Noise Diminution In Industries By Fast Factored Adaptive DCT Method

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ABSTRACT: Industrial noise induced hearing loss is an increasingly prevalent disorder that is the result of exposure to high intensity sounds, especially over a long period of time. Noises of industry can cause partial deafness, interference with communication by speech and annoy. These undesirable effects are best avoided by reducing the noise to acceptable levels. Several investigations on industrial noise proved that industrial workers need at least 10-15 dB higher SNR (Signal to Noise Ratio) than the other places. The objective of this paper is to implement Fast Factored Discrete Cosine Transformation Least Mean Square (DCT-LMS) to reduce the effect of industrial noise and to improve overall sound quality of industrial workers. The computer simulated results show superior convergence characteristics of the adaptive complex transformation algorithm by improving the SNR at least 11dB for input SNR's less than and equal to 0 dB, with excellent convergence ratio, better time and frequency characteristics. These results suggest that a headset with digital signal processing adaptive algorithm are useful for hearing protection in workplaces with high levels of wide band industrial noise.

Keywords: Industrial noise, Hearing protection, adaptive filter, SNR improvement, fast factored DCT-LMS, noise diminution.

1. Introduction

Industrial noise induced hearing loss is an increasingly prevalent disorder that is the result of exposure to high intensity sounds, especially over a long period of time. High-intensity noises are a health hazard for industrial workers, and hearing protection is necessary to prevent hearing loss. Hearing loss caused by occupational noise is one of our biggest industrial diseases. It is a disease that has been recognized since the Industrial Revolution. The conventional passive methods, such as ear muffs, are ineffective against low-frequency noise [3]. This problem can be effectively solved by using the adaptive algorithms for different frequencies [4].

Many researchers has stated that [7] noise can not only cause hearing impairment due to long-term exposures of over 85 dB, but it also acts as a causal factor for stress and raises systolic blood pressure. Additionally, it can be a causal factor in work accidents, both by masking hazards and warning signals, and by impeding concentration [12]. Noise also acts synergistically with other hazards to increase the risk of harm to workers [2]. [10] States that exposure to 85 dB of noise for more than eight hours per day can result in permanent hearing loss. Since decibels are based on a logarithmic scale, every 3 dB sound pressure level increase results in a doubling of intensity, meaning hearing loss can occur at a faster rate. Therefore, gradual developing industrial noise induced hearing loss occurs from the combination of sound intensity and duration of exposure.

Noise induced hearing problems are typically is centered at 4000 Hz. The louder the noise is, the shorter the safe amount of exposure is. Normally, the safe amount of exposure is reduced by a factor 2 for every additional 3 dB. For example, the safe daily exposure amount at 85 dB is 8 hours, while the safe exposure at 91 dB is only 2 hours [8], [9]. Sometimes, a factor 2 per 5 dB is used. Personal electronic audio devices, such as iPods, because iPods often reaching 115 decibels or higher. This can produce powerful enough sound to cause significant hearing loss in the workers, given that lesser intensities of even 70 dB can also cause hearing loss [11]. Different kinds of filtering methods are suggested in the literature for the minimization of noise in industries [5], [6]. However, through the proper use of ear protection, education, hearing conservation programs in the workplace, and audiological evaluations, industrial noise induced problems can be reduced [13].

The DCT is a technique that converts a spatial domain waveform into its constituent frequency components as represented by a set of coefficients. The DCT has good orthonormal, separable, and energy compaction property. Most of the signal information tends to be concentrated in a few low frequency components of the DCT. Although the DCT does not separate frequencies, it is a powerful signal decorrelator. It is a real valued function and thus can be effectively used in real-time operation. It is a close relative of DFT – a technique for converting a signal into elementary frequency components, and thus DCT can be computed with a Fast Fourier Transform. Unlike DFT, DCT is a real valued and provides a better approximation of a signal with fewer coefficients. The DCT is central to many kinds of signal processing. For non-stationary signals the DCT provides good approximation of a signal with fewer coefficients [15]. Hence fast factored DCT-LMS algorithm is suited for non-stationary inputs like industrial noise and the convergence time is also less compare to direct LMS techniques and DFT-LMS algorithms.

2. Fast algorithm for computing the DCT

The entire DCT and even MDCT require complexity of $O(N^2)$. Ideally we would like computation times logarithmic or at least linear in the size of the input block length to make the use of these transforms feasible in real time signals. This in turn motivates us to look for algorithm, which computes the DCT and its inverse expressions as fast as efficiently as possible. This paper uses Chen's fast factored DCT algorithm as described below.

2.1 Chen's Fast Factored DCT

In this algorithm, we are using Fast Factored DCT developed by Chen, Smith and Fralick to construct DCT-LMS. The relationship between a given N point sequence $x(n)$ and the DCT of $x(n)$, $X(k)$ can be described in a matrix form as follows.

$$X = \sqrt{\frac{2}{N}}[A_N]x \qquad 1$$

Where $x = [x(0), x(1), ...x(n), ...x(N-1)]^T$ is the vector form of the given N point sequence $x(n)$, $\{x(n), X = [X(0), X(1), ...X(k), ...X(N-1)]^T$ is the vector form of the DCT coefficient sequence $X(k)$ of $x(n)$ and $[A_N]$ is the N^{th} order of the DCT matrix. When N is a power of 2, the DCT matrix $[A_N]$ can be factorized into a product of sparse matrices. This factorization results in one of the fastest DCT implementation. There are different ways to obtain sparse matrix factorizations, resulting in different fast DCT algorithms. This work uses the fast DCT algorithm developed Chen and company. Chen, Smith and Fralick developed a fast DCT algorithm based on the following sparse matrix factorizations of the DCT matrix:

$$[A_N] = [\overline{P_N}] \begin{pmatrix} [A_{N/2}] & 0 \\ 0 & \overline{\overline{R}}_{N/2} \end{pmatrix} [B_N] \qquad 2$$

