Dual-tone Multifrequency Signal Detection using Support Vector Machines

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***Abstract*—The need for efficient detection of Dual-tone Multifrequency (DTMF) tones for developing telecommunication equipment is justifiable. This paper presents an artificial intelligence based approach for efficient detection of DTMF tones under the influence of White Gaussian Noise (WGN) and frequency variation, using Support Vector Machines (SVM). Additive WGN in the DTMF input samples is removed by filtering out unwanted frequencies. Detection of DTMF carrier frequencies from input samples employs a traditional software based approach using the power spectrum analysis of the Discrete Fourier Transform (DFT) signals. The Goertzel's Algorithm is used to estimate the seven fundamental DTMF carrier frequencies. A SVM classifier is trained using the estimated fundamental DTMF carrier frequencies, and is validated using the input samples for classification of low and high DTMF frequency groups. The tone detection scheme employs decision logic using a rule-base expert system for classification of low and high DTMF frequency groups, corresponding to valid DTMF frequency groups. Comparison of this hybrid DTMF tone detection model with existing DTMF detection techniques proves the merits of this proposed scheme. This hybrid DTMF tone detection scheme is simulated in a MATLAB environment and results from performance tests are given in this paper.**

***Keywords*—Dual-tone multifrequency tone, Discrete fourier transform, Goertzel's algorithm, Support vector machine.**

I. Introduction

TRANSMISSION receivers have wide tolerances to compensate for distortion caused by aging transmitters, variations in keying characteristics and transmission line distortions[1] such as noise and frequency variation. Estimating frequencies of these signals with interferences such as noise is an important problem in signal processing[2].

In the past 20 years telephone networks have been rapidly moving from analog to digital. In digital switching systems, it is desirable to treat all signals uniformly[1]. Therefore, the need for digital Dual-tone Multifrequency (DTMF) tone detection is justifiable to avoid the costs of hardware needed for analog detectors. With the constant advances in VLSI driving DSP costs download, it is economically sound to replace analog detectors with their digital counterparts which are more reliable, maintenance cost effective, and spatially minimal[1].

Efficient voice coding techniques are designed to maximize the subjective quality of reconstructed speech. At low bit rates this goal does not necessarily result in waveform fidelity[3]. Signal detection of DTMF tones involves the detection of each of the signaling tones, validation of a correct tone pair, and timing to determine that a digit is present for the correct amount of time with the correct spacing between tones. In addition, depending on the algorithm used for detecting the carrier frequencies[4], it is necessary to improve the performance of the detection technique to cope with the presence of speech, noise and frequency variation.

This paper develops a software based DTMF detector for detection of DTMF tones under the influence of White Gaussian Noise (WGN) and frequency variation. The proposed DTMF detector employs an artificial intelligence based approach for efficient detection of fundamental DTMF carrier frequencies. The rest of this paper is organized as follows: Section II describes the characteristics and fundamentals of DTMF tones. Section III gives a brief overview of the Goertzel's Algorithm. Section IV introduces Support Vector Machines (SVM) used for classification. Section V discusses the design and implementation of the hybrid DTMF tone detection model. Section VI shows experimental results, and performance characteristics of the DTMF detector. Section VII presents concluding remarks.

II. DTMF Tones

A. Overview

A DTMF tone consists of two superimposed sinusoidal waveforms summed together from a set of seven standardized frequencies[5]. These standardized frequencies consist of two mutually exclusive frequency groups: the low frequency group and the high frequency group[6,7]. Four low frequency tones (< 1 kHz) are assigned to rows, while three high frequency tones (> 1 kHz)[4] are assigned to columns as shown in Table I[3]. This allows a touch tone keypad to have up to twelve unique DTMF tones[5]. Upon pushing a button, two frequencies are transmitted corresponding to the column-row intercept at that button. The general formula for a pure DTMF signal is characterized by the following equation[7]:

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$$x(t) = A_M \cos(2\pi f_L T + \theta) + A_M \cos(2\pi f_H T + \theta) \quad (2.1)$$

where A_M is the amplitude for each DTMF signal, f_L and f_H are the low and high frequencies, θ is the phase shift[7], and T is the duration of the signal based on the number of samples.

