticed only with SNRs in the range of [−5, −4] dB.

This experiment showed that the problem can be dealt with quite simply by a human being and is almost unaffected by the level of noise present.

This led us to conclude that an FL-based approach would give excellent results. As we could not transfer the know-how of our "experts" into a fuzzy system, we thought of constructing one automatically using FuGeNeSys.

4. The parameters considered

The first problem we had to tackle was that of choosing a set of parameters which would permit tone detection. After some study we concluded that various sets of parameters could be used. So we chose the ones we considered to be

most useful, with the fundamental requirement that they were simple to calculate.

In the application we will describe in further detail in the following section, we observed that there are three significant parameters generally already available because they are used for other voice processing algorithms [18,13].

The parameters we used were the first normalized autocorrelation coefficient $\rho_{xx}(1)$, the Zero Crossing Rate (ZCR) and the differential one, $\mathrm{ZCR_d}$. As is well known, these parameters are extremely easy to compute.

We recall that given a discrete time signal $x(n)$ we say that the kth normalized autocorrelation coefficient $\rho_{xx}(k)$ calculated in a frame of N samples is

$$\rho_{xx}(k) = \frac{N \sum_{n=1}^{N-k} x(n)x(n+k)}{(N-k)\sum_{n=1}^{N} x^2(n)}. \tag{7}$$

Consequently, having established a reference signal, $\bar{x}(n)$, a sampling frequency and a sufficiently wide observation window (N), the value of the first autocorrelation coefficient $\rho_{xx}(1)$ takes a precise value, $\bar{\rho}$, which is not significantly affected by the level of noise in the signal.

A generic signal $x(n)$ possessing a $\rho_{xx}(1)$ which is sensibly different from the value $\bar{\rho}$ will certainly not be similar to the reference signal $\bar{x}(n)$.

This information alone is not sufficient to discriminate a sinusoidal signal, but together with two other measures it can, as we shall see be of great help.

The ZCR indicates the number of zero crossings of the signal in an observation window N samples in length, whereas the differential one, $\mathrm{ZCR_d}$, represents ZCR of the signal difference $d(n) = x(n) - x(n-1)$, i.e. the number of maxima and minima of the signal in the observation window.

More precisely, the two parameters Z and Z_d are, respectively, the absolute values of the differences between ZCR and $\mathrm{ZCR_d}$ and the corresponding values of the pure tone to be discriminated.

In the case of a pure tone both Z and Z_d are equal to zero; in the presence of noise they are naturally other than zero. Noise can affect these two parameters quite significantly so we consider them to be important for correct discrimination.

Qualitatively, in a fuzzy sense, we can say that a signal $x(n)$ will be a particular sinusoidal tone if its first normalized autocorrelation coefficient is about the same as that of the reference tone and, at the same time, the two parameters Z and Z_d are approximately null.

So in effect it would be possible, given the application, to generate the rules directly but we observed that the tuning was complicated and extremely tedious.

As we shall see, with an automatic system it is possible to obtain a greatly reduced set of fuzzy rules which has an excellent level of performance.

5. The tone detection application proposed

In this section we present a simple robust algorithm for the recognition of a 2100 Hz tone and the disabling of an echo canceller based on SC. The model proposed meets the requirements laid down by ITU-T Recommendation G.165 for echo canceller disabling.

5.1. Specifications

During voice-to-data transmission, it is often necessary to disable an echo canceller in a telephone exchange. This operation is performed by transmitting a 2100 Hz sinusoidal tone having a level in the range of −6 to −31 dBmO and inserting periodic phase reversals (180°) which occur every 450 ± 25 ms. The specifications made in the ITU-TG.165 Recommendation [19] allow a tolerance in frequency in the range of ±21 Hz and a tolerance in phase in the range of ±25°. It also allows a region of uncertainty 1900 ÷ 2350 Hz for frequency and 180° ± 70° for phase) beyond which disabling of the echo canceller must not occur. It is therefore necessary to have a recognition algorithm for a 2100 Hz tone with periodic phase reversal which, according to the specifications of the standard, will operate perfectly with white noise up to a SNR of 11 dB. The algorithm also has to allow discrimination between tone and other kinds of signal such as voice or data, or simply channel noise.

5.2. Rule extraction

The learning patterns chosen were voice, sinusoidal tones at 1900 Hz, 2350 Hz (FTD output $= y_{\mathrm{FTD}} = 0$, tone absence) and 2100 Hz ($y_{\mathrm{FTD}} = 1$, tone presence) in different SNR conditions. The FTD was also trained with noise sequences (tone absence).

