Edge Entropy Motion Model based Quality Assessment for Low and Natural Videos

Shipra Parihar[1] Mr. Danvir Mandal[2]
[1]M. Tech. Student [2]Associate Professor & HOD
[1,2]Department of Electronics & Communication Engineering
[1,2]CGC Technical Campus Jhanjeri, Mohali, Punjab

Abstract— Video quality estimation plays an important role in various applications of video processing such as compression, restoration, printing, enhancement and watermarking. Now a days the field of objective quality evaluation gets more interest of researchers with affluent algorithms which is being recommended for this purpose. The Quality of the video is accessed by two ways Subjective and Objective. In subjective quality assessment metrics the quality of video is being estimated by human observers. In this humans judge the quality of distorted video. And in objective quality estimation the quality is assessed by quality metrics or algorithms. In this paper we evaluate the quality of the video by using objective quality assessment metrics. There are large numbers of objective quality assessment metrics like PSNR (Peak signal to noise ratio), MSE (Mean square error), RRED (Reduced reference entropic difference), Correlation and BLIINDS model metrics. We apply some distortion effects on video and calculate the quality on the basis of these metrics. We purpose a quality metrics (EMM) Edge entropy motion model. According to this metrics quality of video is assessed on the basis of edges of objects in the frame and the edges are extracted on the basis of gradients and gradients of image extracts the edges on color basis RGB. We take PSNR as a standard metrics and compare the results of BLIINDS model metric and EMM metric with PSNR. BLIINDS metrics gives results on the basis of the shape parameters values of each frame difference. In this we are trying to predict our purposed EMM metrics quality score is more accurate then BLIINDS metrics and its fluctuations is more close to PSNR as compare to BLIINDS.

Key words: FRTV (Full Reference Television Video), VQEG (Video Quality Expert Group), HVS (Human Visual System)

I. INTRODUCTION

There has been fastest growth in the convention of video and images due to growth in internet applications. The usage of digital videos and images are increased because the multimedia services attained the interest of users in large range including video streaming applications, audio and video services over internet and digitization of information in different fields like T.V broadcasting, video conferencing, E-business and information broadcasting websites like YouTube, Flicker Face book etc[1]. At present the technology allows video components which are created transferred, stored and shared among the users on high range of devices like hand-held PDAs and tablets etc [2]. So the growth of video processing and coding techniques quickly increases the interest in improving digital video communication at where the various estimation approaches and quality metrics are used to access the quality of video which performs a main role in whole design of video communication system [3]. Video quality evaluation or estimation plays a significant role in several video processing applications like compression, reproduction, communication printing, intensification and watermarking [4]. The main thing is to evaluate the quality of video or image and judge the distortion which is being added in it during different stages. Before presented to a human observer the image or video may go through many stages of processing. In each stage of processing contortion may introduce in it, which reduce the quality of the final display. In videos the quality is determined by two ways, one is subjective quality assessment and another is objective quality assessment.

A. Subjective Quality Assessment:

In this the quality of video is assessed by human observer and asking the observer to access the quality on predefined scale. Currently it is most common way to access the quality of video. But this approach is not be able to apply where large number of videos because this approach is slow and if we want to insert it in videos then their output quality is maximized for a given set of source [5]. In subjective assessment the quality metrics like Mean Opinion Error (MOE) is to be used in large number of human observers which gives the result more slowly and not exact [3].

B. Objective Quality Assessment:

In this the quality of videos is assessed by algorithmically and by using quality assessment techniques. The main goal of objective quality assessment is, to develop the quantitative measures which unintentionally predict the perceived video/image quality [5]. This approach gives significant and exact results without taking the observer's judgment panel.

In objective quality assessment there are three categories of video quality algorithms which are Full reference, No reference, and Reduced reference. These are the general concepts to evaluate the quality of video in objective assessment. In this the original or non-distorted (video reference) is used to estimate the reduced quality of present distorted video [3]. In this we use some quality metrics to check the quality of the videos like as MSE (mean square error), PSNR (peak signal to noise ratio), RRED (reduced reference entropic difference), correlation and many other metrics. We use all these metrics because they are easy and simple to calculate and have the clear and accurate physical meaning and are easy to mathematically deal. They have been widely used to find faults and errors and well not for correlating with perceived quality measurement [6].

