Classification of Dual-Tone Multi Frequency Tones using Counterpropagation Neural Network

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***Abstract*—Dual Tone Multi Frequency is widely used in telecommunication sector today. In this case, the proper classification of DTMF tones are necessary for development of telecommunication equipments. DTMF generator generates tones and when tones are transferred it added some noise in it. Noise in the DTMF is removed by filtering out the contaminated signals. Seven fundamental frequencies are estimated by applying Goertzel algorithm and construct classification structure from these estimated result. Counter propagation neural network (CPNN) classifies DTMF tones using this constructing structure and divide into groups of low and high frequencies. This paper represents classification model of DTMF tones and compare with existing models. This DTMF tone classification model is simulated in MATLAB and result of performance tests are given in this paper.**

***Keywords*—DTMF, CPNN, DFT, Goertzel algorithm, FIR filter.**

I. Introduction

Communication is essential equipment in the present world. Without communication it is not possible to think anything in this time. For communication with others, there are manufactured various kind of communication and transmission devices. But, variation of noisy and unwanted signal [1]–[6] is created wide tolerances to compensate for transmission media. Estimating real tones with interferences such as noise is an important problem in signal processing scheme.
Telephone network is rapidly converted from analog to digital in the past 20 years. In digital systems, it is desired to treat uniformly all signals. DTMF tone classification is related to detect each signal tone, validate to correct tone pairs and detect correct digit in time with tones. So, It is necessary to improve the performance of classification of DTMF tone with presence of noise, speech and frequency variation. Artificial Neural Network is offered a new approach in this case. This paper is focused on DTMF tone classification approach by using an Artificial Neural Network approach named CPNN [7]–[9] and discusses its performance in details.

II. DTMF Tones

DTMF consists of two sinusoidal waveforms which are generated from seven standard frequencies [10]–[12]. These seven standard frequencies also divided into two groups:

1) Low frequency group
2) High frequency group

Here, four low frequency tones are positioned to the row and three high frequency tones are positioned in the column. This creates twelve column-row combination frequencies in the touch tone keypad. The following formula is generated by-

$$x(t) = Acos(2\pi f_L T + \theta) + Acos(2\pi f_H T + \theta) \qquad (1)$$

Where,
A = Amplitude of DTMF signal,
f_L = Low frequency
f_H = High frequency
T = Duration of signal based on number of samples.

DTMF tone initially developed by Bell Laboratories but later it is redefined by International Telecommunication Union (ITU) and recommended Q.23 and Q.24 standards [13]. This recommendation is specified operational values and technical parameters that is useful for properly generated value and decoding DTMF.

Frequency	**High frequency group f_H**		
Low frequency group f_L	1209	1336	1447
697	1	2	3
770	4	5	6
852	7	8	9
941	*	0	#

TABLE I: Tone Touch Keypad corresponding to DTMF tone frequencies

Characterstics	**Type**	**Specification**
Frequency	Operational	$\leq 1.5\%$ of HZ
Tolerancy	non-operational	$\leq 3.5\%$ of HZ
Signal duration	Operational	40 ms min
	non-operational	23 ms max
Signal Exception	Pause Duration	40 ms min
	SIgnal Interruption	10 ms max
Twist	Forward	8 dB
	Reverse	4 dB
Signal Strenght	Signal to noise ration	15 dB min
	Signal power	-26 dB min

TABLE II: ITU Standard for DTMF signals

III. Goertzel's Algorithm

Goertzel algorithm enables individual DFT generator using simple recursive filter which incorporate a second order digital resonator. Instead of computing N DFT co-efficient, This algorithm detects DTMF frequencies using a group of seven filters. Setting index k to get exact DTMF frequency of interest