After checking the level of energy of the signal, the three above-mentioned parameters were calculated on a window of $N = 160$ samples. Fig. 2 shows the distribution of the selected learning patterns.

After the training phase only three fuzzy rules were obtained.

To make tone detection even more insensitive to noise, the FTD output $y_{\mathrm{FTD}}[w]$, calculated on the actual window, is averaged with the three previous values of a recursive average given by the relation

$$M[w] = \frac{1}{4}\left(y_{\mathrm{FTD}}[w] + \sum_{k=1}^{3} M[\omega - k]\right). \tag{8}$$

The presence of the tone is detected whenever $M[n]$ exceeds a threshold experimentally set at 0.4. Table 1 shows the extracted numerical values needed to calculate the fuzzy inference.

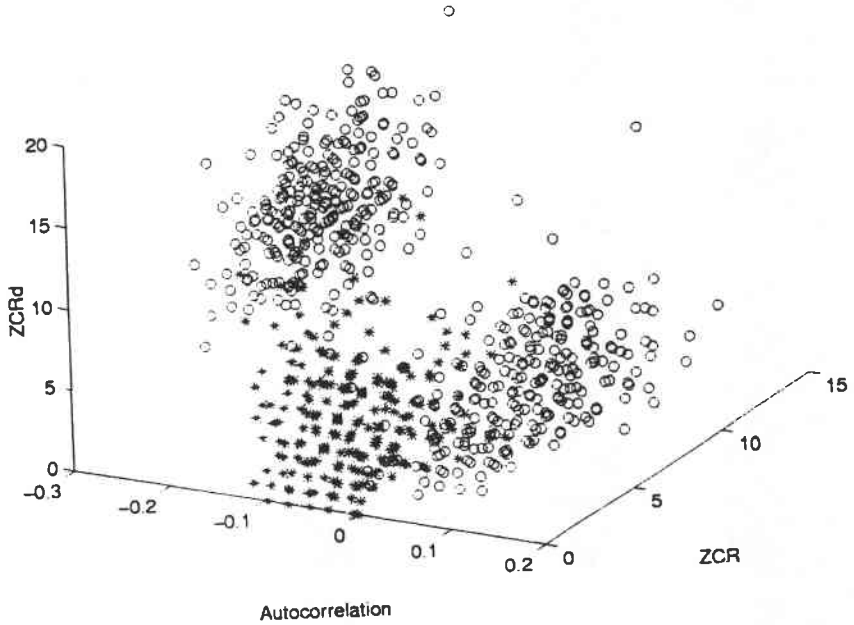


Fig. 2. The distribution of the learning patterns: (*) tone presence, (○) tone absence.

Fig. 3 shows the three FTD fuzzy rules in graphic form. The fuzzy rules in the figure can be interpreted as follows. On the three rows we have the rules, in the first three columns the three fuzzy sets relating to the corresponding inputs, and in the last column the output. When one of the fuzzy sets is missing, it means that the corresponding input is missing in that rule. For the output (fourth column) a Gaussian was drawn with a centre c_{yFTD} and a sigma equal to σ_{yFTD}. The graphic representation thus has to be interpreted as follows: the maximum of the Gaussian corresponds to the crisp output value, while its "breadth" represents the weight of the rule.

In terms of linguistic variables, the rules can be interpreted as follows:

1. **IF (Z is High OR very High) THEN (signal is not a tone)** rule weight $=0.332$
2. **IF ($\rho_{xx}(1)$ is Medium) AND (Z_d is very Low OR Low Or Medium OR High) THEN (signal is a tone)** rule weight $=0.198$

Table 1
FTD rules

r	$c_{\rho r}$	$\sigma_{\rho r}$	c_{Z_r}	σ_{Z_r}	$c_{Z_{dr}}$	$\sigma_{Z_{dr}}$	$c_{y\mathrm{FTD}}$	$\sigma_{y\mathrm{FTD}}$
1			13.439	3.207			0.008	0.332
2	−0.063	0.027			0.258	11.279	0.967	0.198
3	0.153	0.166	11.228	5.508	12.649	1.775	0.032	0.493

