Image Restoration Using RO Learning Approach

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Abstract

In this paper, a machine-leaning-based adaptive approach is proposed to restore image from Gaussian corruption. The well-known Random-Optimization (RO) learning method is used for training of the adaptive filter. With the merit of model-free computation of RO, the derivative information is not required. Combined with block processing technique, the proposed adaptive filtering approach possesses fast convergence, moderate computation and simplicity. The proposed adaptive filter shows excellent filtering performance for image restoration.

Keywords: machine-learning, random-optimization, adaptive filter, block processing.

1. Introduction

In the past few decades, several image restoring filters have been presented for restoration Gaussian degraded images. These filters may be classified roughly into machine-learning-free and machine-learning-based types. Classical filters such as maximum, minimum or medium [1] filters have their own limitation because of no machine learning mechanism. This kind of filters refill corrupted gray level by balancing its surrounding pixels in different order. But they are only workable for less than 50% impulsive noise. In the face of highly nonlinear Gaussian noise or greater than 50% impulsive noise, more powerful machine-leaning-based filter may be needed. Neuro-fuzzy filtering approach [2] possesses highly nonlinear mapping ability of neural network and fuzzy inference system, which can adapt all kinds of noisy environments. The motivation of this research is to apply the Random Optimization [3] as training method for a neural-like filter to achieve a fast convergence, high performance and moderate computation adaptive image noise filtering.

2. Noise Canceling

Adaptive noise canceling concept was proposed by B. Widrow, et.al. [4], and was applied in signal processing successfully [5]. Assume that a clear image $S(m,n)$ is corrupted by an additive noise $\eta(m,n)$, producing a noisy image $D(m,n)$, where (m,n) is the pixel location index. The noise $\eta(m,n)$ is generated from the noise source $N(m,n)$ through an unknown nonlinear channel. The diagram of noise canceling is shown in Fig.1. The right block represents the image restoration system. This system has two inputs, which are the noisy image and the noise source, and one output of the restored image $R(m,n)$.

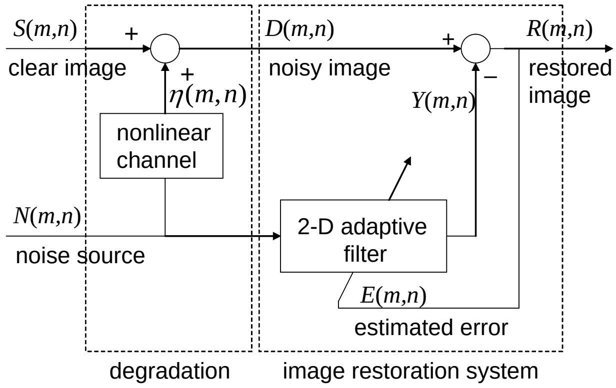

Fig. 1: Schematic diagram of noise canceling.

Based on the following assumptions, noise canceling can be implemented.

1. $N(m,n)$, $S(m,n)$ and $\eta(m,n)$ are zero means.
2. $S(m,n)$ is uncorrelated with both $N(m,n)$ and $\eta(m,n)$
3. $N(m,n)$ and $\eta(m,n)$ are related, because of the non-linear channel function.

The restored image $R(m,n)$ can be expressed as follows.

$$\begin{aligned} R(m,n) &= D(m,n) - Y(m,n) \\ &= [S(m,n) + \eta(m,n)] - Y(m,n) \end{aligned} \qquad (1)$$

Taking statistical mean-square operation of equation (1), based on assumption 2, we have:

$$E\{R^2(m,n)\} = E\{S^2(m,n)\} + E\{[\eta(m,n) - Y(m,n)]^2\} \tag{2}$$

If we can minimize error signal power term $E\{[\eta(m,n) - Y(m,n)]^2\}$, the restored image will be very close to the clear image.