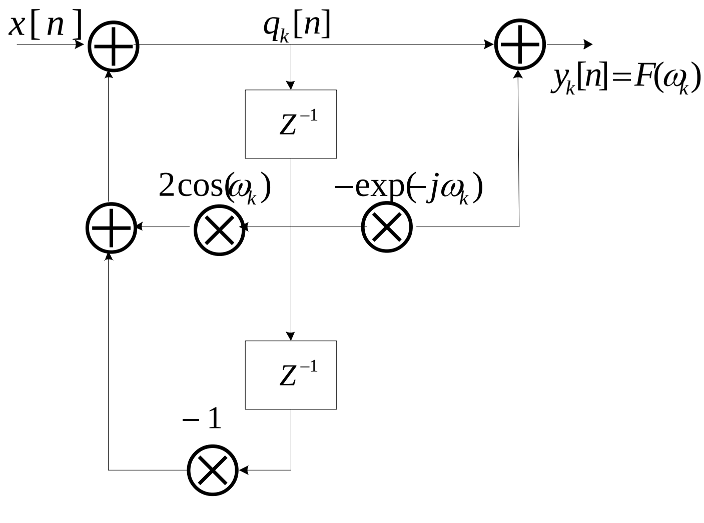

Fig. 1: Block diagram of Goertzel's Algorithm

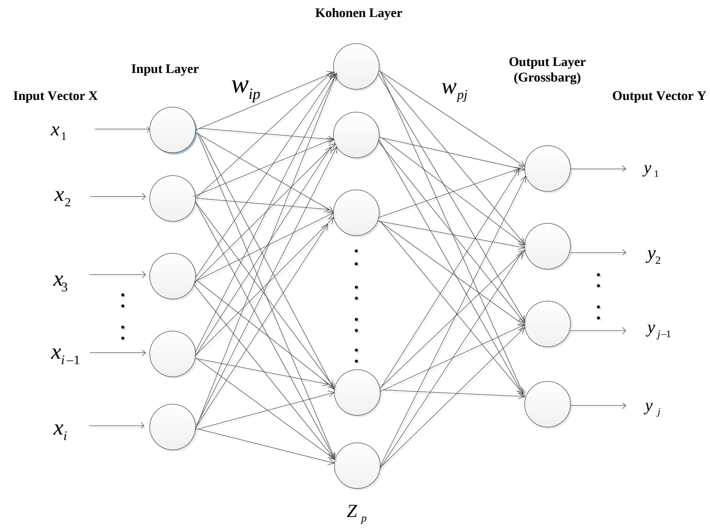

Fig. 2: Counter Propagation Neural Network

f_i in DFT.

$$K = \frac{N f_i}{f_s} \tag{2}$$

Where,
N is the length of block.
f_i is the tone frequency
f_s is the sampling frequency (8 kHz).

Now, the operation of Goertzel algorithm is described:

$$q_k[n] = x[n] + 2cos\omega_k q_k[n-1] - q_k[n-2] \tag{3}$$

$$y_k[n] = q_k[n] - q_k[n-1]e^{-j\omega_k} \tag{4}$$

Where ,
$x[n]$ is the sample of input signals.
n is the number of samples
ω_k is the k_{th} DFT sample
The recursive part of Goertzel algorithm which is executed for input samples in equation 3 and non- recursive part of Goerzel algorithm which is executed N times lower than the sampling rate (8 KHz). So,

$$X(\omega_k) = y_k[n]|_{n=N} = y_k[N] \tag{5}$$

The frequency bins of true DFT are evently spaced,

$$\omega_k = 2\pi f_k = 2\pi k f_s/N \tag{6}$$

IV. Counterpropagation Neural Network

Counterpropagation Neural Network first introduced by Hecht and Nielsen in 1987 [7], [9], [10]. There are two types of Neural Network, full and forward-only. CPN is developed to an approximate method likely $f(x)$ full CPNN is works if inverse f^{-1} exists and for forward CPNN inverse f^{-1} is not necessarily needed.

Forward-only CPNN is divided into three layers [9], [14]. They are:

1) Input layer
2) Hidden (Kohonen) layer
3) Output (Grossberg) layer

Forward only CPNN is a hybrid Neural Network because it is worked both supervised and unsupervised way.

In first stage, unsupervised learning is used for clustering input samples into different set of data. Then next step, weight vectors are adjusted between kohonen layer and output layer and minimizes error rate between CPN output and desired target. The CPNN algorithm in Figure 1 and flowchart in Figure 3 of this model is given below [9], [15], [16]:

Now, CPNN working procedures are described step by step

1) Input vector consist of n input nodes where $x = (x_1, x_2, ..., x_n)^T$ are normalised.
2) The normalized pattern is sent to the network.
3) In hidden layer, Kohonen layer also consist of p with n dimensions. So, Input vector and Kohonen nodes are competed for the winner z_j .
4) Winner node z_j has weight vector $w_j = (w_{1j}, w_{2j}, ..., w_{nj})^T$ which are closest input vector and winner-take-all operation permits only those hidden nodes which are most similar to the input vectors.So, The distance between Input vector and