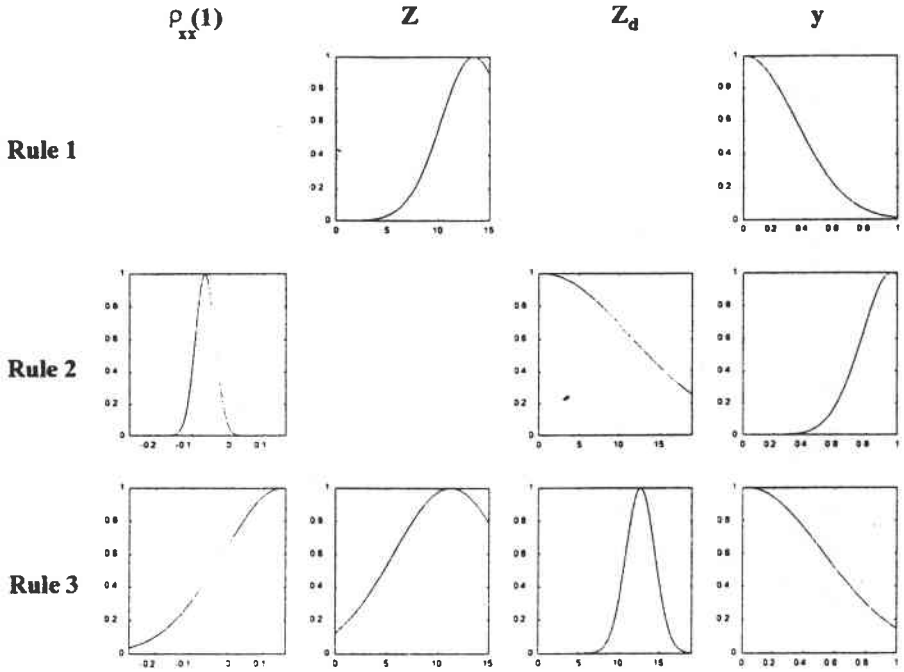


Fig. 3. Graphic representation of the FTD fuzzy rules.

3. **IF** ($\rho_{xx}(1)$ **is Medium OR High OR very High) AND** (Z **is Low OR Medium OR High OR very High) AND** (Z_d **is High and NOT very High) THEN (signal is not a tone)** rule weight $= 0.493$

It is interesting to point out that the statement made at the end of Section 4 is confirmed by these rules. If, in fact, $\rho_{xx}(1)$ is approximately that of the 2100 Hz (−0.0785) sinusoidal tone and the other two parameters are approximately null the fuzzy system detects the tone. This is because:

1. The degree of membership, θ_1, of the first rule is almost null since $\theta_1 = \alpha_{Z1} \cong 0$.
2. θ_2 of the second rule is almost unitary since $\theta_2 = \max\{\alpha_{\rho 2}, \alpha_{Z_{d2}}\}$ and both $\alpha_{\rho 2}$ and $\alpha_{Z_{d2}}$ are equal to about 1.
3. θ_3 è is about null as $\alpha_{Z_{d3}}$ is.

Numerous considerations could be made about these rules, but one in particular explains why, as we shall see below, the system obtained is extremely robust.

Let us assume that because of the presence of noise we have a tone for which a very high Z value is calculated, for instance 7–8, while the other values remain close to the ideal ones. What happens is that rule number two, i.e. the one which detects the tone, remains activated with a degree of about 1 and

at the same time rule number one starts to be activated with a slightly positive θ_1. However, on account of the centroidal nature of the defuzzification process, weighted by the degrees of activation of the rules, although the output of the FTD will no longer be one it will still be quite close to it.

5.3. Simulation and comparison results

A series of tests were performed to check functioning and see whether the detector met the requirements of the ITU-T, as well as to assess performance.

The first test was for failure to detect tone and was performed by sending long voice-data sequences and Gaussian noise in input to the FTD. Subsequently sinusoidal tones with a level of −10 dBmO were sent with varying frequencies in the voiceband range. Fig. 4 shows some of the results of these last tests with various SNRs. As can be seen in the frequency range 2100 ± 21 Hz the values obtained are always above the threshold of 0.4, while with values outside the range 1900–2350 Hz they are below this threshold.