Where $[\overline{P_N}]$ is a permutation matrix, which permutes the even rows in decreasing order in the lower half. The matrix $[B_N]$ is a butterfly matrix: $[B_N] = \begin{pmatrix} I_{N/2} & \bar{I}_{N/2} \\ \bar{I}_{N/2} & I_{N/2} \end{pmatrix}$ 3

Where $[I_{N/2}]$ is the identity matrix of $\frac{N}{2} X \frac{N}{2}$, and $[\bar{I}_{N/2}]$ is the opposite identity matrix of $\frac{N}{2} X \frac{N}{2}$. The matrix $[\overline{\overline{R}}_{N/2}]$ is derived from the matrix $[R_N]$ by reversing the orders of both the rows and columns of $[R_N]$. The (i, k) element $r_{i,k}$, of the matrix $[R_N]$ is given by

$$r_{i,k} = \cos \frac{(2i+1)(2k+1)\pi}{4N} \qquad 4$$

After applying the transformation, described above, normalizing and by passing through LMS filter gives us fast factored DCT-LMS algorithm.

2.2 Computational Complexity

Computational complexity of transform domain LMS (TDLMS) is very high because of the complexity of transformation. Reducing the complexity of transformation can reduce this high complexity of TDLMS. This algorithm requires $\frac{N^2}{4} - 3$ real multiplications and

$[\frac{1}{2}(N^2 - N)] + 1$ real additions. Thus the total complexity of computations is of the order O(42).

Type of transformation	Number of real additions	Number of real multiplications	Total complexity
Direct DCT	64	56	O(120)
Modified DCT	Forward MDCT 32 Inverse MDCT 32	Forward MDCT 28 Inverse MDCT 24	O(116)
Fast Factored DCT	13	29	O(42)

Table 1. Computational complexity for N=8.

3. Performance evaluation

Performance of the adaptive filters are measured, compared and analyzed with the help of following parameters.

a. Convergence rate: The convergence rate determines the rate at which the filter converges to its resultant state. Usually faster convergence rate is the desired characteristic of an adaptive system. Convergence rate is not, however, independent of all other performance characteristics. If the convergence rate is increased, the stability characteristics will decrease, making the system more likely to diverge instead of converge to the proper solution. In this work, convergence rate is measured in terms of eigenvalue ratio.

b. Minimum mean square error (MSE): The MSE is a metric indicating how well a system can adapt to a given solution. A small minimum MSE is an indication that the adaptive system has accurately modeled, predicted, adapted and/or converged to a solution for the system.

c. Stability: Stability is probably the most important performance measure for the adaptive system. The algorithm convergence time and stability depends upon the ratio of the largest to the smallest eigenvalue associated with the correlation matrix of the input sequence. Therefore, stability of the algorithm is defined in terms of eigenvalue ratio.

d. Eigenvalue ratio: Eigenvalue ratio or the eigenvalue spread is the ratio between the maximum eigenvalue and the minimum eigenvalue of the input autocorrelation matrix. The eigenvalue ratio r can be calculated as

$$r = \frac{\lambda_{\max}}{\lambda_{\min}} \qquad 5$$

Where $\lambda_{\max}$ and $\lambda_{\min}$ are the maximum and minimum eigenvalues, which found on the main diagonal of the autocorrelation matrix. Then the rate of convergence can be calculated as

$$C.rate = \frac{(r-1)^2}{(r+1)^2} \qquad 6$$

From the above equation it is clear that, the convergence time decreases if the eigenvalue ratio increases and vice versa.

e. SNR: Amount of noise filtering can be measured from adaptive system with the help of input SNR and output SNR. Input SNR is the ratio between the power of input signal and power of noise at input. Output SNR is the ratio between the power of filtered signal and power of noise at output. In general SNR is defined as

$$SNR = \frac{\sum_n x^2(n)}{\sum_n e^2(n)} \text{ and } SNR(dB) = 10\log_{10} \frac{\sum_n x^2(n)}{\sum_n e^2(n)} \qquad 7$$

Where, $x(n)$ is the input signal and $e(n)$ is the noise.

The algorithm is evaluated for different types of industrial noises with different SNR. In this work $x(n)$ is the speech signal and $e(n)$ is the industrial noise. Results show that, both parameters SNR and eigenvalue ratio are strongly depending on type of noise.

SNR of the input signal	SNR of the output signal	Eigenvalue ratio
0 dB	11.0 dB	6.09
+5 dB	11.29 dB	5.44
+10dB	13.20 dB	5.6
-10 dB	10.2 dB	5.5

Table 2 Outcome of fast factored DCT-LMS Noise canceller

For different input SNR, the output SNR and eigenvalue ratios are calculated as shown in Table 2. The eigenvalue ratio is calculated to find out how well the algorithm converges to the optimum Wiener solution.

4 Conclusions

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The performance of fast factored DCT-LMS is same as DCT_LMS. But the main advantage of this algorithm is its minimal computational complexity. This algorithm is excellent compared to NLMS and DFT-LMS algorithm in terms of convergence performance. The eigenvalue ratio is 7 for zero dB and is very less compared to time domain adaptive methods and DFT-LMS noise reduction. Hence, this real transformed adaptive filter can quickly converge to the optimal solution.

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