RESEARCH ARTICLE OPEN ACCESS

Adaptive Filter Based On TDBLMS Algorithm for Image Noise Cancellation

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Abstract
Images are often degraded by noises. Noise can occur during image capture, transmission, etc. Noise removal is an important task in image processing. In general the results of the noise removal have a strong influence on the quality of the image processing technique. Several techniques for noise removal are well established in color image processing. The nature of the noise removal problem depends on the type of the noise corrupting the image. An adaptive filter for two-dimensional block processing in image noise cancellation is proposed in this paper. The processing includes two phases. They are the weight-training phase and the block-adaptation phase. The weight-training phase obtains the suitable weight matrix to be 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 simulation with the block sizes of 4 x 4, 8 x 8, 16 x 16, and 32 x 32 are performed. The simulation results show that this approach performs well.
Keywords: Adaptive filter, Adaptive algorithm, Least squares approximation, Noise cancellation, PSNR.

I. INTRODUCTION

Noise is the result of errors in the image acquisition process that results in pixel values that do not reflect the true intensities of the real scene. Noise reduction is the process of removing noise from a signal. Noise reduction techniques are conceptually very similar regardless of the signal being processed, however a priori knowledge of the characteristics of an expected signal can mean the implementations of these techniques vary greatly depending on the type of signal. The image captured by the sensor undergoes filtering by different smoothing filters and the resultant images. All recording devices, both analogue and digital, have traits which make them susceptible to noise. The fundamental problem of image processing is to reduce noise from a digital color image. The two most commonly occurring types of noise are (i) Impulse noise, ii) Additive noise (e.g. Gaussian noise) and iii) Multiplicative noise (e.g. Speckle noise).

Many methods have been widely used to eliminate noise like linear and nonlinear filtering methods, adaptive noise cancellation.

1.1 Adaptive Filtering

An adaptive filter is a filter that self-adjusts its transfer function according to an optimization algorithm driven by an error signal. Because of the complexity of the optimization algorithms, most adaptive filters are digital filters. Adaptive filters that are well-known as the filters with the coefficients adjusted by the adaptive algorithms are widely used in various applications for achieving a better performance. The dimension of the adaptive filters varies from application to application.

In the fields of digital signal processing and communication such as the system identification, echo cancellation, noise canceling, and channel equalization [2]-[6], the one dimensional (1-D) adaptive algorithms are generally adopted. The 1-D adaptive algorithms are usually classified into two families. One is the least-mean-square (LMS) family; the other is the recursive-least-square (RLS) family. The algorithms in the LMS family have the characteristics of easy implementation and low computational complexity [1]. In 1981, Clark [7] proposed the block least-mean-square (BLMS) approach which is an application extended from the block processing scheme proposed by Burrus [8]. In such an approach, the computational complexity is dramatically reduced. In addition, the linear convolution operation can be accomplished by parallel processing or fast Fourier transforms (FFT).

In the applications of digital image processing, two dimensional (2-D) adaptive algorithms such as TDLMS, OBA, OBAI, TDBLMS 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 space-varying convergence factors are used in OBA, OBAI, and TDOBSG for better convergence performance.

However, such space-varying convergence factors will increase the computational complexity due to the computations for the new convergence factor of next block.

In this paper, we proposed an adaptive filter with weight training mechanism by finding a suitable weight (coefficient) matrix for the digital filter in advance. Then, treat this weight matrix as the initial weight matrix for the processing of noise cancellation.

II. ADAPTIVE ALGORITHM

Adaptive algorithms are used to adjust the coefficients of the digital filter such that the error signal is minimized according to some criterion.

2.1 2-D Block LMS Algorithm

A 2-D signal is partitioned into blocks 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 G columns of pixel partitioned into R/L * C/L blocks is illustrated in Fig.1.

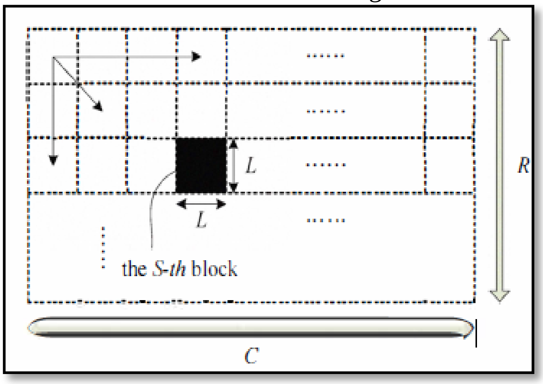


Figure 1. 2-D block-by-block processing with disjoint square blocks of a dimension L x L.