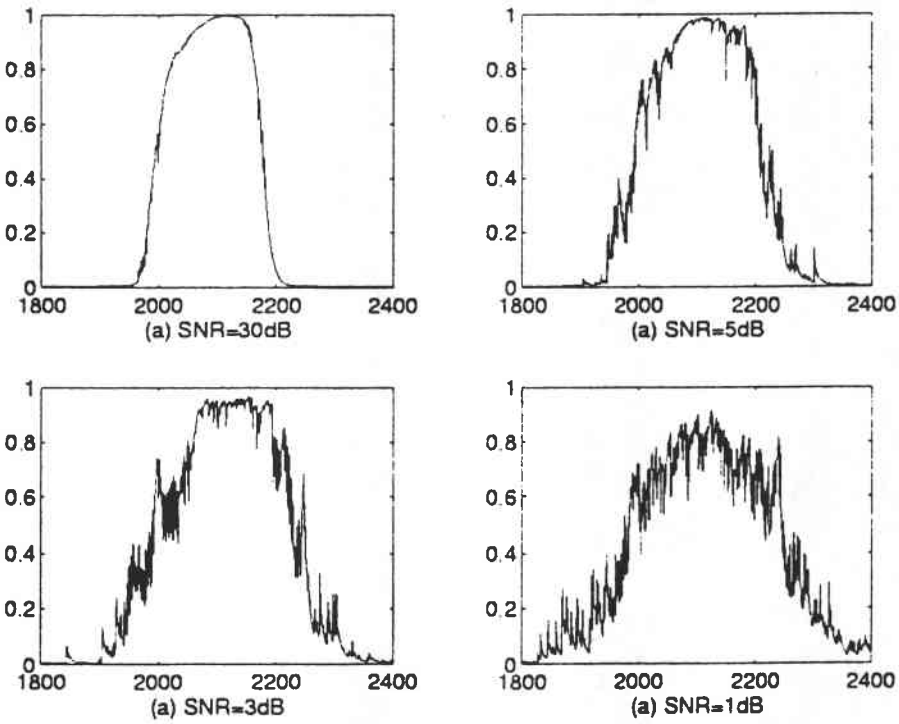


Fig. 4. FTD output with varying tone frequencies.

In terms of probability of false detection and failure to detect, the results were compared with those obtained using a matching model based on the Fisher criterion [?]. It consists of identifying the hyperplane, in the space of the parameters, which best discriminates between two classes. More specifically, if $\bar{x}$ indicates the vector of parameters and $\bar{w}$ the relative weights, classification is based on the following threshold comparison.

$$\bar{x}\,\bar{w} + w_o > w_{th}, \tag{9}$$

where w_o represents the offset constant and w_{th} a fixed detection threshold. The weights vector, in order in which the three parameters adopted are showed in Fig. 3, is $\bar{w} = [-1.1614; -0.0702; -0.0338]$, and $w_o = 0.8667$.

Table 2 shows the comparison results in terms of tone detection probability in the worst-case hypothesis of tones with frequencies on the limits of the region of uncertainty specified by the ITU-T. It was seen that the method proposed works perfectly up to a SNR of 2 dB. With values of SNR = 0 dB performance is still excellent. For applications admitting a greater margin of error, the results obtained with SNRs lower than 0 dB are still interesting. In fact, the FVD starts to misclassify 1900 and 2350 Hz tones as 2100 Hz ones only at 0 dB, but the misclassification error is below 0.7% up to −2 dB. Instead, Fisher's analysis starts to misclassify at 2 dB. The misclassification error ranges within 24.9% ÷ 55.8%. As regards tone presence misclassified as tone absence, we have better performance than Fisher up to 0 dB.

5.4. Fuzzy Logic also helps as a phase reversal detector

Besides the FTD we developed a fuzzy system called FPRD used for the detection of phase reversal. It was essentially inspired by the technique proposed in [8].

Specifically, we calculate the so-called geometric distance between signal samples on the basis of the following relation

$$D_g^2[n] = \frac{(x(n) - x(n+P))^2 + (x(n - \frac{P}{4}) + x(n + \frac{5P}{4}))^2}{A^2} \tag{10}$$

Table 2
Fisher and fuzzy error

SNR	1900 Hz Fisher (%)	Fuzzy (%)	2100 Hz Fisher (%)	Fuzzy (%)	2350 Hz Fisher (%)	Fuzzy (%)
10 dB	0.0	0.0	0.0	0.0	0.0	0.0
5 dB	0.0	0.0	0.0	0.0	0.0	0.0
2 dB	24.9	0.0	0.0	0.0	25.7	0.0
0 dB	43.9	0.6	1.8	0.2	49.6	0.3
−1 dB	35.0	0.7	6.6	17.9	55.8	0.2
−2 dB	30.0	0.3	29.0	50.2	47.8	0.2

Table 3
FPRD rules

r	$c_{D_g^2 r}$	$\sigma_{D_g^2 r}$	$c_{y\mathrm{FPRD}}$	$\sigma_{y\mathrm{FPRD}}$
1	3.429	0.550	0.994	0.021
2	2.419	0.329	0.016	0.514

(for $n = 1, \ldots, P$ and $P = 80$) bearing in mind that, if $f = 2100$ Hz, $x(n) = A\ \sin(2\pi f T_c + \theta)$ is repeated after P samples and the value of A depends on the energy of the analysis frame. Here again a recursive average of the geometric distance is calculated according to a relation similar to (8) and sent to the FPRD which has been trained with only two rules.