Algorithm 1: CPNN learning algorithm

Data: Input vector pair (x, y) from training set
Result: Training data set using counterpropagation network

1 Initialize weights (input and target vector) and learning rate α, β and number of epochs
2 while stopping condition is false do step 3-7
3 for each training input $X(x_1, x_2, x_3, ..., x_i)$ and target vector $Y(y_1, y_2, y_3, ..., y_j)$ do step 3-5
4 Find winner cluster unit and call its maximum index p
5 For unit z_p update weights $w_{ip}^H(t+1) = w_{ip}^H(t) + \alpha[x_i - w_{ip}^H(t)]$ and $w_{pj}^O(t+1) = w_{pj}^O(t) + \beta[y_j - w_{pj}^O(t)]$
6 Reduce learning rate
7 Test stopping condition

weight vector is:

$$D_j = \sqrt{\sum_{i=1}^{n}(w_{ij} - x_i)^2} \tag{7}$$

Where,
D_j = distance between input data and rule.
The minimum distance between input data and rules is given by

$$D_{min} = min_{j=1,p} D_j \tag{8}$$

Where,
D_{min} = the minimum distance between input data and z_j
If D_{min} is smaller than Δ , where Δ is selected before the training of the model, the center of rule,

$$w_{ij}^{new} = w_{ij}^{old} + \alpha[x_i - w_{ij}^{old}] \tag{9}$$

Where, α is the learning rates within the interval $[0, 1]$. If $D_{min} > \Delta$ a new rule will be created and $w_{ij}^{new} = x_i$, The learning rate is usually reduced after entire training data is presented.

5) Repeat 1 to 4 for all training pattern processes will be iterated until the number of rule will be stable.
6) Repeat 5 until each input pattern associated with the same competitive unit.
7) Repeat 2 to 4 to this current pattern and adjust the connection between hidden and output layers and π_{jk} has to be updated as

$$\pi_{jk}^{new} = \pi_{jk}^{old} + \beta[y_k - \pi_{jk}^{old}] \tag{10}$$

Where,
β is the learning rates within the interval $[0, 1]$.
If $D_{min} > \Delta$ a new rule will be created and $\pi_{jk}^{new} = y_k$. The learning rate is usually reduced after entire training data is presented.

8) Repeat 7 for all training pattern processes once will be iterated until the number of rule will be stable.

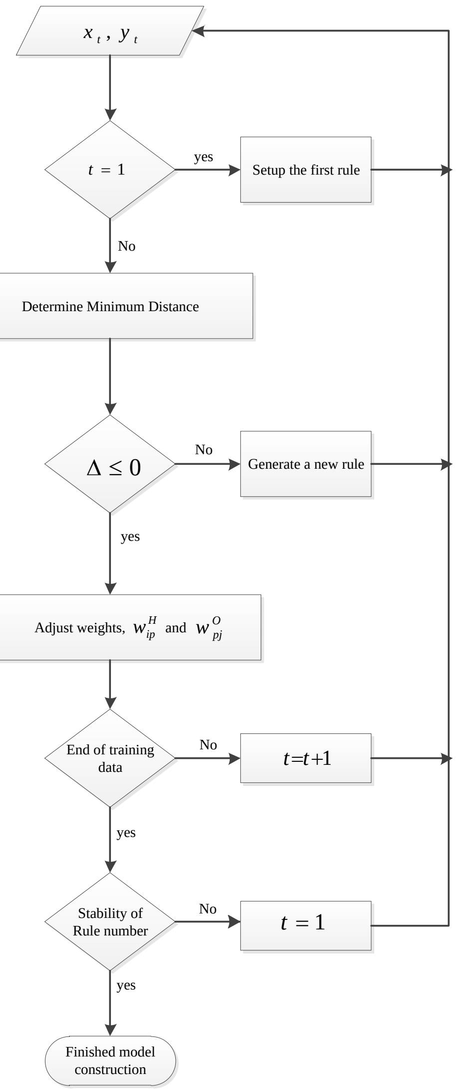

Fig. 3: Flowchart of CPNN model

V. System Methodology

Artificial Neural Network has been proposed in different areas of research. They are more efficient than the conventional algorithms and gives interesting tools for advanced research and applications. Besides, ANNs is more efficient at recognizing and distinguishing complex vectors according to their ability to generate and form some internal representations of the supplied input signal. This ability makes it useful for decoding Dual Tone Multi Frequency Detection.
In this case, Proposed Counter propagation model is worked both supervised and unsupervised way in this model. It is better topological model than back propagation model. It functions as a look up table. The learning process is associated with input vector based on two well known algorithm, which Are Kohonen self organizing map for finding the most similar training Vector and Grossberg outstar map for projecting corresponding output vector. So, Once the network