II. PREVIOUS WORK

A Rosenfeld in 1984 describes about the division of spatial transformation, means in this the structural conversion is divided into two categories one is label based and another is non-label based. First approach describes the related appearance in the picture and also defines the edges, points and area. The label based approach is subjective process in which the image vision is calculated by human estimation. But the non-label approach is objective process which describes the structural conformation which reduces the ratio of the distinction among the substance and the picture when they are conduct as a continued method [7]

Zhou Wang, Hamid R. in 2003 describes the quality metrics which is used to check the quality of videos at low ends like PSNR (Peak Signal to Noise Ratio), MSE (Mean Square Error). We use all these metrics because they are easy and simple to calculate and have the clear and accurate physical meaning and are easy to mathematically deal. They have been widely used to find faults and errors and well not for correlating with perceived quality measurement [6].

Rajiv S. and Alan C. Bovik in 2011 describes about RRED (Reduced Reference Entropic Difference) quality metric. In this the entropic difference of each pixel/frame is calculated which gives the results and then find the total difference of all previous calculated entropic values [8]. Qi Wang, Zhaohong Li in 2014 describes the concept of correlation which is used to find the similarity of the frames from one to another. By this we find the bit information of frame or to measure the corresponding bits means in two frames we calculate how many bits are same. In this due to change in orientation and color shape the correlation values are not affected [9]. Philip Corriveau and Arthur Webster in 2000 describes that the main goal of VQEG is to give power to related standard substance which is reliable for manufacturing international approvals concerning the explanations of impartial video characteristics metric (VQM) in digital field.[10]. Zhou Wang, Ligang Lu and Alan C. Bovik in 2004 described about the hybrid video quality assessment methods was developed, and in this the approaches of proposed quality indexing (C_1=C_2=0) was combined with blurring and blocking measures, Or the algorithms of texture classifications. Simpler methods are to be used in this which activates the SSIM (Structural Similarity Index) index as a simple measure for the diff. types of distortions [11].

K-C Yang, CC Guest, and PK Das in 2007 explains the metrics to determine the quantity of the structure destruction according to effect of noticeable temporary characteristics. The main goal of this metrics is the estimation of the temporary characteristics reduction which happened by both symmetrical and non-symmetrical structure destruction [12]. SS Hemami, AR Reibman in 2010 describes that most of the work has to be done for non reference visual quality assessment or estimation In NR quality assessment three measurement stages is to be involved ,in these stages we discuss about the physical quality measurement which is related to the visual quality and also called as feature or the measured data is to be polled or pooling over time or space ,and the pooled data is to be mapped by which, we evaluate the perceived quality[13]. Z Wang, AC Bovik in 2011describes the concept of determining quantity and the effects of distortion which has been occurred in natural scenes statics (NCC) is to be provided in this, which is totally based upon the NR methods of image quality assessment (IQA) [14]. Anush K. Moorthy, Alan C. Bovik in 2010 describes the video quality estimation algorithm in which it is classified into three categories like FR (Full reference quality assessment),NR(Non reference quality assessment) and RR(Reduced reference quality assessment). In FR entire original video is taken or available as a reference. In this we have to take or access the perfect version of the video against which we can compare it to a distorted version. In this the comparison is bit by bit so it is complex. In NR we do not require any reference video, in this we blindly takes the videos and can be used in any applications, where the quality measurement is required. In NR algorithms we prescribed only the contorted videos/images to conclude quality grade [15]. Florin Dobrian, Asad A. describes in 2013 the illustration of video session Figure (2.1) [16] explains that the video player comes into various stages like linking and joining, playing, paused, buffering and stopped [16].

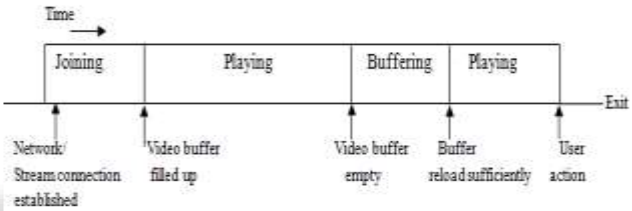

Fig. 2.1: Illustration of video session lifetime and connected video player events

Michele A. Saad, Alan C. Bovik recommended in 2014 a blind video characteristics estimation designs which is particularly not contorted. The method depends on the spatio- temporal designs of the video scenes in discrete cosine transform (DCT) field and the designs which describes the types of motions takes place in the scenes for the divination of video characteristics. This algorithm is called as BLINDS and in this the spatio-temporal statistical model [17].

N. Narvekar, LJ Karam in (2010) describes the blur estimation approaches mainly operates the concept of estimation of edge expansion and blur which shows clearly and reduced the borders [18]. Author Varadarajan in (2008) generates the improved methods of this problem which is some of the borders which cannot be detected [19]. M Ries, C Crespi desc describes that the feature based estimations of components of picture or video which can be applicable on the calculation of intuitive characteristics. Author shows the relatedness of component of attributes of videos in the procedure of definition of seen able characteristics [20].

