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A Novel Edge Preserving Local Linear Stein's Unbiased Risk Surface Estimator Approach for High Dynamic Range Image

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Abstract

Objective: The main objective of this research is to preserve the edges and also remove the noise from high dynamic range videos during filtering process. This methodology attempts to preserve the original quality of the videos and achieves the better compression ration by compressing it with the concern of the edge preservation details. **Methods:** The system proposes a novel edge preserving LLSURE (Local Linear Model, Stein's Unbiased Risk Estimate) surface estimator mechanism which is based on an adaptive local linear model and the principle of Stein's Unbiased Risk Estimate (SURE). Generally, pixels in the edges and near to the edge are affected during noise filtering. Here the LLSURE filter is extended by using Edge-preserving surface estimator. The proposed estimator is used to leave some noise in the vicinity of edges and improve those edges during denoising process. Finally Weighted Residual Mean Squares (WRMS) is used for compute the quality of estimator. **Findings:** The performance evaluation was conducted to prove the efficiency of the proposed methodology by comparing it with the existing approach called OCP based video coding technique. The performance evaluation is conducted in terms of the parameters called the Peak Signal to Noise Ratio, Mean Square Error and Maximum error comparison. The experimental tests conducted were proves that the proposed methodology can lead to efficient preservation of the edge details during noise removal than the existing methodologies. **Conclusion:** The proposed procedure can remove the noise correctly in continuity or surrounding regions of the surface, and preserve discontinuities at the same time.

Keywords: Edge Preserving, LLSURE, Mean Integrated Error, Weighted Residual Mean Squares

1. Introduction

Filtering is perhaps the most significant process of image processing and computer vision. It can be used in a wide range of application, including image smoothing and sharpening, noise removing, particular feature extraction, and edge detection. A Linear Translation Invariant LTI filtering is implemented by using convolution mask. In past years various edge-preserving filtering methods used for minimise undesirable effects of linear filtering. An edge preserving non-linear filtering is used for preserve the edges and local geometries during noise removing process[1].

Edge-preserving filters are useful tool for various image editing process and manipulation task. Most of them are preserving the edge details during noise removal process. Local linear SURE filter is based on a local linear model and it follows the principle of Stein's Unbiased Risk Estimate SURE.

Based on the Partial Differential Equations (PDE's) and variatiotnal models most of the filtering process are introduced. For example, non-linear/Anisotropic Diffusions (AD)[2], as well as regularization process based on the Total Variation (TV)[3], are most fashionable and widely used non-linear filtering technique in signal and image processing. Here the global noise estimation does give accurate local estimation and edge related gradients.

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Based on noise removal algorithm, the system proposed a nonlinear total variation mechanism. The total variation of the image is reduced subject to constraint involving the information of the noise. Solution is based on a time dependent partial differential equation. It is executed as a repeated process which is usually slow[3]. The introduced bilateral filtering method is used for gray and color images. The smoothened image is produced by using Bilateral filtering[4]. The edges are affected by denoising process. This system does not give any solution for this problem.

Most of the edge-preserving filters have been implemented for preserve edges. There are as Weighted Least Squares filter (WLS)[5], Edge Avoiding Wavelets (EAW)[6], and Domain Transform (DT) method[7] to approximate geodesic distance by iterating 1D-filtering operations. To avoid a trivial solution, the regularization parameters is introduced which find out the amount of smoothing[8,10].

The proposed optimal compression plane is used for reduce the redundant data from the video. This optimal compression plane is used as a preprocessing module, which is used before applying the standard video coding method. This optimal compression plane method form the video frame on any two axes among X, Y and T axis. Here the statistical redundancy along one axis is calculated by using the average correlation coefficient between frames, which is formed by using the two remainder axis. If the value of average CC is high, it leads to high statistical redundancy. This method is used with many standard image and video coding technique. This OCP is applicable for natural digital image only[9]. Optimal compression plane does not preserve the edges during noise removal.