3. Block-based Adaptive Image Filtering

To improve processing speed and boost efficiency, the block-based scanning technique [6] is used in the paper. The M×M noise source image is divided into several blocks (sub-images). Each block is with L×L dimension, moving from left to right, and from up to bottom. Similarly, there is a moving window with dimension F×F scanning from left-up corner to right –bottom corner over each L×L block. A single-layered neural network is used as image restoring filter, as shown in Fig.2.

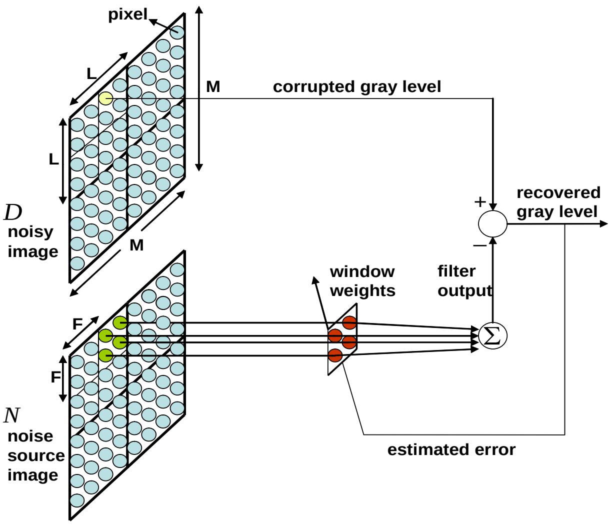

Fig. 2: Adaptive filter for image noise cancellation.

i : current block index, under processing. $i = 1,2,\ldots,(M/L)^2$.

k : current window index, under processing. $k = 1,2,\ldots,L^2$.

(m,n): the indices for the gray level of the m-th row and the n-th column in the image. ($m,n = 1,2,\ldots,M$)

(p,q): the indices for the p-th row and q-th column block in the image. ($p,q = 1,2,\ldots,M/L$)

(r,s): the indices for the r-th row and s-th column gray level in a block. ($r,s = 1,2,\ldots,L$)

(u,v): the indices for the u-th row and v-th column window weight or windowed gray level in a block. ($u,v = 1,2,\ldots,F$)

The (r,s)-th element in the i-th block of the noise source image is denoted by $N_i(r,s)$. The block index i can be expressed in terms of (r,s), given as

$$i = (p-1)(M/L) + q \tag{3}$$

The (r,s)-th element in the i-th block of the received noisy image can be denoted by $D_i(r,s)$.

In the i-th block, the filter output for the (r,s)-th pixel can be expressed as follows.

$$Y_i(r,s) = \sum_{u=1}^{F}\sum_{v=1}^{F} W_i(u,v)N((r-1)+(p-1)L+u,(s-1)+(q-1)L+v) \tag{4}$$

The estimated error is then given as follows.

$$R_i(r,s) = D_i(r,s) - Y_i(r,s) \tag{5}$$

$R_i(r,s)$ is viewed as the estimate of the gray level of the corresponding pixel of the restored image. The square matrix of the estimates can be rearranged into a column vector $\hat{R}_i$ as follows.

$$\hat{R}_i = [R_i(1,1),\ldots,R_i(1,L),R_i(2,1),\ldots,R_i(2,L),\ldots \\ \ldots,R_i(L,1),R_i(L,2),\ldots,R_i(L,L)]^T_{L^2\times 1} \tag{6}$$

With an $F\times F$ window, the elements in the window over the noise source image N can be rearranged as an $F^2 \times 1$ column vector $\hat{N}$ given as

$$\hat{N}(k) = [\hat{N}(1,1),\ldots,\hat{N}(1,F),\hat{N}(2,1),\ldots,\hat{N}(2,F), \\ \ldots,\hat{N}(F,1),\hat{N}(F,2),\ldots,\hat{N}(F,F)]^T_{F^2\times 1}(k) \tag{7}$$

, where k indicates the k-th scanning over the current block for $k = 1,2,\ldots,L^2$. For the i-th block, the matrix X_i is defined as follows.