B. *DTMF Tone Standards*

DTMF signals initially developed by Bellcore, were recently redefined by the International Telecommunication Union (ITU) as Q.23 and Q.24 standard DTMF recommendations[5]. These recommendation standards specify operational values for several technical parameters so as to ensure proper generation and decoding of DTMF signals. Standards for DTMF reception specified by the ITU are shown in Table II[6].

TABLE I
TOUCH TONE KEYPAD CORRESPONDING TO DTMF TONE FREQUENCIES

Frequency (Hz)	High frequency group f_H (> 1 kHz)		
Low frequency group f_L (< 1 kHz)	1209	1336	1477
697	1	2	3
770	4	5	6
852	7	8	9
941	*	0	#

III. GOERTZEL'S ALGORITHM

The Goertzel Algorithm enables individual DFT coefficient generation using a simple recursive filter, which incorporates a second-order digital resonator[1]. Instead of computing all N-DFT coefficients, Goertzel's Algorithm detects DTMF frequencies using a bank of seven filters.

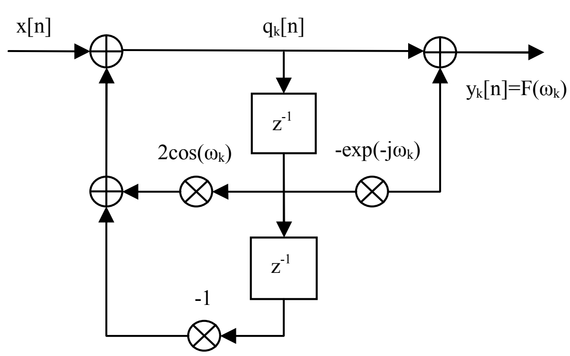

Figure 1. Block diagram of Goertzel's Algorithm

Setting the DFT index k to yield an exact DTMF frequency of interest f_i, i.e., $k = Nf_i/f_s$, where N is the length of the block and f_s is the sampling frequency (8 kHz), the DFT is computed to detect energy at the exact DTMF frequencies[6]. The operation of Goertzel's Algorithm is described by[8]:

$$q_k[n] = x[n] + 2\cos\omega_k q_k[n-1] - q_k[n-2] \quad (3.1)$$

$$y_k[n] = q_k[n] - q_k[n-1]\exp(-j\omega_k) \quad (3.2)$$

where *x[n]* comprises of the samples of the input signals, n is the number of samples, and ω_k is the k^{th} DFT sample. The block diagram of the Goertzel's Algorithm is shown in Figure 1. The recursive part of Goertzel's Algorithm is represented in (3.1), which is executed for every input sample, while the non-recursive part of Goertzel's Algorithm is represented in (3.2), is executed at N times lower than the sampling rate (8 kHz), since[8]:

$$X(\omega_k) = y_k[n]|_{n=N} = y_k[N] \quad (3.3)$$

The frequency bins of the true DFT are evenly spaced[8]:

$$\omega_k = 2\pi f_k = 2\pi k f_s / N \quad (3.4)$$

TABLE II
ITU STANDARDS FOR DTMF SIGNALS

Characteristic	Type	Specification
Frequency tolerance	Operational	≤ 1.5% of Hz
	Non-operational	≥ 3.5% of Hz
Signal duration	Operational	40 ms min.
	Non-operational	23 ms max.
Signal exceptions	Pause duration	40 ms min.
	Signal interruption	10 ms max.
Twist	Forward	8 dB
	Reverse	4 dB
Signal strength	Signal-to-noise ratio	15 dB min.
	Signal power	-26 dBm min.

IV. SUPPORT VECTOR MACHINES

Support vector machines (SVMs) introduced by Vapnik, map data from an input space to a high-dimensional feature space, in which an optimal separating hyper-plane that maximizes the boundary margin between the two classes is established. Given training data consisting of i labeled vectors represented by $\{\vec{x}_i, y_i\}$ for i = *1, 2, ..., k*, where $\vec{x} \in \Re^n$ represents an n-dimensional input vector and $y \in \{-1, +1\}$ represents the class label. These training patterns are linearly separable if a vector $\vec{w}$ (orientation of a discriminating plane) and a scalar b (offset of the discriminating plane from origin) can be defined so that inequalities (4.1) and (4.2) are satisfied[9].

