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Industrial Noise Reduction by Adaptive DCT Method

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Abstract*—Industrial noise is usually considered mainly from the point of view of environmental health and safety, rather than nuisance, as sustained exposure can cause permanent hearing damage.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. 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 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, DCT-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], [16]. 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 Discrete Fourier Transform (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 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.

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 only DCT-2. For DCT-2 $x[n]$ is extended to have period 2N and the periodic sequence is given by

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

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 define by the transform pair

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

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

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. Normalization

Normalization can be applied to define a normalized version of the DCT-2. This normalization creates a unitary transform representation. The DCT would be a unitary transform, if it is orthonormal and also has the property that

$$\sum_{n=0}^{N-1} (x[n])^2 = \sum_{k=0}^{N-1} X^{c2}([k])^2 \ . \qquad 5$$

For example, the DCT-2 form is often defined as

$$X^{c2}[k] = \sqrt{\frac{2}{N}}\beta[k]\sum_{n=0}^{N-1} x[n]\cos\left(\frac{\pi k(2n+1)}{2N}\right), \quad 0 \le k \le (N-1) \qquad 6$$

$$x[n] = \sqrt{\frac{2}{N}}\sum_{k=0}^{N-1} \beta[k] X^{c2}[k]\cos\left(\frac{\pi k(2n+1}{2N}\right), 0 \le n \le (N-1) \qquad 7$$

Where $\beta[k] = \begin{cases} 1/\sqrt{2} & k=0 \\ 1 & k=0,1,....N-1 \end{cases}$ 8

Comparing these equations with equations 2 and 3, it can be noticed that the multiplicative factors 2, 1/N, and $\beta[k]$ have been redistributed between the direct and inverse transforms. Since the DCT are orthogonal transform representations, they have properties similar in form to those of the DFT. In this paper we are using these properties of DCTs to improve the performance of adaptive filters.

B. Energy compaction property of the DCT-2

The DCT-2 is used in many data compression applications in preference to the DFT because of a property that is frequently referred to as "energy compaction". Specifically, the DCT-2 of a finite length sequence often has its coefficients more highly concentrated at low indices than the DFT does as shown in the figure. The importance of this can be shown from Parseval's theorem.

For DCT-2, $\sum_{n=0}^{N-1} |x[n]|^2 = \frac{1}{N}\sum_{k=0}^{N-1} \beta[k] |X^{c2}[k]|^2$ 9

where $\beta[k]$ is defined as in the equation 8. The DCT can be said to be concentrated in the low indices of the DCT, if the remaining DCT coefficients can be set to zero without a significant impact on the energy of the signal.

III. 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 like industrial noise reduction [1], [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 [15]. This type of adaptive filter is called as frequency domain adaptive filter or TLMS filter [5], [8]. In this paper, TLMS is implemented by using DCT-LMS to reduce the computational complexity of DFT-LMS / FFT-LMS.

A. DCT-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

$$T_n T_n^T = T_n^T T_n = I \qquad 11$$

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

$$B_n = E[T_n^T T_n x_n^T x_n] = T_n^T R_x T_n . \qquad 12$$

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

$$S_n \triangleq E(diagB_n)^{-1/2} B_n (diagB_n)^{-1/2} \qquad 16$$

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

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

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 DCT and is called as DCT-LMS.

B. Computational complexity

Computational complexity DCT-LMS is less compared to DFT-LMS as shown in Table 1. The LMS computational complexity is same in both cases. Hence this type of filter is best suited for industrial noise reduction in real time to protect workers.

***Table 1*. Computational complexity of DFT and DCT**

Type of transformation	**Number of real additions**	**Number of complex additions**	**Number of real multiplications**	**Number of complex Multiplications**	**Total complexity**
Direct DFT	4N(N-1)	N (N-1)	$4(N^2)$	N^2	$O(2N^2)$
Direct DCT	N^2	--------	N^2-N	--------	$O(2N^2\text{-}N)$

IV. 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

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

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

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

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

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

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.2* Outcome of DCT-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 2. The eigenvalue ratio is calculated to find out how well the algorithm converges to the optimum Wiener solution.

V. CONCLUSIONS

The DCT has good orthonormal, separable, and energy compaction property. In addition to this, it also powerful signal decorrelator and the computational complexity is also less compared DFT-LMS. 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 and are best suited for real time applications like industrial noise reduction.

REFERENCES

[1]. Bernard Widrow and Samuel D.Stearns. *Adaptive Signal Processing*, Pearson Education Asia, 2002.

[2]. Bauer.P., Korpert, K., Neuberger, M., Raber, A., & Schwetz, F. (1991). *Risk factors for hearing loss at different frequencies in a population of 47 3888 noise-exposed workers.* Journal of Acoustical Society of America, 90(6), 3086-3097.

[3]. Chen & Tsai. (2003). *Hearing Loss among Workers at an Oil Refinery in Taiwan*. Archives of environmental health, 58(1), 55-58.

[4]. Dolan, T. & Maurer, J. (1996). *Noise exposure associated with hearing aid use in industry*. Journal of Speech and Hearing Research, 48, 251-260.

[5]. Fausti. S., Wilmington, D., Helt, P., Helt, W., & Konrad-Martin, D. (2005). *Hearing Health and Care: The Need for Improvised Hearing Loss Prevention and Hearing Conservation Practices*. Journal of Rehabilitation Research & Development, 42(4), 45-62.

[6]. Hetu. R. & Getty, L. (1993). *Overcoming difficulties experienced in the work place by employees with occupational hearing loss*. The Volta Review, 95, 391-402.

[7]. Henderson, Donald; Bielefeld, Eric C.; Harris, Kelly Carney; Hu, Bo Hua, *The Role of Oxidative Stress in Noise-Induced Hearing Loss*, Ear & Hearing. 27(1):1-19, February 2006.

[8]. National Board for Science and Technology, Dublin (Ireland). (1980). *Noise and the environment*. U.S. Department of Commerce Springfield, VA. (NTIS No. PB84-108638).

[9]. National Institute for Occupational Safety and Health. (1988). *Self-reported hearing loss among workers potentially exposed to industrial noise- United States*. Journal of America Medical Association, 259(15), 2213-2217.

[10]. Occupational Safety & Health Administration. (2002). *Hearing Conservation. Retrieved* March 3, 2007, from http://www.osha.gov/Publications/OSHA3074/osha3074.html

[11]. Rosenhall, Ulf, Pedersen, Kai, Svanborg, *Alvar Presbycusis and Noise-Induced Hearing loss*, Ear & Hearing, 11(4):257-263, August 1990.

[12]. Sataloff, R. T., & Sataloff, J. (1987). *Occupational Hearing Loss*. New York: Marcel Dekker, INC.

[13]. Simpson. T., Stewart, M., & Blakley. B. (1995). *Audiometric referral criteria for industrial hearing conservation programs*. Arch Otolaryngol Head Neck Surgery, 121, 407-411.

[14]. Francosie Beaufays, *Transform domain adaptive filters: An analytical approach,* IEEE Trans. on Signal processing, Vol 43 no2. Feb 1995.

[15]. Mohammed A Shamma. *Improving the speed and performance of adaptive equalizers via transform based adaptive filtering.* IEEE Transactions on Signal processing. 2591 Ashurst Rd. University Heights, Ohio, 44118, USA.

[16]. Ying Song, Yu Gong, and Sen M. Kuo, *A Robust Hybrid Feedback Active Noise Cancellation Headset,* IEEE Trans. 617-624, March 2005. 44.