The block index S and the spatial block index (r, c) is related by [12]

$$S = (r-1)\cdot\left(\frac{C}{L}\right) + c \quad (1)$$

where r = 1, 2,… R/L and c = 1, 2,…C/L.

For convenient, the (r, c)-th element d(r, c) of the image can be treated as the (rb, cb)-th element in the S-th block and denoted as the element ds (rb,cb). The relationship is

$$d_s(r_b,c_b) = d[(r-1)L + r_b, (c-1)L + c_b \quad (2)$$

where rb = 1,2,..,L and cb = 1,2,…,L. The block processing is started by processing the image 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 x N.

Adaptive filtering can be considered as a process in which the parameters used for the processing of signals changes according to some criterion. Usually the criterion is the estimated mean squared error or the correlation. The adaptive filters are time-varying since their parameters are continually changing in order to meet a performance requirement. In this sense, an adaptive filter can be interpreted as a filter that performs the approximation step on-line. Usually the definition of the performance criterion requires the existence of a reference signal that is usually hidden in the approximation step of fixed-filter design. The error is then used to form a performance function or objective function that is required by the adaptation algorithm in order to determine the appropriate updating of the filter coefficients. The minimization of the objective function implies that the adaptive filter output signal is matching the desired signal in some sense. Fig. 2 illustrates this approach which performs the operations from (3) to (5) iteratively [10]. That is

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

where $X_s(r_b,c_b)$ is input image of the Sth block, $\gamma_s(r_b,c_b)$ is the image of the S-th block after processing, Ws(i,j) is the (i,j)-th element in the weight matrix Ws of the S-th block. The error signal $e_s(r_b,c_b)$ is then obtained by subtracting the image $\gamma_s(r_b,c_b)$ from the primary input image $d_s(r_b,c_b)$. That is

$$e_s(r_b,c_b) = d_s(r_b,c_b) - \gamma_s(r_b,c_b) \quad (4)$$

The weight matrix W_{s+1} of the (S + l)-th block is then updated by

$$W_{s+1}(i,j) = + \frac{2}{L^2}\mu \sum_{rb=1}^{L}\sum_{cb=1}^{L} e_s(r_b,c_b) \times X(r_b + r - 1, c_{b+cL-j)} \quad (5)$$

where μ is the convergence factor.

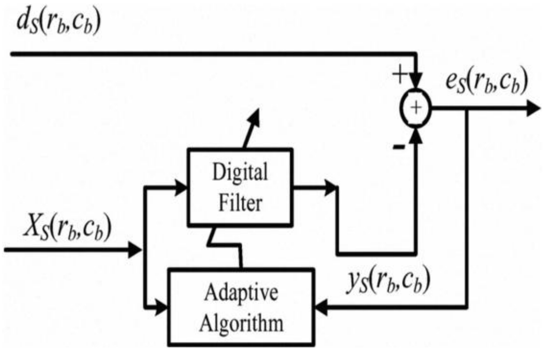


Figure 2. 2-D adaptive filter for image noise cancellation.

III. PROPOSED EXPERIMENTAL WORK

There are two phases in the proposed adaptive filter. They are the weight-training phase and the block-adapting phase. Fig. 3 shows the block diagram of the proposed adaptive filter.

3.1 Weight-Training Phase (WTP)

In order to improve the convergence rate, a suitable weight matrix W_{Ta} that will be treated as the initial weight matrix W_1 for the processing in the block-adapting phase is found in the weight-training phase. In WTP, all the elements of the initial weight matrix W_{T1} are set to be zero. That is, $W_{T1} = [W_{T1}(i,j)]M \times N$ where the element $W_{T1}(i,j) = 0$ for i = 1,2.., M and j = 1,2,..,N. Then, the TDBLMS algorithm is applied to process the original noisy image that will be scanned 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].

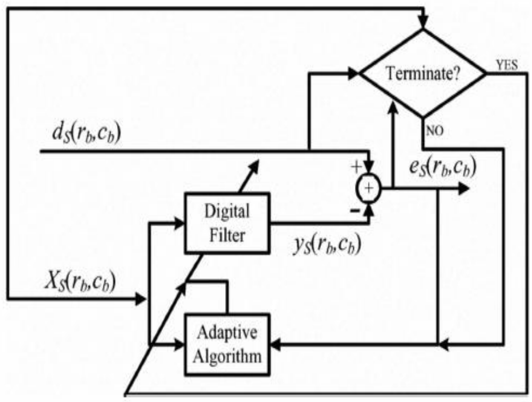


Figure 3: Adaptive filter with weight – training Mechanism.

The operations can be expressed in the equations from (3) to (5).