$$\vec{w} \cdot \vec{x}_i + b \geq 1, \quad if \quad y_i = 1 \quad (4.1)$$

$$\vec{w} \cdot \vec{x}_i + b \leq -1, \quad if \quad y_i = -1 \quad (4.2)$$

A hyper-plane which divides the data is to be determined. This amounts in determining $\vec{w}$ and b so that[9]:

$$y_i(\vec{w} \cdot \vec{x}_i + b) \geq 0, \quad for \quad i = 1,2,...,N \quad (4.3)$$

If a hyper-plane is satisfies (4.3), then the two classes are known to be linearly separable. Then (4.3) is written as[9]:

$$y_i(\vec{w}\cdot\vec{x}_i + b) \geq 1 \quad (4.4)$$

The hyper-plane for which the distance to the closest point is maximal, is called the Optimal Separating Hyper-plane (OSH). If the data is not linearly separable, a slack variable ξ_i for $i = 1, 2, \ldots, N$ is introduced with $\xi_i \geq 10$ such that (4.4) can be represented as[9]:

$$y_i(\vec{w}\cdot\vec{x}_i + b) - 1 + \xi_i \geq 0 \quad (4.5)$$

and the solution to find a generalized OSH, can be obtained using following the conditions[9]:

$$\min_{w,b,\xi_1,\ldots\xi_k} \left[\frac{1}{2}\|\vec{w}\|^2 + C\sum_{i=1}^{k}\xi_i\right] \quad (4.6)$$

$$y_i(\vec{w}\cdot\vec{x}_i + b) - 1 + \xi_i \geq 0 \quad (4.7)$$

$$\text{and} \quad \xi_i \geq 0 \quad \text{for} \quad i = 1, 2, \ldots, N \quad (4.8)$$

The first term in (4.6) controls the learning capacity, while the second term controls the number of misclassified points. The parameter C is selected by the user[9], which is viewed as a regularization parameter that characterizes willingness to accept possible misclassifications in linearly non-separable datasets. The classification function is[10]:

$$f(x) = sign\left(\sum_{i=1}^{k} y_i\alpha_i(\vec{w}\cdot\vec{x}_i + b)\right) \quad (4.9)$$

where *sign* represents the signum function, a nonlinear function of the original input vector, and α_i is the support vector of non-negative Lagrange multipliers. In order to solve nonlinear problems, SVMs use a kernel function to allow better fitting of the hyper-plane to more general datasets. A new feature space is constructed by transforming a multi-dimensional space (of $\vec{x}$ and y), where the dimensionality of the feature space is high enough to allow the target patterns to be linearly separable with a high probability[10]. In this case, a mapping function ϕ is used to map x in the feature space $\phi(\vec{x}_i)$ [9] in order to find the OSH. The training samples in the high-dimensional space then become $(\phi(\vec{x}_i), y_i)$ [10]. Accordingly, the kernel function K introduced directly to define an inner product is:

$$K(\vec{x}_i, \vec{x}_j) = \phi(\vec{x}_i)^T \cdot \phi(\vec{x}_j) \quad (4.10)$$

V. Methodology

A. Architecture of Hybrid Model

The proposed hybrid DTMF tone detection model is shown in Figure 2. The model is based on a six-step procedure, which is outlined as follows:

1. The DFT is used to transform the time-domain input DTMF samples to the frequency-domain.
2. A Kaiser Window FIR bandpass filter is applied to the power spectrum of the DFT signals for noise reduction.
3. The power spectrum analysis technique is used to realize two DTMF carrier frequencies from each DTMF input sample.
4. Goertzel's Algorithm is used to estimate the seven fundamental DTMF frequencies of the input samples.
5. DTMF carrier frequencies obtained from the power spectrum analysis are used to train a C-Support Vector Classifier (C-SVC), where the seven estimated DTMF carrier frequencies are used to validate the SVC; separation of low and high DTMF frequency bands into two groups.
6. Decision logic is used for classification of low and high DTMF frequency groups, corresponding to valid DTMF tones.

The hybrid DTMF tone detection model presented in this paper is developed and simulated using MATLAB® R2007b v7.5.0. The DFT and Goertzel's Algorithm models were implemented using the MATLAB Signal Processing Toolbox, and the SVC model was implemented using the MATLAB Bioinformatics Toolbox.

