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Design of Navel Adaptive TDBLMS-based Wiener Parallel to TDBLMS Algorithm for Image Noise Cancellation

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***Abstract*— In this paper, we proposed a navel digital adaptive algorithm that filtered highly contaminated noisy images. The new algorithm so called as Design of A Navel Adaptive TDBLMS–Based Wiener parallel to TDBLMS algorithms for Image Noise Cancellation. To improve the quality of images, adaptive filter technique applied here on the Car image, Lena image, Boat image, Houselights image, mammography image and ultrasound image. These images are corrupted by additive white Gaussian noise and multiplicative noise, like Gaussian noise. Proposed algorithm deal with noise contaminated image that is processed by block-by-block operations. A weight matrix was taken into account with suitable block size (4×4) in the proposal. Block-adaptation phase can be make a important phenomenon in the digital image processing. Proposed method implies the quality results in terms of PSNR and minimize the RMSE and visual appearance of the final image, given proposal achieved the higher PSNR, minimize RMSE and visual appeal of the final image.**

Keywords—Design of A Navel adaptive TDBLMS-Based wiener filter parallel to TDBLMS algorithm, PSNR, RMSE, Gaussian noise, Block-by-block, adaptive, weight training phase.

I. INTRODUCTION

A navel Adaptive TDBLMD-Based wiener filter provides less complicity than conventional algorithms TDBLMS. This joint process is much superior to TDBLMS algorithm for Image Noise Cancellation..

In 1981, Clark [7] extended the block processing scheme proposed by Burros [8] and proposed block the block least-mean-square (BLMS) approach. Computational complexity is dramatically reduced and provides quality of image in that approach. Besides, either parallel processing or fast Fourier transform (FFT) can be applied to accomplish the linear operations. On the other hands, the adaptive algorithms with two dimensions (2-D) are generally applied to the applications of digital image processing. An adaptive filter uses the initial weight matrix decision mechanism with the smaller block size of 4 x 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 as the initial weight matrix for the processing of noise cancellation.

TDBLMS ALGORITHM

An image signal of 2-D is usually partitioned into block with a dimension of L X 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 $\frac{R}{L}$X$\frac{C}{L}$ block is illustrated in Fig. 1.2 The relationship between the block index s and the spatial block index (r, c) is [12]

S = (r-1)C/L **+c (1)**

Where r =1,….,R/L and C= 1,….,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

$$d_s(r_{b,} c_b) = d[(r-1)L + r_b, \frac{c-1}{L} + c_b] \qquad (2)$$

Where $r_b = 1 \ldots L$ and $r_b = 1 \ldots L$

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 MXN. Fig. 2 illustrates this approach which performs the operations from (3) to (5) iteratively [10]. That is $y_s(r_{b,} c_b)$ =

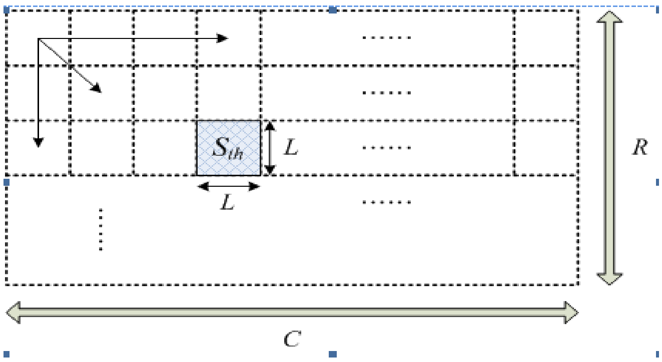

Figure1.2. 2-D partition diagram

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

Where $y_s(r_{b,}c_b)$ the image of the S-block is after processing, $W_s(i,j)$ is the (i,j) –th element in the weight matrix W_s of the S-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

$$\frac{2}{LXL}\mu\sum_{r_b}\sum_{c_b} e_s(r_b,r_c)\,X\left(e_s\left(r_b + r_{L-i,}c_{L-j}\right)\right) \quad (5)$$

Where μ is the convergence factor.

II PROPOSED ADAPTIVE FILTER ALGORITHMS

The operations of this proposed adaptive filter can be divided into two phases. In beginning, the adaptive filter operates in the initial weight matrix decision phase where the initial weigh matrix for a better performance will be obtained. Then, the adaptive filter enters the block adapting phase where the TDBLMS-based wiener filter and TDBLMS-Based are algorithm parallel to applied to block-by-block process for enhancing the PSNR and minimize the RMSE for the noise image. Fig.1.3. show the block diagram of the proposed adaptive filter.