$$X_i = [\hat{N}(1),\hat{N}(2),\ldots,\hat{N}(L^2)]_{F^2\times L^2} \tag{8}$$

Similarly, for the $F\times F$ window, the window weights can be rearranged into an $F^2 \times 1$ column vector $\hat{W}_i$ given as

$$\hat{W}_i = [W_i(1,1),\ldots,W_i(1,F),W_i(2,1),\ldots,W_i(2,F), \\ \ldots,W_i(F,1),W_i(F,2),\ldots,W_i(F,F)]^T_{F^2\times 1} \tag{9}$$

The block-based 2-D LMS equation can be given as follows.

$$\hat{W}_{i+1} = \hat{W}_i + \Delta\hat{W}_i = \hat{W}_i + \gamma X_i \hat{R}_i \tag{10}$$

where the learning factor γ controls the learning speed, accuracy and stability of the adaptive filter, and it is assumed to be fixed. The window weight vector is the same in a block and to be updated in the next block. For an $M\times M$ image to be divided into $(M/L)^2$ blocks, the window weight vector will be updated $(M/L)^2$ times in the image processing.

4. Random Optimization with Jumps

A real-valued cost function $J(X)$ is given with $X=[x_1,x_2,...,x_n]^T$, and the objective is to find an optimum vector X^* such that cost value $J[X^*]$ is minimized. Maximum search number $k_{\max}$ bounds epochs in a finite number. The Gaussian random vector with zero mean is used in the RO and a variance is set for local search range. Local search number $\lambda_{\max}$ is set to detect local minimum.

Step 1: Choose a given initial point $X=X_0$.

Set an epoch counter k and a local search counter λ. At beginning, let $k=0$ and $\lambda=0$.

Step 2: Generating a Gaussian random vector dX with a specific mean μ_k and a fixed variance σ^2.

Step 3: Compute cost value $J(X\pm dX)$,

if $J(X+dX)<J(X)$, update parameter:

$\mu_{k+1}=0.4dX+0.2\mu_k$, $\lambda=0$

$X'=X+dX$, go to step 6.

if $J(X-dX)<J(X)$, update parameter:

$\mu_{k+1}=0.4dX-0.2\mu_k$, $\lambda=0$

$X'=X-dX$ go to step 6.

else, go to Step 4.

Step 4: compute interpolation point,

$$\alpha=\frac{J(X-dX)-J(X+dX)}{J(X-dX)+J(X+dX)-2J(X)}$$

compute cost value $J(X\pm\alpha dX)$,

if $J(X+\alpha dX)<J(X)$,update parameters:

$\mu_{k+1}=\alpha\mu_k-0.4dX$, for $-1<\alpha<0$,

$\mu_{k+1}=0.2\alpha\mu_k+0.4dX$, for $1>\alpha>0$,

$X'=X+\alpha dX$, $\lambda=0$, go to step 6.

if $J(X-\alpha dX)<J(X)$, update parameters:

$\mu_{k+1}=\alpha\mu_k-0.4dX$, for $-1<\alpha<0$,

$\mu_{k+1}=0.2\alpha\mu_k+0.4dX$, for $1>\alpha>0$,

$X'=X-\alpha dX$, $\lambda=0$, go to step 6.

else, go to Step 5.

Step5: Now, $J(X)=J(X\pm dX)=J(X\pm\alpha dX)$,

if λ reaches to local search number $\lambda_{\max}$, $\mu_{k+1}=0$, $dX=\beta dX$, where β is jump factor, normally, $\beta>1$, go to step 6.

else, $\lambda=\lambda+1$, go to step 6.

Step6: if k reaches to the maximum search number $k_{\max}$, or $J(X)<\varepsilon$. Stop! where ε is acceptable cost,

else, $k=k+1$, return to Step 2.

For adaptive noise filtering problem, the cost function defined as follows.

$$J(\hat{W})=\frac{1}{L^2}\sum_{r=1}^{L}\sum_{s=1}^{L}[D(r,s)-Y(r,s)]^2 \quad (11)$$

The training process is done in the first block, and the trained window weighs are used in following blocks.

