Noise Control in Industries by Adaptive MDCT 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 Modified Discrete Cosine Transformation Least Mean Square (MDCT-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, noise control, adaptive filter, SNR improvement, MDCT-LMS.

I. 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 MDCT-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.

II. DISCRETE COSINE TRANSFORM

On the basis of periodicity, DCT can be classified into four types DCT-1, DCT-2, DCT-3 and DCT-4. Of these, the DCT-1 and DCT-2 representations are the most used transforms. In this work we have used the modified version of DCT-2. For DCT-2 $x[n]$ is extended to have period 2N and the periodic sequence is given by

$$x_2[n] = x[((n))_{2N}] + x[((-n-1))_{2N}] \tag{1}$$

Because the endpoints do not overlap, no modification of them is required to ensure that $x[n] = x_2[n]$ for $n = 0,1,.....N-1$. The DCT-2 can defined by the transform pair

$$X^{c2}[k] = 2\sum_{n=0}^{N-1} x[n]\cos\left(\frac{\pi k(2n+1)}{2N}\right), 0 \le k \le (N-1) \tag{2}$$

$$x[n] = \frac{1}{N}\sum_{k=0}^{N-1} \beta[k] X^{c2}[k]\cos\left(\frac{\pi k(2n+1}{2N}\right), 0 \le n \le (N-1) \tag{3}$$

Where the inverse DCT-2 involves the weighting function $\beta[k] = \begin{cases} 1/2 & k=0 \\ 1 & 1 \le k \le (N-1) \end{cases}$. (4)

A. MDCT

A block transform based on the DCT or DFT is equivalent to a filter bank consisting of multiple band pass filters. Such a filter bank is called as a Time Domain Aliasing Cancellation Filter bank (TDAC). Additionally this method provides an added advantage in the block processing of discrete time signals such as audio and speech. The next step in designing a fast algorithm based on a TDAC filter bank is to select the transform that will be used. A number of transforms, which have a meaningful interpretation in the transform domain, are used in the digital processing of signals. More notably are the DFT and DCT. Of these it was found that the DCT offers maximum advantages [1], [15]. The DCT of a data sequence is defined as in equations (2) and (3). The basis set actually used in TDAC systems is slightly modified and takes on the form:

$$X(k) = 2\sum_{n=0}^{N-1} z(n)\cos\left(\frac{2\pi}{N}(n+n_0)(k+\frac{1}{2})\right), \qquad 0 \le k \le N/2 \tag{5}$$

Where $z(n)$ is the windowed input sequence $z(n)$

$$x(n) = \frac{2}{N}\sum_{k=0}^{\frac{N}{2}-1} X(k)\cos\left(\frac{2\pi}{N}(n+n_0)(k+\frac{1}{2})\right), \qquad 0 \le n \le N \tag{6}$$

Where, $X(k)$ are the spectral co-efficient. $n_o = (N/2+1)/2$ in the equations (5) and (6). Such TDAC with the DCT as the transform is called as the MDCT.

B. MDCT-LMS

In general TLMS has been discussed in three different stages: First stage, *transformation* is explained for general unitary transform. The remaining two stages are power normalization and LMS are as follows.

Stage 1: Transformation of Input Signal

The input to the filter is $x(n) = \left[x(n), x(n-1), ..., x(n-p)\right]^T$ (10)

This vector is processed by a unitary transform T. Once the filter order N is fixed, the transform is just a NXN matrix T with orthogonal rows. We have orthogonal transform matrix T such that the transform matrix T is selected to be a unitary matrix, that is

$$T_n T_n^T = T_n^T T_n = I \tag{11}$$

It is assumed that the input signals of the filter are real-valued and the elements of T are also real valued. Transforming an input signal (equation 10) by a matrix T_n transforms its Toeplitz autocorrelation matrix R_x into a non-Toeplitz matrix

$$B_n = E[T_n^T T_n x_n^T x_n] = T_n^T R_x T_n . \tag{12}$$

The transformed vector is $u_k = T_n[x_n]$ (13)

The matrices R_x and B_n are similar, their eigenvalues are also same. This means no gain in convergence speed when using just orthogonal transformation. However transformed vector can be power normalized, that causes the eigenvalues of the LMS filter to cluster around one and speeds up the convergence of the adaptive weights.