1 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 initial weight matrix $[W_{T1}]$ is set a value of zero. That is $W_{T1} = [W_{T1}[i,j)]_{MXN}$ where the element $W_{T1}[i,j=0]$ for $i = 1,\ldots M$ and $j = 1,\ldots N$ Then Design of A Navel Adaptive TDBLMS–Based Wiener parallel to TDBLMS algorithms for Image Noise Cancellation applied to process the original noise image in the manner of the scanning block-by-block from left to right and top to down for updating the weigh matrix of each block iteratively until the termination criterion is reached [10]. In this phase, the block size $L_t X L_t$ is chosen as 4 x 4 which is smaller than LXN in most cases (8x8, 16x16, 32x32,) and such that there are enough block for updating the weight matrix especially when the value of L is large. The termination criterion (P=-10) for this face is defined as

$$\text{BNCR} < \text{P} \quad (6)$$

Where p is the termination parameter and BSNR stands for the block-noise-cancellation ratio that is define as (7)

$$\text{BSNR} = \log 10$$

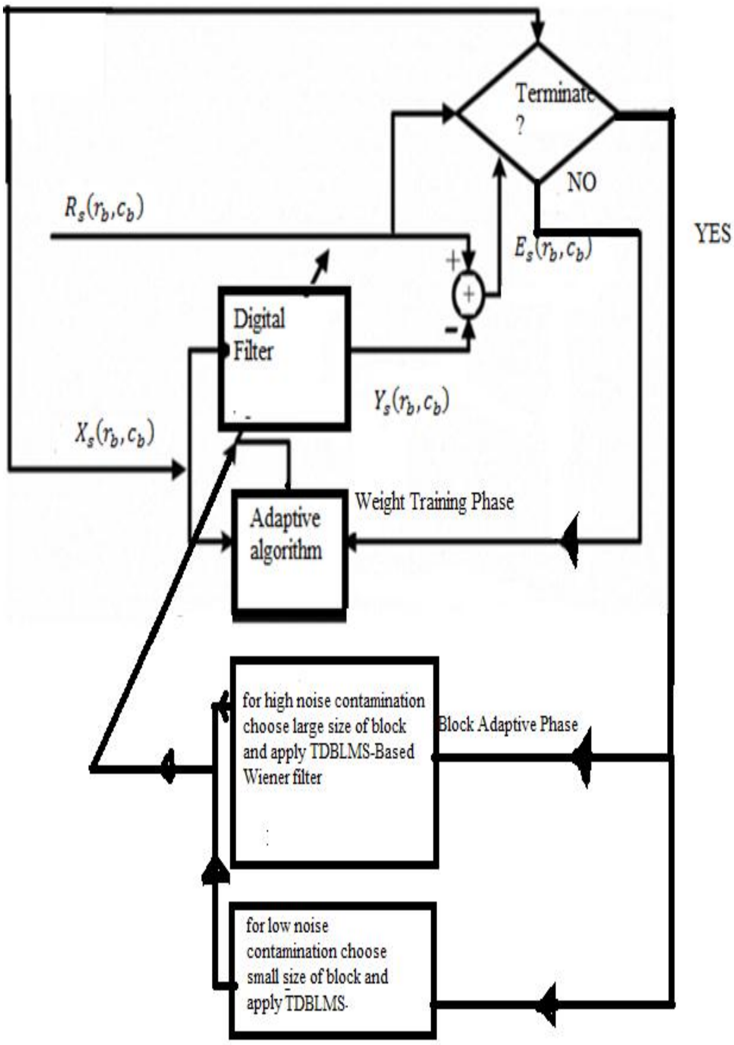

Figure.1.3 Proposed Design of A Navel Adaptive TDBLMS–Based Wiener parallel to TDBLMS algorithms for Image Noise Cancellation with noise dependent block mechanism.

In the (7), ${\sigma_x}^2$ stand for the power of the reference signal , $R_s(r_{b,}c_b)$ and can be expressed as

$$\sigma_x^2 = \frac{\sum_{K=1}^{L_t+M-1}\sum_{L=1}^{L_t-M-1}[R_s(r_{b,}c_b) - X_{mean}]^2}{[L_t+1][\,L_t-1]} \quad (8)$$

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The term $\sigma\sigma_x{}^2$ is the power of the primary input signal $d_s(r_{b,}c_b)$, and can be expressed as

$$\sigma_x^2 = \frac{\sum_{K=1}^{L_t+M-1}\sum_{L=1}^{L_t-M-1}[d_s(r_{b,}c_b)-X_{mean}]^2}{[L_t+1][L_t-1]} \quad (9)$$

The term $\sigma_x{}^2$ is the power of the primary input signal $e_s(r_{b,}c_b)$, and can be expressed as

$$\sigma_x^2 = \frac{\sum_{K=1}^{L_t+M-1}\sum_{L=1}^{L_t-M-1}[e_s(r_{b,}c_b)-X_{mean}]^2}{[L_t+1][L_t-1]} \quad (10)$$

X_{mean}, d_{mean} and e_{mean} stand for the means of X_s, d_s, e_s, respectively. e_{mean}

2. Block Adaptive Phase:

Once the suitable weight matrix W_{Ta} is found, then the output of the weight training phase is treated as the initial (W_1) input for the block-adaptive phase.