2. Novel Edge Preserving Local Linear Stein's Unbiased Risk Surface Estimator Approach

The proposed system uses edge preserving image filtering technique in high dynamic range video image. High dynamic range images are broadly used since they have wider intensity range than normal digital images, which fit the intensity range of actual scene recognized by human eyes. During that filtering process vicinity of edges are improved.

The system propose an edge preserving image filtering method which is an adaptive local linear model and the principle of Stein's unbiased risk estimate (SURE) such as LLSURE.

SURE is represented by the following Equation

$$\mathrm{SURE}(\hat{X}) = \frac{1}{N\left\|Y-\hat{X}\right\|^2} + \frac{2\sigma^2}{N}\mathrm{div}_y\{\hat{x}\} - \sigma^2 \tag{1}$$

Where $\mathrm{div}_y\{\hat{x}\}$ is the divergence of the output estimate with respect to the measurements

$$\mathrm{div}_y\{\hat{x}\} = \sum_{i=1}^{N}\frac{\partial \hat{x}_i}{\partial y_i} \tag{2}$$

σ^2 represented as noise variance. It can be easily estimated from measured data.

The Local Linear Stein's Unbiased Risk Estimate (LLSURE) is based on the local linear model and the principle of Stein's Unbiased Risk Estimate (SURE). Each and every window has N pixels. Each pixel involved in N windows. For every window, there is a set of a_w, b_w. Where a_w, b_w are some affine transform coefficients assumed to be constants in window w_j. Let w_j be a local window around the j position, y_w and x_w represents an input image and a filtered output image respectively according to the window w_j. Here, for simplicity, the system consider w_j as a square window of pixels with a fixed size.

The LLSURE method can be represented as

$$\hat{x} = LLSURE(Y, r, \sigma^2) \tag{3}$$

Where Y represented as input signal and $\hat{x}$ represent filterd output signal, r denoted as window radius. σ^2 is a noise variance. Stein's unbiased risk estimate as an estimator for the mean squared error from the noisy image

$$\mathrm{MSE}(\hat{X}) = \frac{1}{N\left\|X-\hat{X}\right\|^2} \tag{4}$$

X - Noise free signal

$\bar{X}$ -Filtered out put

If the two images are same scene, they are combined by using joint LLSURE filter for obtains a more satisfactory image. Multiscale edge-preserving decomposition is built by using LLSURE filter. Here two methods are taken for computing the sequence. At the first LLSURE filter is used for filter the original images at k times. Every time parameter σ^2 value is increased.

$$[Y]_j = \mathrm{LLSURE}(Y, r, c_j\ \sigma^2) \tag{5}$$

The second method is to obtain each image in the sequence by applying LLSURE to the previous image.

$$[Y]_j = \mathrm{LLSURE}(Y_{(j-1)}, r, c_i\ \sigma^2) \tag{6}$$

Here the image is repeatedly smoothed, and the resulting coarsened images tend more strongly towards piecewise constant regions separated by strong edges. Although the process producing the sequence is different. The two methods give the results as same results. Generally, pixels in the edges and near to the edge are affected during noise filtering. Here LLSURE filter is extended by using novel Edge-preserving surface estimator. Since it may leave some noise in the vicinity of edges and preserve those edges in denoising process. The edge can be represented as a curve in the (X, Y) plane, along which the surface is discontinuous. If an edges in the neighbour of (x, y) plane, for compute m(x, y) the conventional estimator $\hat{a}_c$ (x, y) is biased. The system has established three estimators for m(x, y): one is $\hat{a}_c$ (x, y) which conventional estimator and another is $\hat{a}_1$ (x, y) and $\hat{a}_2$ (x, y) which are one-sided estimators.