III. BLINDS MODEL METRIC

In this the Spatio-temporal statistical DCT technique is used. It is based on Gaussian density standard deviation. The aim of BLINDS model is to find the statistical or structural difference and quantify it for perceptual video quality score prediction. By this method we find the shape parameters values of each frame difference. In this the pristine video and distorted video is to be taken then find their shape score values and then compare it with PSNR (Peak signal to noise ratio) because PSNR gives the exact values of noise and signals.

Gaussian density Standard Deviation: Generalized Gaussian density determines the non-linear distortions. Gaussian means for a given data a certain amount of non-linearity is to be calculated because in this the nature of occurrence is unknown. So dividing the data into different regions of same size.

A. *Working of Blinds Model:*

- Firstly consider a video containing large number of frames, each frame indexed is i+1 is subtracted from frame I then the resulting m-1 difference frames which is called as Temporal difference of frames then calculate the Gaussian Derivative.
- Then the generalized Gaussian returns the shape features means it return the value of gradient magnitude.
- Then by magnitude value drive the equations of α and β. These are normalized scale parameters means in which the normal factor is determined.
- Then integrate α and β and apply Laplacian distribution on it.
- Then it calculates the shape score from change in one frame to another.

$$f(x/\alpha,\beta,\gamma) = \alpha e^{-(\beta/x-\mu/)^{\gamma}} \quad (1.1)$$

B. *Problem Formulation in Blinds Model Metrics:*

BLINDS model metrics gives inaccurate results in Non-Linear environment means distorted environment. It does not depend on the motion stability of video means does not give accurate results in detailed movement of video frames. And if we compare it with PSNR (Peak Signal to noise ratio) metrics then there is more fluctuations in BLINDS as compare to PSNR.

IV. PURPOSE OF WORK

- To study the quality of the data using PSNR, MSE and RRED, correlation and other methods using original and low quality video data.
- To apply the proposed metric for quality assessment using (EMM) Edge entropy motion model.
- To Use different error estimates to study the difference in accuracy and reduction in error for making the system more close to Human vision estimate.

V. PROPOSED WORK

Our proposed work is to evaluate the quality of the video on the basis of edges of the objects in the frames. We apply this quality assessment metric in original and distorted videos and evaluate the quality on the basis of this metric.

Edge Entropy Motion Model metrics calculate the quality score on the basis of edges. So the edges are extracted on the basis of gradients. The image gradient is a directional change in intensity or color in an image. Gradients extract the edges on the basis of color RGB. Mathematically the gradient of two variable functions at each image point is a 2-Dim vector with the components given by the derivatives in horizontal and vertical directions. Apply threshold on it and calculate the score. We find the edge score of video means we estimate the quality of the video according to the movement of their edges by applying distortions on it. In this the edging values is to be segmented on the basis of entropy. By this method we find the edge parameter values of each frame difference. In this we take videos blindly and then apply some effects on it like noise and blur filter and then find its Edge parameters values and compare it with PSNR (Peak Signal to Noise Ratio) because in low end videos PSNR gives accurate results on the basis of noise distortion and signals. We compare Edge Entropy Motion Model and BLINDS Model with PSNR. Then according to PSNR the fluctuations in Edge entropy motion model is more accurate as compare to BLINDS Model.

A. *Working Of Edge Entropy Motion Model:*

- In this first we segment the edging values on the basis of entropy due to motion of the video scene.
- Then the entropy values are calculated by block-by-block manner.
- Entropy defines the total change of that block due to the intensity of pixels in the given block and previous block.
- Then for extracting the edges within the frame we use Gradients. Gradients images are created from the original image. For this purpose each pixel of gradient image measures the change in intensity of that same point in the original image in given direction to get the full range of direction gradients images in x and y directions are computed. It is calculated by:

  $$\theta = \text{a tan } 2\left(\frac{\partial f}{\partial y},\frac{\partial f}{\partial x}\right) \quad (1.2)$$

  in this RGB2GRAY is used which converts RGB images to grayscale by eliminating the hue and saturation information while retaining the luminance.
- To calculate gradients first vertical edges are detected then horizontal edges are detected and at last diagonal gradient detection. So the edge detection in combined vertical and horizontal gradients image with threshold is

  $$B(j,k) = /B_h(j,K) + B_V(j,K)/ \quad (1.3)$$
- After this find the dimensions of the image by which we find number of pixels stored in one place.
- Then find the Discreet Wavelet Transform extensions because this represents different ways of handling the problem of borders distortion analysis.
- Then find contrast standard factorization and then find the threshold of all this. By summation we calculate the quality score of one frame.
- Similarly the process happens for all frames in video and we collect all the entropy values of video frames and deduce the motion or movement of one frame to another.
- In this pixel values moves vertically &horizontally the place where the regions match it counts the score of pixel values from one frame to another and if there is a symmetrical difference between one frame to another then the score drops, this diff. occurs due to distortion.
- Using this we estimate the probability of occurrence of error in the movement of data from one frame to another and grade the video on the basis of

fluctuation produced in the video by noise or distortion.