We define the termination criterion as

IBNCR I < P (6)

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

BNCR= 10log $[(\sigma_x^2 - (\sigma_d^2 - \sigma_e^2)) / \sigma_x^2]$ (7)

In (7), σ_x^2stands for the power of the reference signal $X_s(r_{b,}c_b)$, and can be expressed as

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

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

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

the term σ_e^2 is the power of the error signal $e_s(r_{b,}c_b)$, and can be expressed as

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

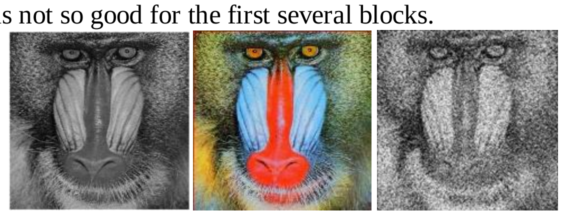
In (8)-(10), X_{mean} , d_{mean} , and e_{mean} stand for the means of X_S, ds, and e_s, respectively.

B. Block-Adapting Phase (BAP)

Once the suitable weight matrix W_{Ta} in the weight training phase is found, this weight matrix is treated as the initial weight matrix W_1 in the block-adapting phase (BAP). In this phase, the original noisy image is processed according to the TDBLMS algorithm [10] again for the noise cancellation.

IV. SIMULATION RESULTS

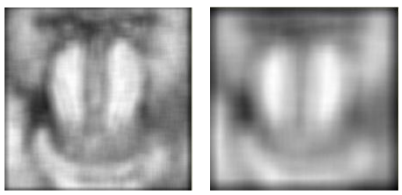
The primary input signal with a dimension of 256 x 256 in the simulation phase is created by adding a white-Gaussian noise with zero mean to the ideal image Baboon with 256 gray-levels in Fig. 4(a).Fig (b) shows the primary input image with a dimension of 400 x 400 and Fig. 4(c) shows the noisy primary input image with an SNR of 0 dB. The convergence factor is 4.5 X 10-7. For the digital filter, the 4-th order transversal FIR filter is chosen to convolved the reference image and the filter window with a dimension of 2 x 2 (M = 2, N = 2). In order to observe the effect of block size on the performance, four different block sizes of 4 x 4 (L = 4), 8 x 8 (L = 8), 16 x 16 (L = 16), and 32 x 32 (L = 32) are simulated. Table 1 lists the performance comparison. The simulation results indicate that the proposed adaptive filter achieves a better performance; however, the performance of the TDBLMS algorithm is not so good for the first several blocks.



(a) (b) (c)

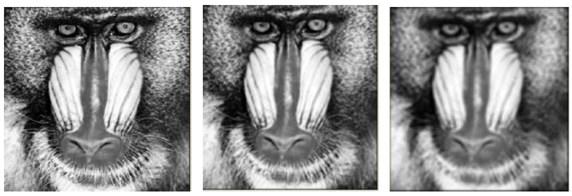
Figure 4 (a), (b) Primary input image Baboon with a dimension of 256x256 and 400x400. (c) Noisy primary input image with SNR= 0 dB.

(a) (b) (c)

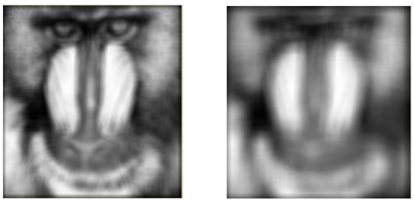


(d) (e)

Figure 5: Output of noisy input image for block size of (a) 2x2 (b) 4x4 (c) 8x8 (d) 16 x 16 (e) 32 x 32



(f) (g) (h)



(i) (j)

Figure 6: Output of primary input image with dimensions of 400 x 400 for block size of (f) 2x2 (g) 4x4 (h) 8x8 (i) 16 x 16 (j) 32 x 32

TABLE 1 Output PSNR of the 2-D adaptive noise canceller for noisy image with SNR = 0 db

Block size (LxL)	**PSNR(dB)**	
	TDBLMS	**Proposed Adaptive Filter**
2 x 2	50.2754	63.5161
4 x 4	53.2134	66.1827
8 x 8	53.8987	66.7429
16 x 16	52.1246	65.3567
32 x 32	50.0712	63.3042

V. CONCLUSION

This work proposed an adaptive filter for two dimensional block processing in image noise cancellation. The simulation performed on the noisy image baboon with a dimension of 256 x 256 with an SNR of 0 dB shows that this approach can achieve the PSNR's of 63.5161, 66.1827, and 66.7429 for the block sizes of 2 x 2, 4 x 4, 8 x 8, 16 x 16, 32 x 32 respectively. The proposed method provides better image. The proposed has been tested on well-known benchmark images, where their PSNR and visual results show the superiority of the proposed technique over the conventional techniques.

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