B. DTMF Tone Generation with Additive WGN

In the first stage, input samples of DTMF tones containing two sinusoids are generated using (2.1). The low and high DTMF frequency groups illustrated in Table I (f_H and f_L) are used to generate the dual-tone signal $x(t)$ (defined in 5.1) with parameters $\theta = 0$ and $A_M = 1$. The default DTMF tone sampling frequency f_s = 8 kHz is used, and T = 512 are the number of samples generated for each DTMF tone. The number of DTMF tones (input samples) generated for evaluating the proposed hybrid DTMF tone detection model is 120, i.e., 10 samples generated for each DTMF keypad digit. Since, detection of DTMF tones corrupted with noise requires addition of WGN digitally, additive WGN was implemented using:

$$n(t) = \sqrt{\alpha} \times r(t) \quad (5.1)$$

where α is the variable noise coefficient and $r(t)$ is a vector of pseudo-random values, generated using Gaussian distributed random numbers. The noise term $n(t)$ is linearly summed with $x(t)$ for every DTMF input sample, to generate DTMF signals with WGN.

C. DFT and FIR Filter Implementation

The properties of the DFT enable it to determine the two carrier frequencies present in each DTMF signal sample, by computing the power spectrum of the DFT signal. For the experiment, the 512-point DFT is computed using the FFT algorithm, for all DTMF input samples. The FIR bandpass filter used in the experiment is a Kaiser Window FIR filter, using the default DTMF tone sampling frequency, f_s = 8 kHz. The designed filter has a scaled pass-band and filter order of 823, with the following parameters: F_{stop1} = 550 Hz, F_{pass1} = 600 Hz, F_{pass2} = 1550 Hz and F_{stop2} = 1600 Hz, where

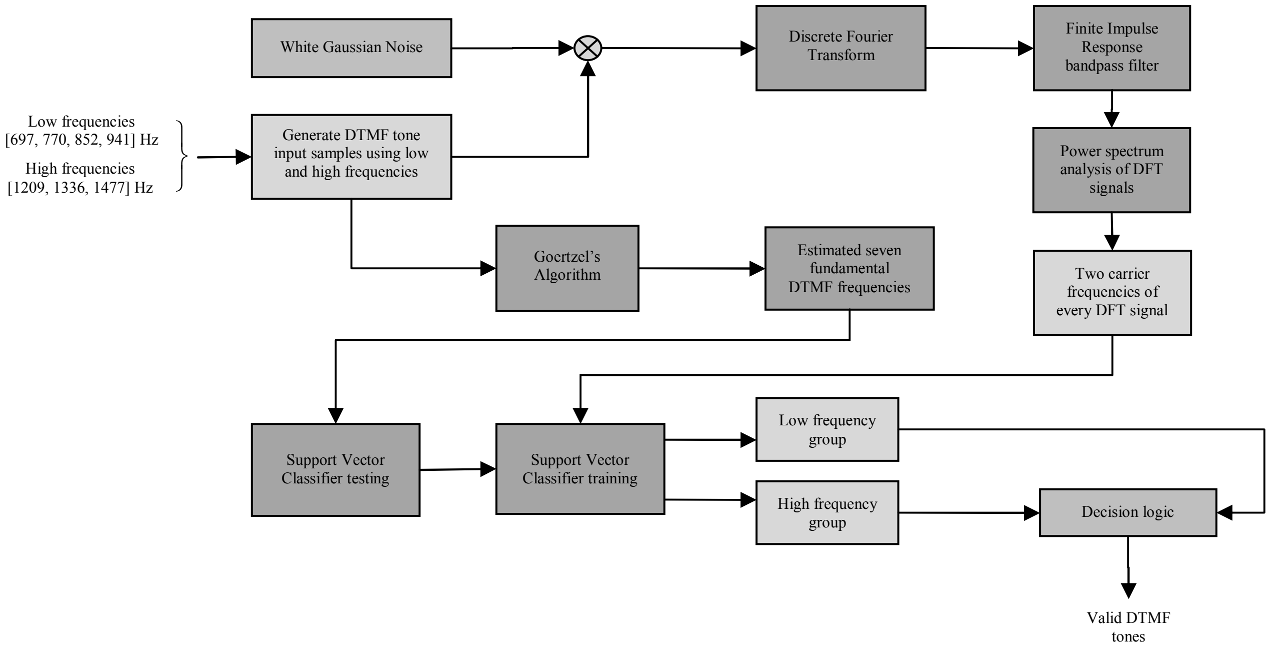

Figure 2. Proposed hybrid DTMF tone detection model

parameters with subscript *stop* and *pass* represent the stop-band edge and pass-band edge frequencies respectively.

