# TDBLMS-Based Adaptive Filter for Image SNR Enhancement

Chuen-Yau Chen, Chih-Wen Hsia, and Cheng-Yuan Lin

***Abstract*—In this paper, we proposed an image noise canceller achieved by an adaptive filter in two-dimensional block processing based on the least-mean-square algorithm. In this adaptive filter, each image is processed in two phases. In the initial weight matrix decision phase, the block-by-block operations with the smaller block size of 4 × 4 are applied to the original noisy image for getting the suitable weight matrix that will be used as the initial one for the block-adaptation phase such that a higher signal-to-noise ratio can be achieved. To verify the feasibility of this approach, the simulations in the block-adaptation phase with the block sizes of 4 × 4, 8 × 8, 16 × 16, and 32 × 32 are performed. The simulation results show that this approach achieves a higher signal-to-noise ratio in each case of block size.**

***Index Terms*—Adaptive filter, noise cancellation, least-mean-square**

## I. Introduction

Adaptive filters that use the error signals estimated from the input signals and the expected signal to adjust the coefficients for achieving a better performance are widely used in various applications [1]. The dimension of the adaptive filters varies from application to application.

The adaptive algorithms with one-dimension (1-D) generally play the important roles in digital signal processing and communication such as the system identification, echo cancellation, noise cancelling, and channel equalization [2]-[6]. There are two families of adaptive algorithms usually applied in the 1-D cases. One is the least-mean-square (LMS) family; the other is the recursive-least-square (RLS) family. Easy implementation and low computational complexity are the main characteristics of the algorithms in the LMS family [1]. In 1981, Clark [7] extended the block processing scheme proposed by Burrus [8] and proposed the block least-mean-square (BLMS) approach. The computational complexity is dramatically reduced in that approach. Besides, either parallel processing or fast Fourier transform (FFT) can be applied to accomplish the linear convolution operations.

On the other hands, the adaptive algorithms with two-dimension (2-D) are generally applied to the applications of digital image processing. In these applications, TDLMS, TDBLMS, OBA, OBAI, and TDOBSG are usually used [9]-[12]. Either in TDLMS or TDBLMS, the convergence factors are constant. Instead of the constant convergence factors in TDLMS and TDBLMS, the convergence factors in OBA, OBAI, and TDOBSG are space-varying such that the better convergence performance can be achieved. However, the computational complexity will increase in such space-varying convergence factors due to the computations for the new convergence factor of next block.

In this paper, we proposed an adaptive filter with the initial weight matrix decision mechanism using the smaller block size of 4 × 4 instead of the larger ones like those in the block-adapting phase for finding a suitable weight (coefficient) matrix of the digital filter in advance. Then, treat this weight matrix as the initial weight matrix for the processing of noise cancellation.

## II. TDBLMS Algorithm

An image signal of 2-D is usually partitioned into blocks with a dimension of $L \times L$ for each in the 2-D disjoint block-by-block image processing. An image with $R$ rows of pixel and $C$ columns of pixel partitioned into $\frac{R}{L} \times \frac{C}{L}$ blocks is illustrated in Fig. 1. The relationship between the block index $S$ and the spatial block index $(r, c)$ is [12]

$$S = (r-1)\frac{C}{L} + c \tag{1}$$

where $r = 1, \cdots, R/L$ and $c = 1, \cdots, C/L$. For convenient, the $(r, c)$-th element $d(r, c)$ of the image can be treated as the $(r_b, c_b)$-th element in the $S$-th block and denoted as the element $d_S(r_b, c_b)$. The relationship is

$$d_S(r_b, c_b) = d[(r-1)L + r_b, (c-1)L + c_b] \tag{2}$$

where $r_b = 1, \cdots, L$ and $c_b = 1, \cdots, L$.

The image is processed block-by-block sequentially from left to right and from top to bottom in which each pixel is convolved the pixel in a filter window with a dimension of $M \times N$. Fig. 2 illustrates this approach which performs the operations from (3) to (5) iteratively [10]. That is,

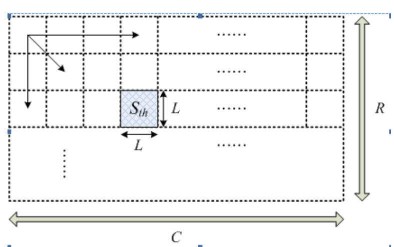


Fig. 1. Partition of a 2-D image.

Manuscript received April 1, 2012; revised June 2, 2012.