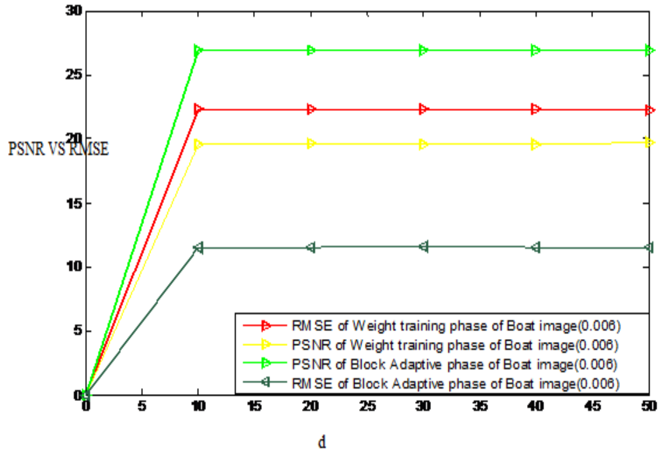
In this phase, the suitable block is chosen that truly depends on noise contamination. After that if noise is high then take large size of block and apply TDBLMS-Based wiener filtering for the image noise cancellation else noise is low take small size of block only apply TDBLMS algorithm.

The PSNR of TDBLMS-Based Wiener filter is much better than conventional TDBLMS method in for different block size and different noise level.

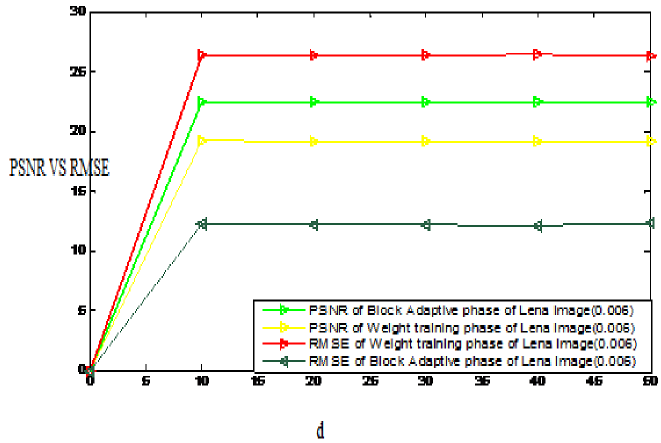
The RMSE of TDBLMS-Based Wiener filter is much less than conventional method for different block size and different noise level.

III SIMULATION RESULTS

We created the primary input signal with a dimension of 256x256 in the simulation by adding a white-Gaussians noise with zero mean to the ideal image Lena, Car, and Boat, with 256 gray-levels in Fig. (a). the noise primary input image with an SNR of 0 dB shown in Fig.2.2. in the simulation convergence factor µ in (5) set to 4.5×10^{-7}. The 4-th order transversal FIR filter is chosen to convolve the reference image. The dimension of the filter window is chosen as 4x4 (M=2, N=2). We applied four difference block of 8x8(L=8), 16x16(L=16), and 32x32(L=32), 64x64(L=64) in the simulation for observing the effect of block size on the performance. Table 1.1 lists the performance comparison. the Design of A Navel Adaptive TDBLMS–Based Wiener parallel to TDBLMS algorithms for Image Noise Cancellation using a block size of 4x4(L=4) Fig 2.4 is the restored image for the proposed adaptive filter where the termination parameter p is chosen be -10 dB. Fig 5(1.4) show the simulation result for the block size of 4x4. It is obviously that the proposed approach cancels the noise with a nearly constant BSNR, however the performance of the TDBLMS algorithms is not good for the first several blocks. But in this proposed algorithm performance of parallel TDBLMS-Based wiener filter and TDBLMD overcome this problem. Moreover performance factor listed in Table 1, Table 2, and Table 3, the PSNR of the Design of A Navel Adaptive TDBLMS–Based Wiener parallel to TDBLMS algorithms for Image Noise Cancellation. RSNR become greater and RMSE minimizes of Design of A Navel Adaptive TDBLMS–Based Wiener parallel to TDBLMS algorithms for Image Noise Cancellation..