Surface estimation is based on the LLSURE,

$$\hat{a}_c(\mathrm{x,y}),\ \hat{a}_{c,x}(\mathrm{x,y}), \hat{a}_{c,y}(\mathrm{x,y}) = \arg\min_{(\mathrm{a,b,c})}$$
$$\sum_{(i=1)}^{n} \equiv [z_i] - a - b(\mathrm{X_i - x}) - C(\mathrm{Y_i - y})^2$$
$$L_B^j\ ((X_i - x), (\mathrm{Y_i - y})) \tag{7}$$

The system defines the two one-sided local linear SURE surface estimator follows:

$$\hat{a}_j(\mathrm{x,y}),\ \hat{a}_{j,x}(\mathrm{x,y}), \hat{a}_{j,y}(\mathrm{x,y}) = \arg\min_{(\mathrm{a,b,c})}$$
$$\sum_{(i=1)}^{n} \equiv [z_i] - a - b(X_\mathrm{i} - \mathrm{x}) - C(\mathrm{Y_i - y})^2$$
$$L_B^j\ ((X_i - x), (\mathrm{Y_i - y})) \tag{8}$$

The conventional estimator $\hat{a}_c$ (x, y) will be chosen for compute m(x, y) if there are no edge pixels in the neighbourhood of (x, y). It gathers more observations around the point (x, y) and which is great in removing noise. The Conventional estimator $\hat{a}_c$ (x, y) is not a well estimator of m(x, y) if there is an edge segment around (x, y). Here two one-sided estimators $\hat{a}_1$ (x, y) and $\hat{a}_2$ (x, y) is compute the surface well. Because most observations used by this estimator are located on a single side of the edge segment. This novel Edge-preserving surface estimator is to improve vicinity of edges during filtering process.

The quality of the three estimators $\hat{a}_c$ (x, y), $\hat{a}_1$ (x, y) and $\hat{a}_2$ (x, y) are computed by the Weighted Residual Mean Squares (WRMS) of the related fitted surfaces, defined by:

$$WRMS_c(x,y) = \frac{1}{\sum_i L_{B(\mathrm{i})}} \sum_i z_i - \hat{a}_c(x,y)$$
$$-\hat{a}_{c,x}(x,y)(X_i - x) - \hat{a}_{c,y}(x,y)(y_i - x)]^2\, \mathrm{L_B(i)} \tag{9}$$

$${}_j(x,y) = \frac{1}{\sum_i L_{Bj(\mathrm{i})}} \sum_i z_i - \hat{a}_j(x,y)$$
$$-\hat{a}_{j,x}(x,y)(X_i - x) - \hat{a}_{j,y}(x,y)(y_i - x)]^2\, \mathrm{L_B(i)} \tag{10}$$

$\mathrm{L_B}$ –Local linear SURE

$\mathrm{Z_i}$ = Discontinuous surface estimation is:

$$\mathrm{Z_i = m(X_i + Y_i) + \varepsilon_i,\ i = 1,\ldots,n}$$

Where,

m - True surface continuous

ε_i –Random errors with zero mean

The behaviour of Weighted Residual Mean Squares depends on whether there are boundary pixels in the neighbourhood of the point (x, y). If there are no edge pixels in the neighbourhood, then all WRMS's are good estimators of the noise variance σ^2. At last, the final filtered image will be obtained by taking average of all filtered output images. Finally smoothing and enhancement works will be carried out on the video frames. Detail smoothing and enhancement are basic and common image processing operations, available in most image editing software. The flow of the project is given in the Figure 1 which is in the image results of the existing and proposed methods are shown in Figure 2 and Figure 3.

3. Experimental Result

The existing system of Optimal Compression Plane (OCP)-based video coding is compared with proposed LLSURE method. Final results proved that the proposed methodology works produces better results than the existing methodology. This performance evaluation is done based on the performance metrics called the Peak Signal to Noise Ratio (PSNR), the Mean Square Error (MSE) and Maximum error rate. In the Figures 1a-1d compressed video frames have been given. This performance analysis is represented in the graphical and Table format which is explained in the detailed manner in the proceeding sections.