As an example, for the DTMF keypad digit 3 corrupted with noise coefficient $\alpha = 0.5$, the FIR bandpass filter implemented is shown in Figure 3. The filter significantly reduces all baseline noises from the DFT signal, as shown in Figure 4.

D. Power Spectrum Analysis

The power spectrum technique is used to realize the two DTMF carrier frequencies from each DTMF input sample, using:

$$P_s(k) = \frac{X(k)X^*(k)}{k}, \ k = 512 \qquad (5.2)$$

where $X(k)$ represents the DFT signal and $X^*(k)$ represents the complex conjugate of the DFT signal. The power spectrum analysis used $k = 257$ number of samples out of the total 512 samples to measure the power of the frequencies. One half of the samples are used because, the other 255 points of the power spectrum are redundant on a meaningful frequency axis. The two frequencies corresponding to the maximum power (DFT magnitude) in every signal are realized for all input samples using the power spectrum analysis technique.

E. SVM Classifier Training

Frequencies obtained from the power spectrum analysis of the input samples are used to train a C-SVC, using two features obtained from the input samples:

- Two carrier frequencies from every input sample
- DFT magnitude at every carrier frequency

Firstly, all training data for the SVM classifier is linearly scaled (normalized) in the range from 0 to 1. The C-SVC is then trained using the Sequential Minimal Optimization (SMO) training algorithm with the parameters: $\rho = 0.001$, $\tau = 15000$, and $\lambda = 0$, where ρ is the tolerance with which the KKT (Karush-Kuhn-Tucker) conditions are checked, τ is the maximum number of iterations of the main loop, and λ is specifies the variables allowed to violate the KKT conditions. Additionally, optimal C-SVC kernel and its parameters are determined through trial and error simulations.

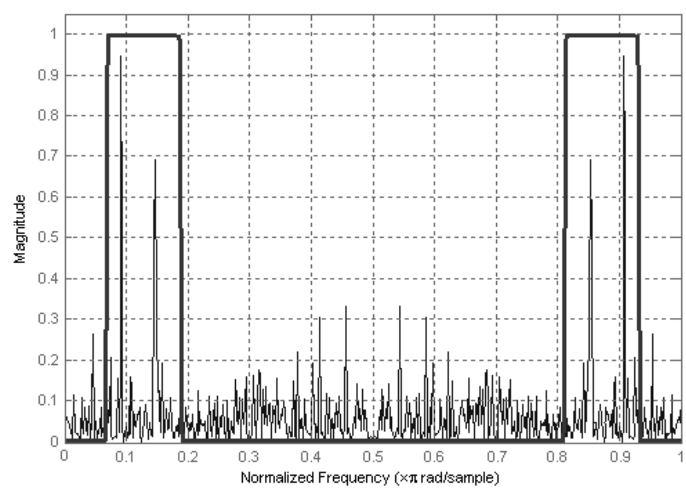

Figure 3. FIR bandpass filter applied to power spectrum of DTMF signal corrupted with noise coefficient $\alpha = 0.5$

F. Goertzel's Algorithm

In the second stage, the second-order Goertzel's Algorithm is used with 1-base indexing to compute the seven fundamental DTMF frequencies defined in Table I, where the default DTMF tone sampling frequency $f_s = 8$ kHz is used. The value of N selected for the Goertzel's Algorithm is based on the number of samples in a half DTMF signaling interval (N < 400), which is a conventional value of $N = 205$.

G. *SVM Classifier Testing*

The seven estimated DTMF frequencies and their respective DFT magnitudes computed from Goertzel's Algorithm are used to validate the trained C-SVC. All testing data for the SVM classifier is linearly scaled in the range from 0 to 1, similar to the training data samples. The C-SVC is validated to classify the training data into two separate groups comprising of the low and high DTMF frequency groups, as shown in Figure 2. Additionally, N-fold Cross-validation is performed by dividing the training data into two sets: training set and validation set, for optimum SVC accuracy.