1.1 Plot of Boats image



1.2 Plot of Lena image

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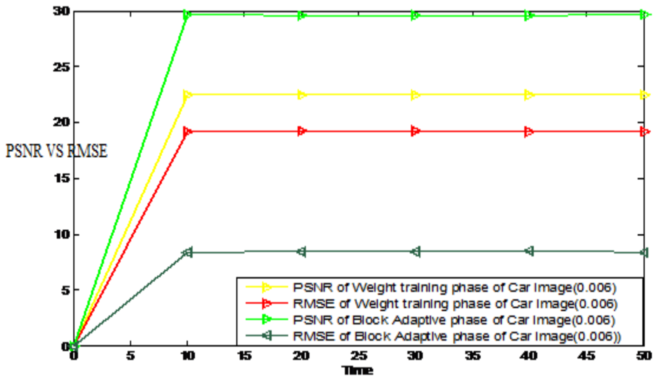
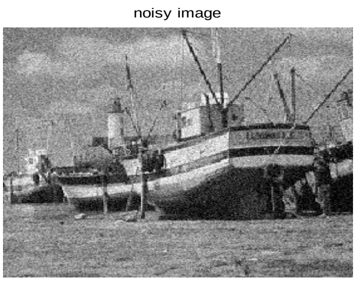


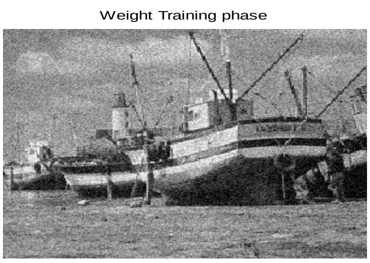
d

1.3 Plot of Car image

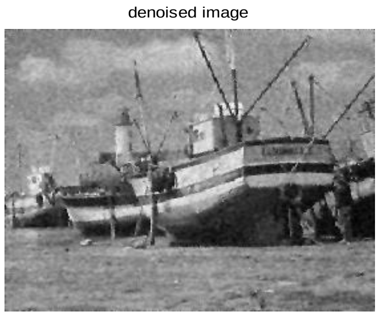
(a) original image



(b) noisy image



(c) weight tarining phase



(d) de-noised image

Boats image	SNR=0 DB, P=-10 DB			
Gaussian noise (.006)	**TDBLMS-Based filter**		**TDBLMS-Based Wiener filter**	
Block size(LxL)	PSNR	RMSE	PSNR	RMSE
4x4	22.2993	19.5693	26.9263	11.4875
8x8	22.2859	19.5995	26.8912	11.5340
16x16	22.3057	19.5549	26.8675	11.5655
32x32	22.3054	19.5556	26.9036	11.5175
64x64	22.2553	19.6686	26.9283	11.4848

Figure.1.4. (a) original image (b) noisy image (c) weight tarining phase and (d) de-noised image

Table-1.1 of Boats image

Lena image	SNR=0 DB, P=-10 DB			
Gaussian noise(0.006)	TDBLMS-Based filter		TDBLMS-Based Wiener filter	
Block size(LxL)	PSNR	RMSE	PSNR	RMSE
4x4	22.4492	19.2345	26.3421	12.2868
8x8	22.4714	19.1853	26.3951	12.2119
16x16	22.4864	19.1522	26.3972	12.2090
32x32	22.4633	19.2032	26.4329	12.1590
64x64	22.4619	19.2063	26.3083	12.3346

Table-1.2 of Lena image

Car image	SNR=0DB, P=-10 DB			
Gaussian noise(0.006)	TDBLMS-Based filter		TDBLMS-Based Wiener filter	
Block size(LxL)	PSNR	RMSE	PSNR	RMSE
4x4	22.4805	19.1652	29.6324	8.3989
8x8	22.4595	19.2116	29.5935	8.4501
16x16	22.4606	19.2092	29.5905	8.4531
32x32	22.4748	19.1779	29.5434	8.4991
64x64	22.4718	19.1846	29.6576	8.3881

Table-1.3 of car image

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IV CONCLUSION

In this work we are proposing design of a navel adaptive TDBLMS-Based Wiener parallel to TDBLMD-Based filter for image noise cancellation with noise dependent block mechanism. In this mechanism a suitable weight matrix was found by scanning the image then first, a suitable weight matrix was found by scanning the image block-by-block and updating the weight matrix for each unit the termination criterion is reached in the weight-training phase (WTP) then, the suitable weight matrix in the block adaptive phase. The simulation performed on the noise image Lena, Car, and Boats with a dimension of (256× 256) with an SNR of 0 dB shows that this approach can achieve the PSNR'S values and RMSE values of Lena image, Car image, and Boat image. All the PSNR values and RMSE values result has been shown by table 1, table 2, table 3 table respectively. Above all the discussion Design of proposal provides better performance over only TDBLMS-based algorithms.

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