3.1 Peak Signal to Noise Ratio

The Peak Signal to Noise Ratio (PSNR) is used to compare image compression quality**.**This ratio is often

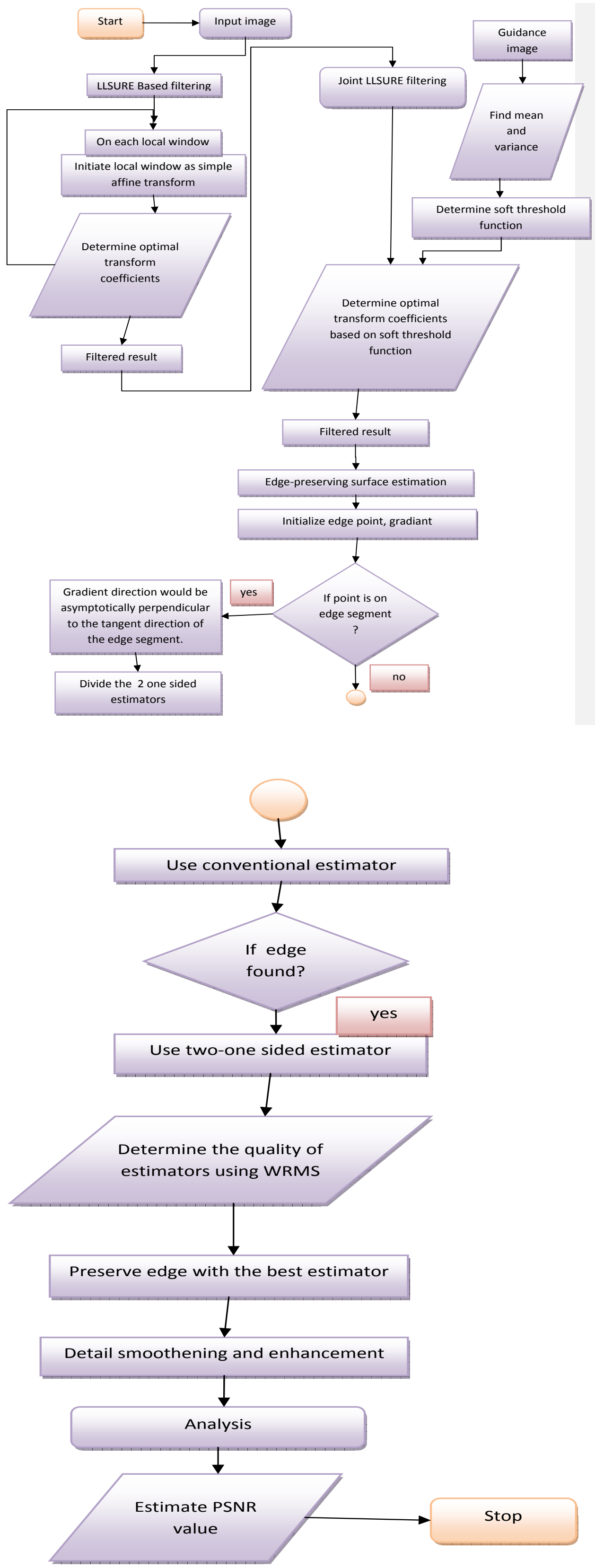
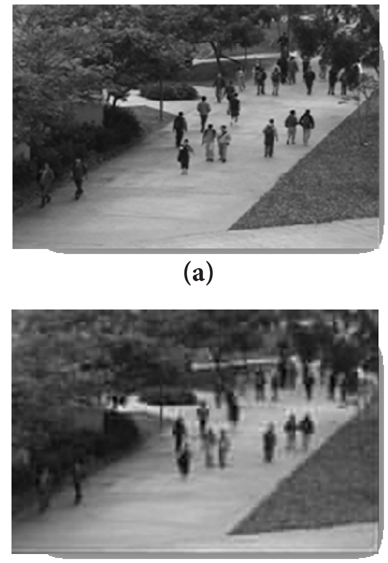


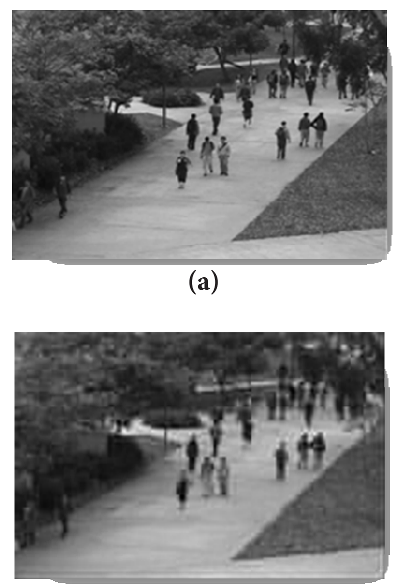
Figure 1. The flow of the project.