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$$y_S(r_b, c_b) = \sum_{i=1}^{M}\sum_{j=1}^{N} W_S(i, j) \times X[(r-1)L + r_b + (M-1) - i, (c-1)L + c_b + (N-1) - j] \quad (3)$$

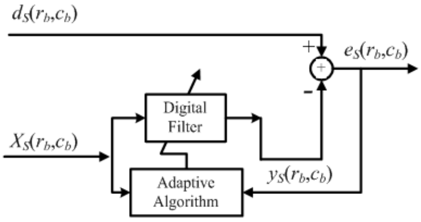


Fig. 2. 2-D adaptive filter.

where $y_S(r_b, c_b)$ is the image of the $S$-th block after processing, $W_S(i, j)$ is the $(i, j)$-th element in the weight matrix $W_S$ of the $S$-th block. The error signal $e_S(r_b, c_b)$ is the difference between the image $y_S(r_b, c_b)$ and the primary input image $d_S(r_b, c_b)$. That is,

$$e_S(r_b, c_b) = d_S(r_b, c_b) - y_s(r_b, c_b) \quad (4)$$

The updating mechanism of the weight matrix $W_{S+1}$ of the $(S+1)$-th block is expressed as

$$W_{S+1}(i, j) = W_S(i, j) + \frac{2}{L \times L}\mu \sum_{r_b=1}^{L}\sum_{c_b=1}^{L} e_S(r_b, c_b) \times X(r_b + rL - i, c_b + cL - j) \quad (5)$$

where $\mu$ is the convergence factor.

## III. Proposed Adaptive Filter

The operations of this proposed adaptive filter can be divided into two phases. In the beginning, the adaptive filter operates in the initial weight matrix decision phase where the initial weight matrix for a better performance will be obtained. Then, the adaptive filter enters the block adapting phase where the TDBLMS algorithm is applied to enhance the SNR for the noisy image. Fig. 3 shows the block diagram of the proposed adaptive filter.

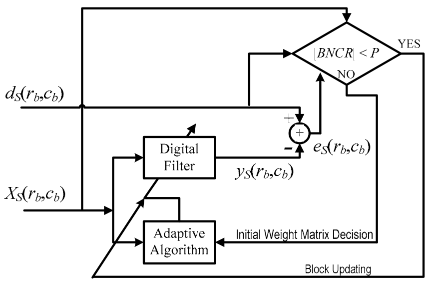


Fig. 3. Proposed adaptive filter.

### A. Initial Weight Matrix Decision Phase

In the initial weight matrix decision phase, a suitable weight matrix $W_{Ta}$ will be found to be treated as the initial weight matrix $W_1$ for the processing in the block-adapting phase. First, each element of the initial weight matrix $W_{T1}$ is set to a value of zero. That is, $W_{T1} = [W_{T1}(i, j)]_{M \times N}$ where the element $W_{T1}(i, j) = 0$ for $i = 1, \cdots, M$ and $j = 1, \cdots, N$. Then, the TDBLMS algorithm is applied to process the original noisy image in the manner of scanning block-by-block from left to right and from top to down for updating the weight matrix of each block iteratively until the termination criterion is reached [10]. In this phase, the block size $L_t \times L_t$ is chosen as $4 \times 4$ which is smaller than $L \times L$ in most cases ($8 \times 8, 16 \times 16$, and $32 \times 32$) such that there are enough blocks for updating the weight matrix especially when the value of $L$ is large. The termination criterion for this phase is defined as

$$|BNCR| < P \quad (6)$$

where $P$ is the termination parameter and *BNCR* stands for the block-noise-cancellation ratio that is defined as

$$BNCR \equiv 10\log\frac{\sigma_x^2 - (\sigma_d^2 - \sigma_e^2)}{\sigma_x^2} \quad (7)$$

In (7), $\sigma_x^2$ stands for the power of the reference signal $X_S(r_b, c_b)$, and can be expressed as

$$\sigma_x^2 = \frac{\sum_{k=1}^{L_t+M-1}\sum_{l=1}^{L_t+N-1}[X_S(k,l) - X_{mean}]^2}{[L_t + (M-1) - 1][L_t + (N-1) - 1]} \quad (8)$$

The term $\sigma_d^2$ is the power of the primary input signal $d_S(r_b, c_b)$, and can be expressed as

$$\sigma_d^2 = \frac{\sum_{r_b=1}^{L_t}\sum_{c_b=1}^{L_t}[d_S(r_b, c_b) - d_{mean}]^2}{(L_t - 1)(L_t - 1)} \quad (9)$$

The term $\sigma_e^2$ is the power of the error signal $e_S(r_b, c_b)$, and can be expressed as

$$\sigma_e^2 = \frac{\sum_{r_b=1}^{L_t}\sum_{c_b=1}^{L_t}[e_S(r_b, c_b) - e_{mean}]^2}{(L_t - 1)(L_t - 1)} \quad (10)$$

In (8)-(10), $X_{mean}$, $d_{mean}$, and $e_{mean}$ stand for the means of $X_S$, $d_S$, and $e_S$, respectively.

