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Adaptive Complex Transformation for Sensorineural Impairment: A Practical Approach

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Abstract— Hearing impairment is the number one chronic disability affecting many people in the world. Background noise is particularly damaging to speech intelligibility for people with hearing loss especially for sensorineural loss patients. Several investigations on speech intelligibility have demonstrated that sensorineural loss patients need 5-15 dB higher SNR than the normal hearing subjects. This paper describes a practical approach using adaptive complex transformation filtering for sensorineural impairment to improve the SNR of the speech signal. The computer simulated results show superior convergence characteristics of the adaptive complex transformation algorithm by improving the SNR at least 7dB for input SNR's less than and equal to 0 dB, with 120 convergence ratio, better time and frequency characteristics.

Index Terms— Hearing Impairment, Adaptive filter, Sensorineural loss, complex transformation and SNR improvement.

1 Introduction

HEARING impairment is the preamble chronic disability, affecting people in the world. Many people have great difficulty in understanding speech with background noise. This is especially true for a large number of elderly peoples and sensorineural impaired persons.

Hearing loss or deafness can be broadly classified into 2 types. Conductive loss: This type of hearing disability can be measured by audiograms and the intelligibility of the signal can be easily resorted by amplification.

Sensorineural loss: This is a broad class of hearing impairments its origin is in the cochlea or auditory nervous system. sensorineural loss disorders are difficulty to remedy. This type of defects may be due to congenital or hereditary factors, disease, tumors, old age, long-term exposure to industrial noise, acoustic trauma or the action of toxic agents etc. The sensorineural loss patient's experiences difficulty in making fine distinction between speech sounds, particularly those having a predominance of high frequency Energy [6], [10]. He may hear the speaker's voice easily, but be unable to distinguish. For example between the words 'fat' and 'sat' [7], [15]. Two features of sensorineural impairment particularly detrimental to the perception of speech are high tone loss and compression of the dynamic range of the ear. A high tone loss is analogous to low pass filtering. Amplification of the high tones may improve intelligibility, but in these circumstances dynamic range of the ear is a handicap [9], [4]. Because, the dynamic range of the impaired ear may not be sufficient to accommodate the range of intensities in speech signals. So, the stronger components of speech are perceived at a level, which is uncomfortably loud, while the weaker components are not heard at all [2], [4]. Most of the defects in transmission chain up to cochlea can be successfully rehabilitated by means of surgery. The great majority of the remaining inoperable cases are sensorineural hearing impaired patients [3]. Digital technology has made an important contribution in the field of audio logy. Digital signal processing methods offer great potential for designing a hearing aid but, today's Digital Hearing Aid are not up to the expectation for sensorineural loss patients. Hearing-impaired patients applying for hearing aid reveal that more than 50% are due to sensorineural loss. So for only direct Adaptive filtering methods are suggested in the literature for the minimization of noise from the speech signal for sensorineural loss patients [7], [13].

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2 Transform Domain Adaptive Filter

Adaptive NLMS noise canceller provides SNR improvement, with less complexity and is having the capability to track the non-stationary environment. But they are having poor convergence performance. Hence they need more time to converge into the optimal solution and become less feasible in real time applications for digital hearing aid [1], [11] & [14].

Convergence speed of time domain LMS adaptive filters depends on the ratio of the maximum to minimum eigenvalues of the input autocorrelation matrix. Filters having inputs with wide eigenvalue spread requires longer time to converge. Convergence performance of the standard LMS algorithm can be improved by using frequency domain filtering [16]. This type of adaptive filter is called as frequency domain adaptive filter or transform domain adaptive LMS (TDLMS) filter [5], [8]. In this paper, TLMS is implemented by using Running DFT-LMS to reduce the computational complexity of FFT-LMS.

2.1 Running DFT-LMS

The transformation in the transform domain LMS filter can be implemented in a variety of ways. This transform is "continuous flow" transformation and therefore computations can be reduced. The LMS spectrum analyzer is an adaptive system that can be used for the calculation of DFT-LMS as shown in Fig.1.

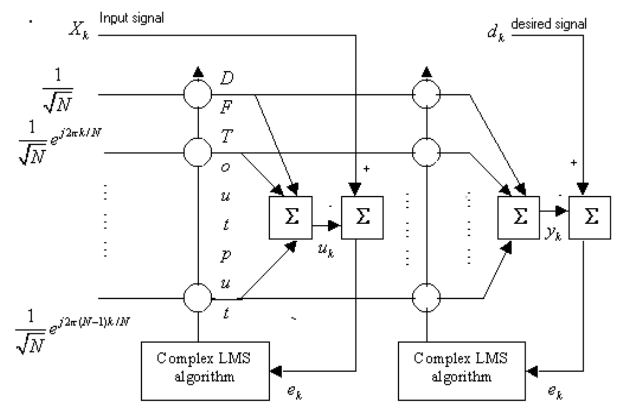

Fig. 1. LMS spectrum analyzer-LMS

At time lN, W_k becomes.

$$W_{lN} = \sum_{m=lN-N}^{lN-1} X_m \overline{a_m}$$

$$= \frac{1}{\sqrt{N}} \begin{bmatrix} \sum_{m=lN-N}^{lN-1} X_m \\ \sum_{m=lN-N}^{lN-1} X_m e^{-j2\pi m/N} \\ \vdots \\ \sum_{m=lN-N}^{lN-1} X_m e^{-j2\pi(N-1)m/N} \end{bmatrix}$$

1

W_k is proportional to the DFT of the input signal X_k. Thus, if we set $\mu = \frac{1}{2}$, the weight vector W_k will be exactly proportional to the DFT of the previous N samples of the input X_k at times k that are integer multiples of N as shown in Fig 1. The remaining part will performer as an adaptive filter. The function of LMS spectrum analyzer-LMS is same as conventional FFT-LMS with less computational complexity.