(a)

(b)

Figure 2. **(a)** OCP before compression. **(b)** OCP after compression.



(a)

(b)

Figure 3. **(a)** LLSURE before compression. **(b)** LLSURE after compression.

used as a quality measurement between the original and a compressed image. PSNR represents a measure of the peak error. If the PSNR value is high better the quality of the compressed or reconstructed image is obtained. PSNR value of the proposed methodology should be high which indicates the better compression quality of the videos without noise. The methodology with high PSNR rate can be reconstructed by preserving the original quality of the video which is computed as like follows: PSNR value is computed by using the following Equation:

$$PSNR = 10\log_{10}\left(\frac{R^2}{MSE}\right)$$

R - Maximum fluctuation in the input image data type
MSE - Mean Square Error

The graphical representation of the PSNR rate is given in the following Figure 4 whose measurement values are obtained in the matlab simulation environment. In that graph, existing and the proposed methodologies are compared with each other.

In this graph, numbers of frames are taken in the x axis and the Peak signal-to-noise ratio values are plotted in the y axis. The existing system of OCP-based video coding is compared with proposed LLSURE method. From this graph, it can be proved that PSNR values are high in the proposed methodology than the existing approach. And also PSNR rate is linearly increased and decreased for the increased number of frames present in the system. The original performance measures which was used to plot this graph is given in the Table 1.

The values given in graph are illustrated in the table format as like follows in Figure 3. This table illustrates the Peak signal-to-noise ratio which is evaluated according to number of pixel is taken.

3.2 Mean Square Error

The Mean Square Error stand for cumulative squared error between compressed image and original image. If the mean square value is low, lower error rate will be occurring. The mean-squared error using the following Equation

Table 1. Peak signal to noise ratio

Number of Frames	Peak Signal to Noise Ratio	
	OCP-based video coding	LLSURE
Frame 2	12.0859	12.1271
Frame 4	12.0803	12.1165
Frame 6	12.0775	12.1124
Frame 8	12.0754	12.1123
Frame 10	12.0749	12.1138
Frame 12	12.0815	12.1209
Frame 14	12.0907	12.1316

$$MSE = \frac{1}{MN}\sum_{y=1}^{M}\sum_{x=1}^{N}[I(x,y) - I'(x,y)]^2$$

Where,
I(x, y) - original image,
I'(x, y) - approximated version (which is actually the decompressed image)
M, N - dimensions of the images

The mean square error of the proposed methodology should be less for the proposed methodology which will indicates the less errors present in the videos after reconstructing the videos from the compressed video. Less number of errors indicates that the qualified video reconstruction without noises. The graphical representation of comparison of the proposed methodology with the existing methodology is given in the following Figure 5.

In this graph, numbers of frames are taken in the x axis and the mean square error values are plotted in the y axis. The Mean Square Error value of OCP-based video coding system is compared with the LLSURE method. From this graph, it can be proved that the means square error values are considerably less in the proposed methodology whereas in the existing methodology it is high. Mean square errors values in the graph show considerable improvement of the proposed approach. The original measure values are indicated in the Table 2.