Stage 2: Power Normalization

The transformed signal $u_k(i)$ is then normalized by the square root of their power $p_k(i)$. Where $i = 0,1,.....n-1.$

Power normalizing $T_n X_k$ transforms its elements $(T_n X_k)(i)$ into $\dfrac{(T_n X_k)(i)}{\sqrt{Powerof\,(T_n X_k)(i)}}$.

Where the power of $(T_n X_k)(i)$ can be found on the main diagonal of B_n.

Then the power-normalized signal is $v_k(i) = \dfrac{u_k(i)}{\sqrt{p_k(i) + \varepsilon}}$ (14)

Where $p_k(i) = \beta p_{k-1}(i) + (1-\beta) u_k^2(i)$ (15)

for $i = 0,1,.....n-1.$ The small constant ε is introduced to avoid numerical instabilities when $p_k(i)$ is close to zero. The signals $v_k(i)$ are equal to the transformed outputs $u_k(i)$, but the learning constant μ in LMS filtering is replaced by a diagonal matrix whose elements are proportional to the inverse of the powers $p_k(i)$. This type of LMS is referred to as power-normalized LMS. Transformation followed by a power normalization stage, causes the eigenvalues of the LMS filter inputs to cluster around one and speeds up the convergence of the adaptive weights. The autocorrelation matrix after transformation and power normalization is thus $S_n \triangleq E(diagB_n)^{-1/2} B_n (diagB_n)^{-1/2}$ (16)

If T_n decorrelated x_k exactly, B_n would be diagonal, S_n would be an identity matrix I_n, and all the eigenvalues of S_n would be equal to one, but since practically the DFT is not a perfect decorrelator, this does not work out exactly [14]. But the power normalization makes the eigenvalues of the LMS filter inputs to cluster around one and speeds up the convergence of adaptive weights. The output vector after power normalization is

$$v_k(n) = [v_k(0), v_k(1), ...v_k(n-1)]^T \tag{17}$$

Stage 3: LMS filtering

The resulting equal power signals v_k are applied as an input to an adaptive linear combiner whose weights W_k are adjusted using LMS algorithm.

For real input $W_{k+1} = W_k + \mu e_k v_k$ (18)

And for complex $W_{k+1} = W_k + 2\mu e_k \overline{v_k}$. (19)

This type of adaptive filter is called as frequency domain adaptive filter or TLMS filter. In this paper, TLMS is implemented by using the MDCT (equations 5 and 6) resulting algorithm is called as MDCT-LMS.

C. Computaional Complexity

Computational complexity of TDLMS is very high because of the complexity of transformation. Reducing the complexity of transformation can reduce this high complexity of TDLMS.

MDCT: The entire MDCT requires $\frac{N^2}{2}$ real multiplications and $\frac{N}{2}(N-1)$ real additions. Thus the complexity of computations is of the order $O(N^2)$. Similarly for the IMDCT, we require $\frac{N^2}{2}$ real multiplications and $N(\frac{N}{2}-1)$ real additions, hence a complexity of. $O(N^2)$.

TABLE I. COMPUTATIONAL COMPLEXITY FOR N=8

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)

III. 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

$$r = \frac{\lambda_{\max}}{\lambda_{\min}} \tag{20}$$

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

$$C.rate = \frac{(r-1)^2}{(r+1)^2} \tag{21}$$

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

$$SNR = \frac{\sum_n x^2(n)}{\sum_n e^2(n)} \text{ and } SNR(dB) = 10\log_{10}\frac{\sum_n x^2(n)}{\sum_n e^2(n)} \tag{22}$$

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.

TABLE II. OUTCOME OF MDCT-LMS NOISE CANCELLER

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

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

IV. CONCLUSION

The performance of MDCT-LMS is same as DCT-LMS. But the main advantage of MDCT is it's less computational complexity. This algorithm is excellent compared to NLMS and DFT-LMS algorithm in terms of convergence performance. The SNR improvement of MDCT-LMS is same as DCT-LMS. 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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