It was found that a phase reversal occurs if

$$\sum_{n=1}^{P} \mathrm{FPRD}[n] > P_{\mathrm{th}}, \tag{11}$$

having fixed the value of P_{th} experimentally.

Table 3 and Fig. 5 show the FPRD rules the program extrapolated from the examples. The continuous nature of the FPRD output was extremely useful in

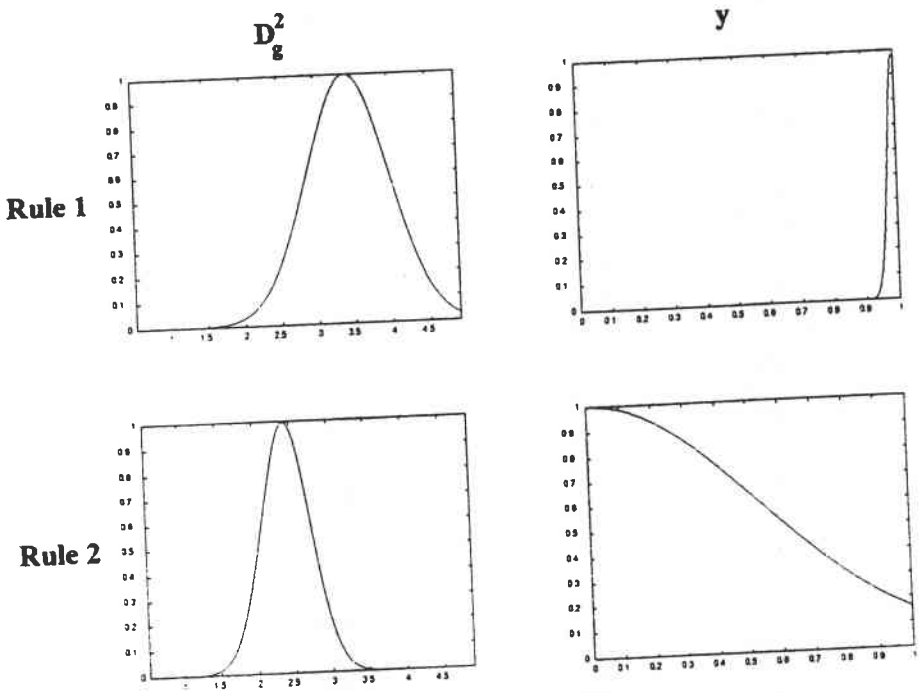


Fig. 5. Graphic representation of the FPRD fuzzy rules.

determining the performance obtained by applying Eq. (11). In fact, the average calculated on these values gave better performance than those obtainable with traditional threshold techniques which have a Boolean output.

The results obtained for phase reversal detection indicate that the detector works perfectly up to SNR = 2 dB while when SNR = 1 dB there is a 1% probability of false or failed detection. As the G.165 Recommendation allows an error probability of 1% for each dB below SNR = 11 dB, for the detection of phase reversal, all the requirements are fully met.

As compared with the performance of the threshold algorithms presented in [8], this technique is more robust to channel noise by about 3 dB.

For this second fuzzy system we are studying the possibility of developing an enhanced version with more inputs. We think that the new FPRD should offer better performance in terms of noise as the effects due to noise can be minimized by the redundant input information supplied.

6. Conclusions

The authors have proposed a new in-band SC-based phase reversal tone detector for use in a digital echo canceller. Through a novel tool that is able to extract fuzzy knowledge, by learning from examples, simple fuzzy rules were obtained for the recognition of a 2100 Hz tone and the periodic phase reversal present in it. The test carried out showed that the algorithm fully meets the specifications of CCITT G.165 up to SNRs of 2 dB. As compared with solutions existing in literature, the fuzzy approach to signal detection proposed here is certainly more efficient in terms of robustness to channel noise and can therefore be usefully applied in all cases in which signals are to be detected with very low SNRs.

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