Variable Step Size TDBLMS Filter For Video Denoising

Fancy Joy, Dr. V. Vijayakumar

Abstract: Video denoising is the significant task in various video processing applications. Two Dimensional Block Least Mean Square (TDBLMS) approach with adaptive learning rate presents in this paper. Paper proposes Variable step size Two Dimensional Block Least Mean Square (VS-TDBLMS) method that applies a variable learning rate in TDBLMS filter rather than a fixed learning rate. The experimental results proves that the new approach improved the convergence speed and quality compared to TDBLMS approach.

Index Terms: video denoising, TDBLMS, learning rate, least mean square, weight filter, error.

1. INTRODUCTION
Video quality enhancement is one of the challenging areas in many applications such as street monitoring, suspicious event detection, and object tracking etc. in various domains [6]. The process of eliminating noise and improving the quality of video for further processing is known as video denoising[5]. Noise enters in to the video during the fast acquisition and transmission which leads major degradation of video quality. There exists many image and video filtering algorithms. Adaptive LMS algorithm is one of the old benchmark algorithm for image denoising [3,4,17]. The algorithm can be extends to video by considering each frame as image. But it exhibits slow convergence and more time consumption. TDBLMS approach is a variation of adaptive LMS and also shows slow convergence[3,17]. Hence an adaptive learning rate introduces to the algorithm which improves the performance of the algorithm. TDBLMS approach for video consists of two steps: noise filtering step reconstruct the original frame from noisy frame using weight filter and weight updating step updates weight filter value according to the error matrix [5]. The main contributions of this paper as follows. First the approach extends the TDBLMS method from image to video and monocular image to color image. Second an adaptive learning rate is introduced to improve the algorithm. Experimental results proves that the method enhances the quality of video. The rest of the paper structured as follows. Section II discusses related works in this area and TDBLMS approach describes in section III. Experimental results demonstrated in section IV. Finally it draws a conclusion in section V.

2 RELATED WORKS
Current noise reduction methods are based on conventional image filtering approaches, where the denoising is attain by processing a video frame by frame. Image filtering algorithms were categorized in to linear and non-linear filtering. Linear filtering includes mean filter and adaptive filter. The drawbacks of these are smoothing and motion blur. Median filter is a non linear filter method also cause blur in images[14].Some of the methods for video denoising are non local means, least mean square[3,4,17], spatio-temporal filtering and block matching 3D filtering etc. During 2010 Hui Ji et.al [9] developed patch based low rank matrix completion approach for robust video denoising. The approach was able to handle mixed type of noises and the algorithm validated in various experiments. Method requires improvement to eliminate Poisson noise. The authors H.Guo and Namratha [8] splits the video as the combination of low rank and sparse layer then apply the VBM3D approach for noise elimination. The layering increases the accuracy and performance of algorithm. Almahdi and Hardie[13] described an extension of recursive non local means algorithm for handling poisson and Gaussian noise. The method was capable of balancing elimination of noise and preservation of details. The method proves that it is well suitable for real time due its low computational cost. Yahya et.al[1] proposed spatio temporal filtering for video denoising. The method completed in three stages a spatial filter i.e wiener filter, temporal filter and motion detector. The approach improved the efficiency of denoising. In order to reduce the computational complexity they again combines the VBM3D and K Means clustering to the method. Adaptive thresholding concept introduced for i.e. soft thresholding for small noise and hard thresholding for heavy noise. Arias and Morel[11] extended nonlocal Bayesian denoising algorithm from image to video. The method does not require motion estimation. Extension requires reducing the computational complexity by spatiotemporal patches. To overcome the drawback authors[12] introduced spatio-temporal patch based empirical Bayesian method for video denoising in 2018. It gives very good result without considering motion estimation. Expansion required for reducing computational complexity. Patch based non local Convolutional Neural Network (CNN) method for video denoising was introduced by Davy et.al[2]. Non local feature vector from a frame was extracted then fed into CNN for training and it helps to predict the clean frame. It is the first CNN based state of art method for video denoising. More works in CNN is considered necessary in this area.