5. Experimental Results

The Lena image with dimension 256×256 is used in experiment. The reference noise source image is generated with Gaussian distribution of zero mean and a variance of unity. Initial settings are given as follows.

1. Block processing setting:
   L=8, F=2, M=256, learning constant is chosen to be $\gamma=2.2\times10^{-4}$. Window weight vector $\hat{W}_0=[-0.17,0.34,1.55,0.88]^T$ is given initially.
2. RO learning setting:
   Maximum epochs $k_{\max}$=1500, local search number $\lambda_{\max}$ = 20, Gaussian random vector with a fixed variance σ^2 =0.03 and zero mean initially, acceptable cost ε=1, and jump factor β=3.
3. Nonlinear channel transfer function is defined as

$$\eta(m,n)=N(m,n)^2-\frac{1}{2N(m,n)}+40N(m,n) \quad (12)$$

The performance is evaluated with Mean-Square-Error (MSE) of the image, which is defined as follows.

$$MSE\equiv\frac{1}{M^2}\sum_{m=1}^{M}\sum_{n=1}^{M}[R(m,n)-S(m,n)]^2 \quad (13)$$

The noisy image is shown in Fig. 3, whose MSE is 1557.9. For comparison purpose, the proposed approach is compared to 2-D block LMS approach [7]. The MSE of restored image using 2-D block LMS is 176.42, shown in Fig. 4. The MSE of restored image using the RO-based learning approach is 9.7346, shown in Fig. 5. Further more, to compare with the convergence of these two methods, Block-Mean-Square-Error (BMSE) for the i-th block is defined as follows.

$$BMSE_i=\frac{1}{L^2}\sum_{r=1}^{L}\sum_{s=1}^{L}[S_i(r,s)-E_i(r,s)]^2 \quad (14)$$

Convergence responses by both the 2-D LMS and by the RO are shown in Fig.6. In 1024 block iterations, the 2-D block LMS filter needs a longer period of settling time to reach the optimum weight vector, while the training for the filter by RO is concentrated on the first block. For the same initial weight vector, the 2-D block LMS finally converges to $\hat{W}^*_{LMS}=[39.80,0.74,0.81,0.77]^T$ within around 500 blocks, and to $\hat{W}^*_{RO}=[37.33,-1.16,0.09,0.84]^T$ by RO after 1419 learning epochs.

6. Discussion and Conclusion

The well-known Random Optimization (RO) has been applied to noise canceling for image restoration successfully. Compared with the 2-D block LMS, the performance by the RO has been shown improved significantly. We have used the RO in single-layered neural-like filter. A single-layered neural network (filter) has limitation on nonlinear mapping ability. In the face of high nonlinear problems, the research is expected to extend to more powerful, multi-layered neural network, to cope with such complicated problems, and the RO is still a good candidate as training method, based on the results obtained so for.

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Fig.3: Noisy image, MSE=1557.9.

Fig.4: Restored image by 2D Block-based LMS filter (L=8, F=2), MSE=176.42.

Fig.5: Restored image by adaptive RO-based filter (L=8, F=2), MSE=9.7346.

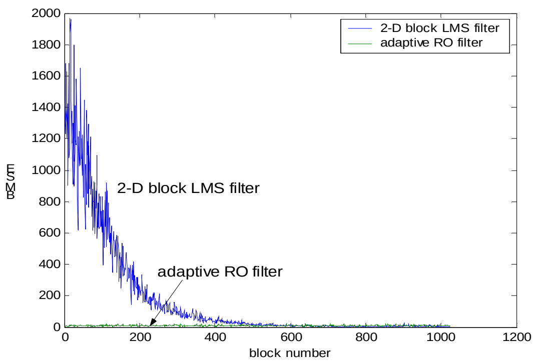

Fig.6: Convergence comparison of 2-D block LMS and adaptive RO-based filter.