The mean square error values of existing and proposed system represented in table format. The Mean Square Error value of OCP-based video coding system is compared with the LLSURE method according to number of

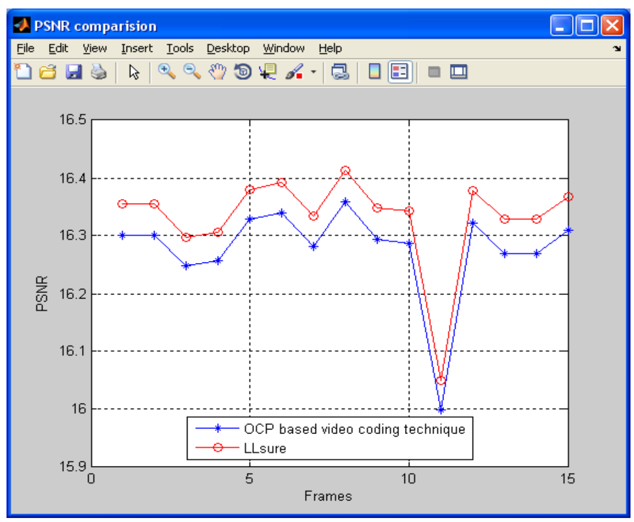


Figure 4. Peak signal-to-noise ratio.

Table 2. Mean square error

Number of Frames	Mean Square Error	
	OCP-based video coding	LLSURE
Frame 2	4022	3984
Frame 4	4028	3993
Frame 6	4030	3998
Frame 8	4032	3999
Frame 10	4033	3997
Frame 12	4025	3989
Frame 14	4019	3981

frames taken. If the mean square value is low, lower error rate will be occurring. The mean square error value of proposed system is highly better than existing system.

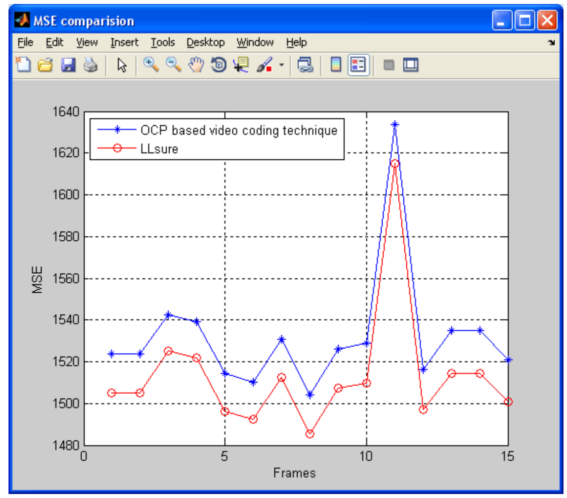


Figure 5. Mean square error.

3.3 Maximum Error Comparison

The maximum error rate occurs at the margins of the bioequivalence interval. The maximum error increases as noise variance increases. This measure is used to denote the degradation of video quality in case of reconstruction of the compressed videos. The maximum error rate is directly proportional to the noise rate which will increases gradually for the increased value of the noise rate as like follows:

Maximum Error Rate α Noise Rate

Graphical representation of the proposed methodology is depicted in the following Figure 6. In this graph, numbers of frames are plotted in the x axis and the maximum error values are plotted in the y axis. It is proves that the maximum error values of proposed methodology is lower than the existing approaches. And also the maximum error rate is increasing and decreasing in the proposed methodology in the non-linear sequence. The exact values of maximum error rate are given in the following Table 3.

The Maximum error values of existing and proposed system are represented in table format. These values are represented in the table form to show the accurate difference between the proposed methodology and the existing methodology. The Maximum error values of LLSURE system is low compared to the existing system.

Table 3. Maximum error comparison

Number of Frames	Maximum error	
	OCP-based video coding	LLSURE
Frame 2	179	162
Frame 4	179	162
Frame 6	179	161
Frame 8	179	168
Frame 10	185	169
Frame 12	185	166
Frame 14	182	170

3.4 Normalized Absolute Error Comparison

Normalized absolute error comparison is used to predict the average of correct prediction that was made in terms of the predicted outcomes. Normalized absolute error is used to find the average success rate of video compression which was made. The comparison of existing and proposed methodology in terms of normalized absolute error was given in the following Figure 7. In this graph, numbers of frames are plotted in the x axis and the normalized absolute error values are plotted in the y axis. It is proves that the NAE of proposed methodology is lower than the existing approaches.