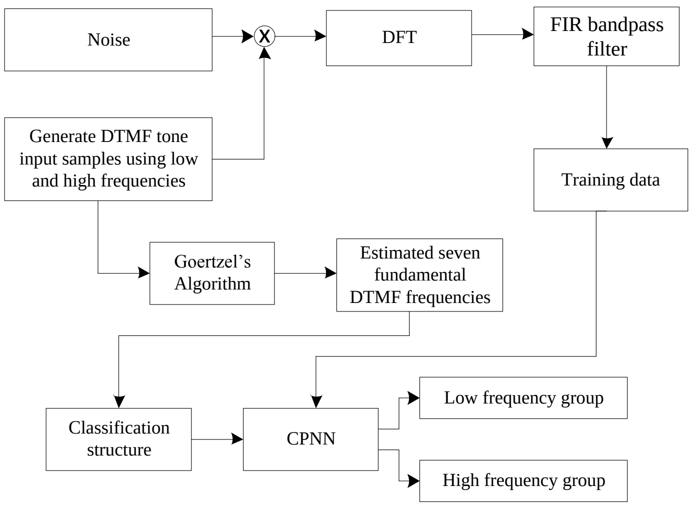

Fig. 4: DTMF Tone classification model

is trained, the application of input vector can quickly produce corresponding output vector.

The proposed DTMF tone detection model is shown in Figure 4 and working steps are described below:

1) DFT is used to transform DTMF input time domain samples into frequency domain.
2) Since, the period of classification DTMF tones are corrupted with noise using following way

$$n(t) = \sqrt{\alpha} \times r(t) \tag{11}$$

Where,
α = noise co-efficient $r(t)$ = vector of psudo-random value $n(t)$ = noise term which is linearly summed with DTMF input samples and generate signal with noise.
3) A FIR bandpass filter is applied for the filtering unwanted noise from noisy signal and Generate training data.
4) Goertzel's algorithm used to estimate seven fundamental DTMF frequencies of input samples.
5) Then, Generate CPNN class vector from estimated results which is used to classify training data.
6) DTMF input samples are used to train by Counter-propagation Neural Network and calculated error-rate and accuracy of predicted samples and separated them low and high frequencies groups.

The DTMF classification model is developed and simulated MATLAB R2013a version 8.1 .Besides, DFT and Goertzel algorithm is implemented using Signal Processing Toolbox and CPNN model is implemented Kohonen CPNN Toolbox.

VI. Result and Discussion

In this experiment, twelve DTMF frequency pairs are generated from low frequency and high frequency dataset [17], [18]. Then, 204 input samples are generated by adding low and high frequency with amplitude and send it to the network with 26.5 ms for minimizing error for further processing. Now, generate the class or target vector from real DTMF tones. Then, train input samples with several number of neuron and epochs result is show in table and best possible results is given Table III.

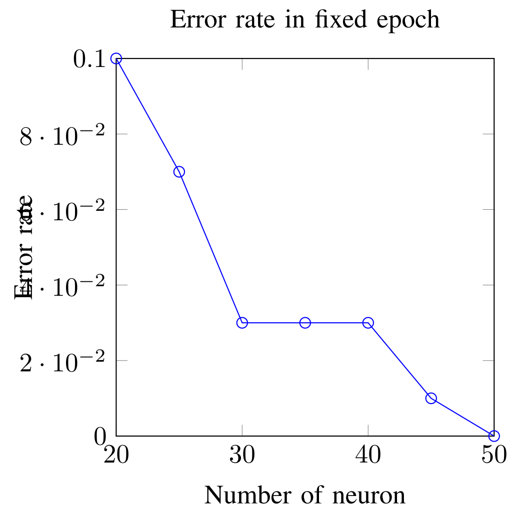

Fig. 5: Error rate of different DTMF tones prediction

Epochs	Neurons	Error rate
10	20	0.093
10	25	0.069
10	30	0.034
10	35	0.029
10	40	0.025
10	45	0.005
10	50	0.000

TABLE III: Experiment Result

Training result show by graphically in figure 5.