3. Results and Evaluation

The performance of the algorithm has been evaluated using output SNR, eigenvalue ratio, time plots and intelligibility tests.

3.1 Performance Evaluation by Using Output SNR, Eigenvalue Ratio and Time Plots

The algorithm is evaluated for corrupted speech signals with different types of noises like cafeteria, low frequency and babble noise with different SNR. The input signal is recorded with sampling frequency 22050 Hz in different noisy conditions to evaluate the performance of the algorithm. For different input SNR, the output SNR and eigenvalue ratios are calculated as shown in Table 1. Results show significant improvement in convergence performance by reducing the eigenvalue ratio to 120.09 and 6.7 dB output SNR improvements for 0dB input SNR. Fig. 2 shows the time plots for pure signal, corrupted signal (input signal) with –5dB SNR, and the FFT-LMS filtered signal. Fig. 3 shows the autocorrelation of the corrupted signal after DFT.

The eigenvalue ratio of complex-LMS is less compared to NLMS methods. Hence the convergence performance of the algorithm is significantly improved. Table 1 show that the noise is reduced from the corrupted signal and the speech quality is also improved. The eigenvalue distribution of the input auto correlation matrix has been derived after DFT and power normalization.

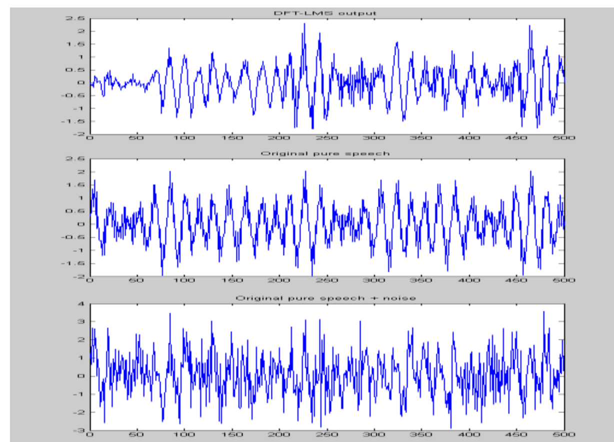

Fig. 2. Original, contaminated and filtered signal for adaptive complex transformation algorithm LMS spectrum analyzer-LMS

TABLE 1

SNR of input and output signals.

Input signal SNR in dB	Output signal SNR in dB	Eigenvalue ratio
0	6.7	120.09
+5	9.01	92.05
-5	3.95	112.6

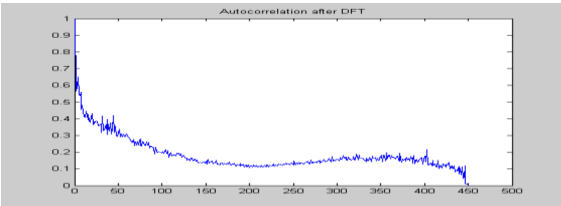

Fig. 3. Autocorrelation of the input corrupted signal after DFT.

3.2 Intelligibility Test

In order to measure the performance of clinical intelligibility tests of the algorithms, listening tests were carried out. The tests were conducted on both hearing impaired and normal hearing persons. The experiment was carried out in a room whose size was about 4 m by 5 m. The room was carpeted but no attempt was made to improve the room acoustics otherwise. The main speaker and the noise source were placed 2.5 feet away from the microphones. For speech intelligibility test, we processed 10 sentences with different noise. These tests were performed on 15 subjects, 5 with normal hearing (Group 1), 5 with a mild to moderate SNHL (Group 2) and 5 with moderate to severe SNHL loss (Group 3).

In the experimental evaluation, the target source was a male speaker reading sentences and interference consisted of 3 different types of noise (1) cocktail party noise (2) five speaker babble (3 male and 2 female) (3) low frequency noise. The noise level is varied to get different SNR. The subjects were listened the original, the noisy and the filtered signals. The percentage of correct responses was recorded. The results are displayed in Tables 2, 3 and 4 for –5dB input SNR. The results indicate that a considerable improvement is obtained, particularly for moderate to severe SNHL subjects. Filter shows reduced average intelligibility of 4 % with normal subjects, 13 % with mild to moderate SNHL subjects and 9 % with moderate to severe SNHL subjects as compared to NLMS with cocktail party noise.

TABLE 2

Average intelligibility score for the noiseless signal

Group1	Group 2	Group 3
96 %	78 %	63 %

TABLE 3

Average intelligibility score for the signal plus noise

Types of noise	Cocktail party noise	Babble noise	Low frequency noise
Group1	73 %	78 %	83 %
Group 2	31 %	34 %	38 %
Group 3	15 %	13 %	16 %

TABLE 4

Intelligibility improvements by complex transformed LMS for three groups of subjects.

Types of noise	Cocktail party noise	Babble noise	Low frequency noise
Group1	90 %	91 %	92 %
Group 2	62 %	61 %	65 %
Group 3	54 %	55 %	53 %

4. Conclusion

Running DFT-LMS method can be used for noise reduction in speech signals. This algorithm is excellent compared to NLMS and single source NLMS algorithm in terms of convergence performance. The eigenvalue ratio is 120 for zero dB and is very less compared to time domain adaptive methods. Hence, this complex transformed adaptive filter can quickly converge to the optimal solution. Off line tests under different conditions show output SNR improvement is lesser than NLMS methods.

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