X Tian et.al [19] presented coefficient shrinkage using threshold adjustment method. Here the threshold adjustment was based on surfacelet transform method. Method shows very good suppression of noise and improves the visual quality. Improvement is needed to reduce the computational complexity. Adaptive video denoising using Block matching 3D filtering was introduced by Chen et.al[7]. Algorithm mainly based on BM3D and VBM3D approach. Further studies required to apply the approach for noises other than Gaussian noise. Xin Tan et.al [18] implemented pixel similarity weighted frame averaging (PSWFA) for video denoising. The approach

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was based on hybrid method PSWFA and gaussian filter as pre-filter. Method mainly suitable for video contains large noises. Approach shows excellent denoising for digital video cameras. The method for denoising color video using a fusion of epitome and sparse coding was proposed by H Y Lee et.al[10]. Video epitome eliminate the redundacy of video and uses dictionary learning approach for denoising. Further enhancement required for improving the efficiency of algorithm by applying multiple epitomes instead of single epitome. The authors Zhang et.al [20] developed a new noise reduction for video based on texture metric and adaptive structure variance. Technique shows better denoising compared to BM3D and BM4D approaches.

3 TDBLMS ALGORITHM

Single frame representation of a video is depicted in Figure 1. Consider a frame Cf represented as rows and columns of matrix and these further divided into blocks with a specific block size called ‘L’. Index for each block is calculated as the difference between frame and the reference frame. Here least mean square between the frame is considered as the error. A weight matrix(Wf) is initialized as block size ‘L’. Weight matrix updates when the Ef is large.

![Image](Image 58x290 to 290x419)

**Figure 1. Single frame representation - TDBLMS**

The main objective of variable step size is to update the learning rate depend on the square of the error. The proposed method generates the low step size (slow adaptation) when error become low and fast adaptation when error become high[15].

4 EXPERIMENTAL RESULTS

To prove the efficiency of VS-TDBLMS algorithm the method tests three publically available video sequences can download from [https://media.xiph.org/video/def/][16]. Table 1 shows the comparison of TDBLMS and VS-TDBLMS method in terms of PSNR (Peak signal to noise ratio) values.

<table>
<thead>
<tr>
<th>Noise (σ)</th>
<th>Method</th>
<th>Video sequences</th>
</tr>
</thead>
<tbody>
<tr>
<td>5</td>
<td>TDBLMS</td>
<td>35.399 36.364 35.385</td>
</tr>
<tr>
<td>15</td>
<td>TDBLMS</td>
<td>37.975 39.422 37.881</td>
</tr>
<tr>
<td>28</td>
<td>TDBLMS</td>
<td>26.572 27.078 26.078</td>
</tr>
<tr>
<td>30</td>
<td>TDBLMS</td>
<td>28.959 30.656 28.737</td>
</tr>
</tbody>
</table>

Table 1: PSNR comparison of TDBLMS and VS-TDBLMS in three different gaussian noise standard deviation (σ)
From the above table it is clear that the VS-TDBLMS performs better than TDBLMS algorithm.

Figure 2 shows the visualization of video frame, noisy frame, reconstructed frame using TDBLMS method and, reconstructed frame using VS-TDBLMS method from frame 5 of tennis and foreman sequence. The results of figure 2 indicates that the visual quality of the video improved by using VS-TDBLMS than TDBLMS method.

![Figure 2](image)

(a) frame (b) frame + noise(σ=15) (c) result of TDBLMS(d) result of VS-TDBLMS

5 CONCLUSION

This paper presents VS-TDBLMS approach for video denoising. The method uses varying learning rate which improves the performance of the TDBLMS method. The method eliminates the noises from video and improves its quality. Experimental results show that the proposed method can achieve better PSNR and SSIM compared to TDBLMS algorithm. Future, it is intended to extend the approach to non Gaussian noise.

REFERENCES


[16] url=”https://media.xiph.org/video/def”