TABLE III
DETECTION RATE BASED ON KERNEL TYPE

Kernel type	Kernel parameters	Detection rate for 10 trails
Linear	no values	98.82%
Polynomial	$\sigma = 0.45$, d = 3, r = 1	99.37%
RBF	$\sigma = 0.45$	100%
Sigmoidal	$\sigma = 0.45$, r = 0	99.18%

H. *Tone Detection*

After separation of the low and high DTMF frequency groups from all input samples, the DTMF detection model employs decision logic to detect valid DTMF tones, as shown in Figure 2. The separated data obtained from the SVM classifier is un-normalized back to its original magnitude before being validated in the decision logic system.

The logic system uses a rule-based expert system to calculate and compare the sum of the low and high frequencies with respect to their magnitude. Based on the decision of the expert system, frequency pairs (low and high frequencies) are found corresponding to the twelve DTMF tones given in Table I. DTMF tones found by the decision logic system are classified as detected, for all cases of phone number sequences.

TABLE IV
ACCURACY OF DTMF TONE DETECTION MODEL

DTMF input samples	Variable noise coefficient α	Detection rate for 10 trials
120	≤ 0.62	100%
	0.65	99.53%
	0.7	99.24%
	0.9	98.69%
	1.2	97.72%

VI. EXPERIMENTAL RESULTS

A. *Kernel Selection*

The behavior of four different kernels namely: linear, polynomial, radial basis function (RBF) and sigmoidal on the detection rate of the C-SVC were observed, using noise coefficient $\alpha = 0.5$ for the 120 input samples. The parameter values selected for the kernels are shown in Table III, where the kernel parameter σ was selected to be 0.45 for optimal results. From the results obtained, the RBF kernel yielded 100% detection rate for all 120 DTMF input samples. Hence, from this point onwards, all tests performed were done using the RBF kernel and 120 DTMF input samples.

B. *Detection Rate*

The detection rate of the proposed hybrid DTMF detection model was observed using different values of noise coefficient α (defined in 5.1) for the noise term *n(t)*. Table IV indicates the detection rate of the model for 10 consecutive trials, for detection of the low and high DTMF frequency groups from the WGN corrupted input samples.

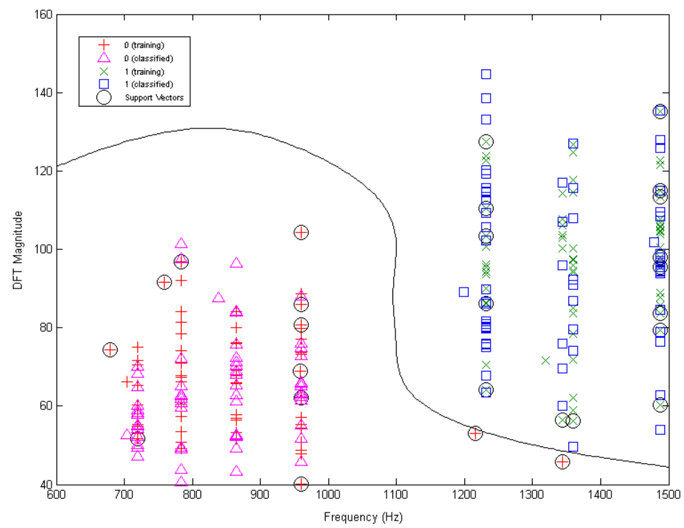

Figure 6. Detection rate of low and high DTMF frequency groups for $\alpha = 0.62$

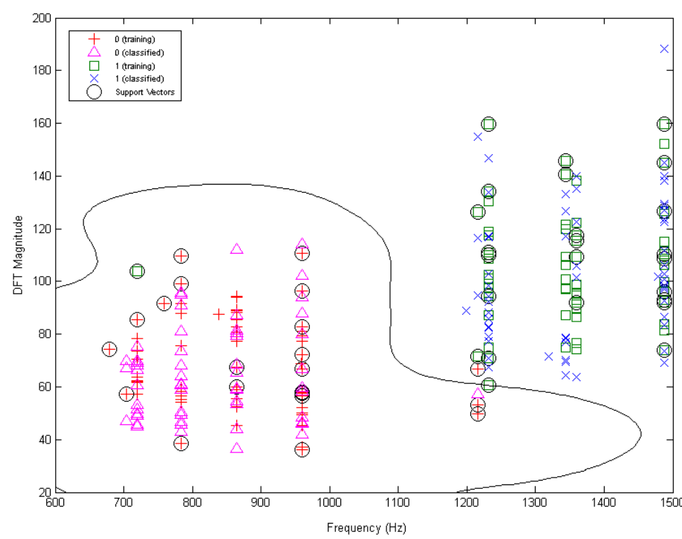

Figure 7. Detection rate of low and high DTMF frequency groups for $\alpha = 1.2$