3.5 Maximum Difference Comparison

Maximum difference parameter is used to evaluate the variation present in the decompressed image than the compressed image in terms of improved performance ratio. The comparison of maximum difference parameter value is given in the following Figure 8. In this graph, numbers of frames are plotted in the x axis and the maximum difference values are plotted in the y axis. It is proves

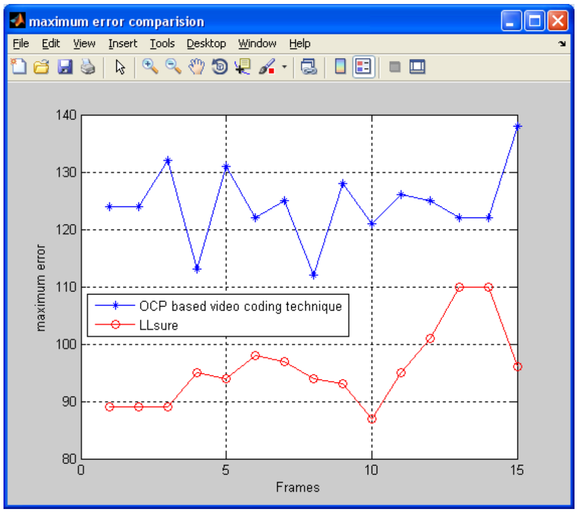


Figure 6. Maximum error measure.

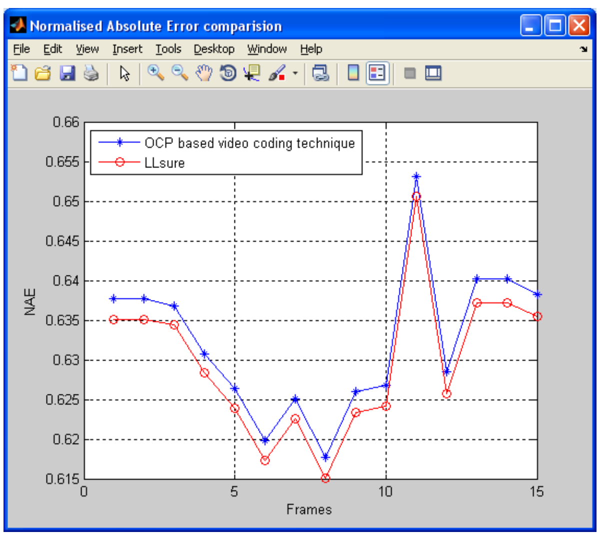


Figure 7. Normalized absolute error.

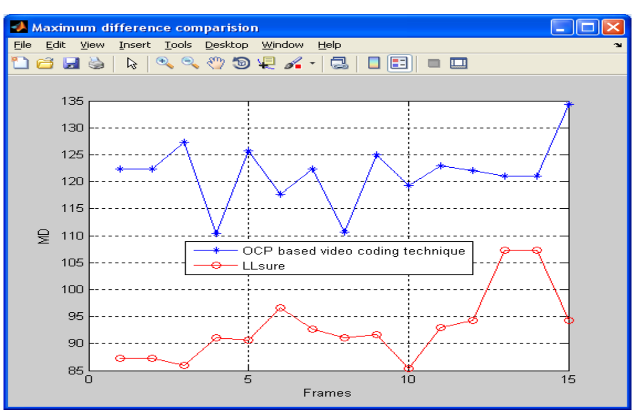


Figure 8. Maximum difference.

that the NAE of proposed methodology is lower than the existing approaches.

4. Conclusion

The proposed system introduces a novel edge preserving LLSURE surface estimator mechanism which is based on the local linear model and the principle of Stein's Unbiased Risk Estimate (SURE). Generally, pixels in the edges and near to the edge are affected by noise filtering process. To overcome this problem the Edge-preserving surface estimator is introduced which is used for improve vicinity of edges during filtering process. Weighted Residual Mean Squares (WRMS) is used for compute quality of the estimator. The system procedure can therefore remove noise correctly in continuity or surrounding regions of the surface, and preserve discontinuities at the same time.

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