### B. Block-Adapting Phase

Once the suitable weight matrix $W_{Ta}$ in the initial weight matrix decision phase is found, this weight matrix is treated as the initial weight matrix $W_1$ in the block-adapting phase. In this phase, the original noisy image is processed with the block size $L \times L$ according to the TDBLMS algorithm [10] again for the noise cancellation.

(a)

(b)

Fig. 3. (a) Ideal image Lena. (b) Noisy primary input image with SNR = 0 dB.

(a)

(b)

Fig. 4. Simulation results of the 2-D adaptive noise canceller with (*L*, *M*, *N*) = (16, 2, 2) for the noisy image with SNR = 0 dB. (a) Restored image for the TDBLMS algorithm. (SNR = 2.4270 dB.) (b) Restored image for the proposed adaptive filter. (SNR = 10.5627 dB, $P = -10$ dB, $L_t = 4$).

## IV. Simulation Results

We created the primary input signal with a dimension of $256 \times 256$ in the simulation by adding a white-Gaussian noise with zero mean to the ideal image Lena with 256 gray-levels in Fig. 3(a). The noisy primary input image with an SNR of 0 dB is shown in Fig. 3(b). In the simulation, the convergence factor $\mu$ in (5) is set to be $4.5 \times 10^{-7}$. The 4-th order transversal FIR filter is chosen to convolve the reference image. The dimension of the filter window is chosen as $2 \times 2$ $(M = 2, N = 2)$. We applied four different block sizes of $4 \times 4$ $(L = 4)$, $8 \times 8$ $(L = 8)$, $16 \times 16$ $(L = 16)$, and $32 \times 32$ $(L = 32)$ in the simulations for observing the effect of block size on the performance. Table 1 lists the performance comparison. Fig. 4(a) is the image restored from the original noisy image with an SNR of 0 dB by the TDBLMS algorithm using a block size of $16 \times 16$. Fig. 4(b) is the restored image for the proposed adaptive filter where the termination parameter $P$ is chosen to be $-10$ dB. Fig. 5 show simulation results for the block size of $32 \times 32$. It is obviously that the proposed approach cancels the noise with a nearly constant BNCR, however, the performance of the TDBLMS algorithm is not so good for the first several blocks. This phenomenon can be also found in Fig. 5(a) for the blocks near the top of this image. Moreover, as the performance factors listed in Table 1, the SNR of the TDBLMS becomes lower and lower when the block size increases.

(a)

(b)

Fig. 5. Simulation results of the 2-D adaptive noise canceller with (*L*, *M*, *N*) = (32, 2, 2) for the noisy image with SNR = 0 dB. (a) Restored image for the TDBLMS algorithm. (SNR = 0.6710 dB.) (b) Restored image for the proposed adaptive filter. (SNR = 8.7657 dB, $P = -10$ dB, $L_t = 4$).

## V. Conclusions

An adaptive filter with initial weight matrix decision mechanism was proposed in this paper. First, a suitable weight matrix was found by scanning the image block-by-block with the block size $L_t \times L_t$ instead of $L \times L$ and updating the weight matrix for each until the termination criterion is reached in the initial weight matrix decision phase. Then, the suitable weight matrix became the initial weight matrix in the block-adaptation phase. The simulation performed on the noisy image Lena with a dimension of $256\times256$ with an SNR of 0 dB shows that this approach can achieve the SNR of 19.7836 dB, 14.0858 dB, 10.5627 dB, and 8.7657 dB for the block sizes of $4\times4$, $8\times8$, $16\times16$, and $32\times32$, respectively.

TABLE I: OUTPUT SNR OF THE 2-D ADAPTIVE NOISE CANCELLER FOR NOISY IMAGE WITH SNR = 0 DB AND $P = -10$ DB. ($L_T = 4$)

| Algorithms | Block Sizes | | | |
|---|---|---|---|---|
| | $L = 4$ | $L = 8$ | $L = 16$ | $L = 32$ |
| TDBLMS [10] | 13.1657 dB | 7.0656 dB | 2.4270 dB | 0.6710 dB |
| This work | 19.7836 dB | 14.0858 dB | 10.5627 dB | 8.7657 dB |

## ACKNOWLEDGEMENTS

This work was supported by the National Science Council, Republic of China, under Grant NSC-99-2221-E-390-038-MY2.

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