From the results obtained, it is observed that for noise coefficient $\alpha \leq 0.62$, the DTMF tone detection model detected all DTMF input samples as valid DTMF tones. However, for $\alpha > 0.62$ the model did not accurately validate all DTMF input samples as valid DTMF tones, as illustrated by Figures 6 and 7. The DTMF tone detection model met the ITU Q.23 and Q.24 standard DTMF recommendations. The generated DTMF input samples with noise coefficient $\alpha = 0.62$, lied within $0.57\% \leq$ Hz $\leq 1.48\%$ of the original DTMF carrier frequencies for an operational frequency tolerance of $\leq 1.5\%$ Hz, as specified in Table II.

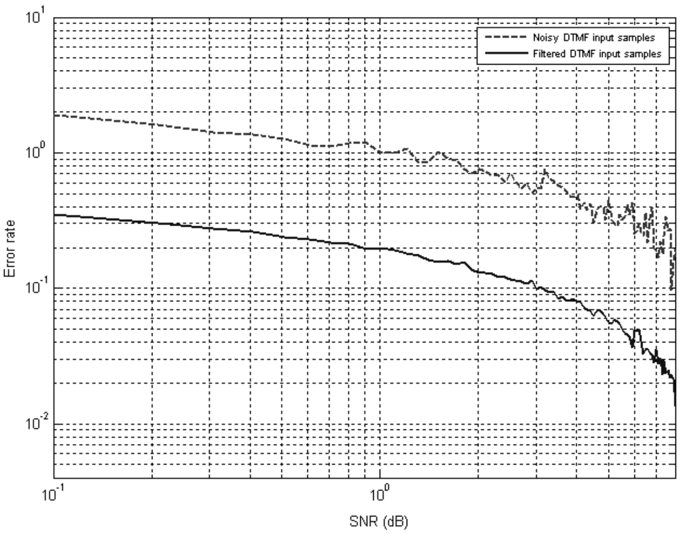

Figure 8. SNR vs. error rate for noisy and filtered DTMF input samples

C. *Signal-to-Noise Ratio*

The signal-to-noise ratio (SNR) for the DTMF input samples with noise coefficient $\alpha = 0.62$ was computed. Additionally, error rates were computed for all 120 sample validations, to determine the efficiency of the proposed hybrid DTMF detection model. The overall system performance obtained for the noisy and filtered input samples is compared in Figure 8. For the filtered DTMF input samples it was observed that, at the higher SNR levels error rates begin to decrease gradually. In comparison with noisy DTMF input samples, filtered DTMF input samples contained a higher degree of tolerating noise; produced lower error rates with same level of WGN.

Comparisons with similar DTMF signal detection techniques were conducted to prove the efficiency of the proposed model. Firstly, comparison with previous work done on DTMF tone detection under the influence of variable noise in [2], revealed that our proposed model has superior performance with aspect to lower error rates at higher SNR levels, compared to the earlier model. In addition, comparison with [11] revealed that our proposed DTMF detection model is more efficient for noise reduction, through the use of a window based FIR filter.

VII. CONCLUSION

In this paper, an artificial intelligence based approach for detection of DTMF tones under the influence of WGN and frequency variation is presented. The toolboxes in the MATLAB environment were used in the experiment for DTMF tone generation, signal analysis and phone number detection. The hybrid DTMF tone detection model is based on the power spectrum analysis by means of the DFT and Goertzel's algorithm, where the SVM classifier separates low and high DTMF frequency groups realized from the DTMF input samples. Experimental results obtained demonstrate the feasibility of applying this new hybrid model as a software based approach for DTMF tone detection. Apart from the quality of the input signal, the DTMF tone detection model proved to be successful on all given cases of phone numbers. In addition, comparisons with previous DTMF tone detection schemes in [2,11] show that this hybrid model produces far better detection rate compared to previously proposed DTMF detection models.

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