In this experiment, It is notice that this neural network tone classification approach is useful for detect any tone according to class value is time-consuming, faster and easier implementation than previous process. Besides, it also provide low error rate and high accuracy than any other process.

VII. Conclusions

In this experiment, DTMF tones can be classified very faster, easier and effective way using counterproagation neural network and in this approach we simply classify DTMF tones and divide them into low and high frequency groups.But, we simply simulate DTMF tones classification into MATLAB environment and apply conventional CPNN model. So, In future, we have to implement this approach in practical devices and try to implement CPNN Neural Network with various faster classification approach to get more accurate result using our proposed model.

References

[1] P. K. Vyas, P. Rawat, and S. Khatri, "Back propagation based adaptive noise chancellor," *International Journal of Computer Technology and Electronics Engineering (IJCTEE)*, vol. 1, pp. 14–16, 2011.

[2] C. Ching-Haur, C. Kang-Ming, and K. Hsien-Ju, "Removal of random noises for electrocardiogram (ecg) signals using adaptive noise canceller without reference input," *International Journal of Physical Sciences*, vol. 6, no. 24, pp. 5699–5705, 2011.

[3] M. A. G. Correa and E. L. Leber, "Noise removal from eeg signals in polisomnographic records applying adaptive filters in cascade," 2011.

[4] J. Mahil and T. S. R. Raja, "An intelligent biological inspired evolutionary algorithm for the suppression of incubator interference in premature infants ecg," *Soft Computing*, vol. 18, no. 3, pp. 571–578, 2014.

[5] L. Badri, "Development of neural networks for noise reduction." *Int. Arab J. Inf. Technol.*, vol. 7, no. 3, pp. 289–294, 2010.

[6] Z. Vahabi and S. Kermani, "Desired accuracy estimation of noise function from ecg signal by fuzzy approach," *Journal of medical signals and sensors*, vol. 2, no. 3, p. 176, 2012.

[7] S. Juang, Y. Tarng, and H. Lii, "A comparison between the back-propagation and counter-propagation networks in the modeling of the tig welding process," *Journal of Materials processing technology*, vol. 75, no. 1, pp. 54–62, 1998.

[8] P. J. Roberts and R. A. Walker, "Application of a counter propagation neural network for star identification," *American Institute of Aeronautics and Astronautics*, 2005.

[9] F.-J. Chang and Y.-C. Chen, "A counterpropagation fuzzy-neural network modeling approach to real time streamflow prediction," *Journal of hydrology*, vol. 245, no. 1, pp. 153–164, 2001.

[10] P. Daponte, D. Grimaldi, and L. Michaeli, "Neural network and dsp based decoder for dtmf signals," *IEE Proceedings-Science, Measurement and Technology*, vol. 147, no. 1, pp. 34–40, 2000.

[11] J. Nagi, S. Tiong, K. Yap, and S. Ahmed, "Dual-tone multifrequency signal detection using support vector machines," in *Telecommunication Technologies 2008 and 2008 2nd Malaysia Conference on Photonics. NCTT-MCP 2008. 6th National Conference on*. IEEE, 2008, pp. 350–355.

[12] B. Widrow, J. R. Glover Jr, J. M. McCool, J. Kaunitz, C. S. Williams, R. H. Hearn, J. R. Zeidler, E. Dong Jr, and R. C. Goodlin, "Adaptive noise cancelling: Principles and applications," *Proceedings of the IEEE*, vol. 63, no. 12, pp. 1692–1716, 1975.

[13] Wikipedia, "Dual-tone multi-frequency signaling," http://en.wikipedia.org/wiki/Dual-tone_multi-frequency_signaling, Jan 2014, [Online; accessed 02 Mar. 2014].

[14] D. Anderson and G. McNeill, "Artificial neural networks technology," *Kaman Sciences Corporation*, vol. 258, pp. 13 502–462, 1992.

[15] K. Mehrotra, C. K. Mohan, and S. Ranka, *Elements of artificial neural networks*. MIT press, 1997.

[16] L. V. Fausett, *Fundamentals of neural networks*. Prentice-Hall, 1994.

[17] H. Hsu, "Schaum's outline series, signals and systems," 1995.

[18] S. Haykin and B. Van Veen, *Signals and systems*. John Wiley & Sons, 2007.