VI. METHODOLOGY

- Select any video and then frame by frame analysis for study the video data.
- Now apply some effects on video like noise and blur and then access the quality of original and distorted video.
- Put (10-30%) noise on video and also apply blur filter on it.
- In Blur Filter we take only two Blurring effects, Gaussian blur and Pixelize blur.
- So when input is given then only one time one effect is in use.
- Then the quality of the video is assessed on the basis of some quality metrics like PSNR (Peak signal to noise ratio), MSE (Mean square error), RRED(Reduced reference entropic difference) and correlation.
- Then we use BLIINDS Model which we consider as a base Metrics for evaluating the quality of the video.
- Then apply our purposed Quality assessment Metrics which is Edge Entropy Motion Model. By this metrics we evaluate the quality of original and distorted video on the basis of edges of the objects per frame in video.
- Then we take PSNR as a standard Metrics and then compare the results of BLIINDS Model Metric and Edge Entropy Motion Model Metric with PSNR.
- And then find their error estimate in tabulation form.
- At last the results shows that our purposed quality metrics EMM gives more accurate results as that the BLIINDS model Metrics

VII. RESULTS

A. We take 45-55 frames of the video and put 20% noise in it, and then the graphs of metrics are:

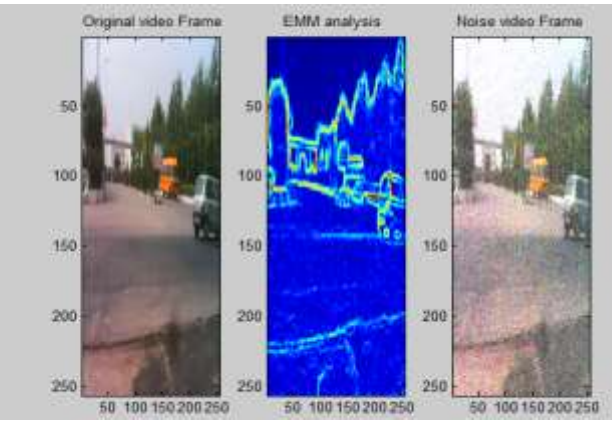

Fig. 1: Original and distorted frame

In Fig.1 the left sided frame is original video frame or the right sided frame is noisy video frame and the middle frame shows EMM (Edge entropy motion model) analysis of noisy frame on the basis of edges.

1) PSNR (Peak Signal To Noise Ratio):

It is defined as the Maximum possible absolute value of data. PSNR quality assessment metric is broadly used in FR objective picture and videos. The equation of the PSNR is:

$$\mathrm{PSNR} = 10\log_{10}\frac{L^2}{\mathrm{MSE}} \qquad (1.4)$$

"Equation (1.4) respectively defines L is the effective dimensions of the pixel values". So for 8bits/pixels the unchanging signal, L is equal to 255. So both MSE and PSNR metric is broadly used because they are quite smooth to calculate, have clear physical content and it is simple to deal mathematically.

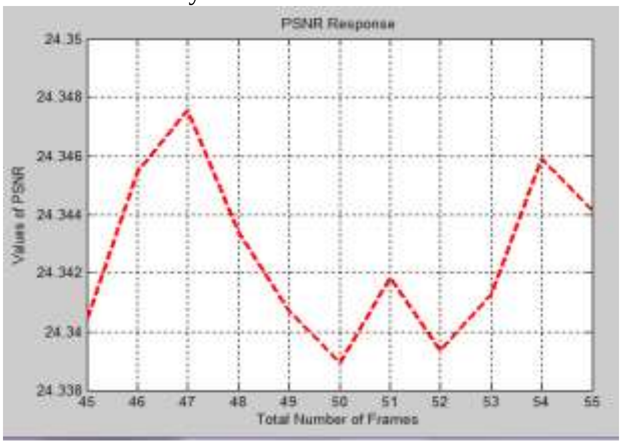

Fig. 2: Quality evaluation through PSNR Metrics

Fig.2 shows the quality estimation of Noisy video frames on the basis of PSNR (Peak signal to noise ratio) which is a quality assessment metrics.

2) MSE (Mean Square Error):

It is defined as the difference of images divided by total number of pixels. Recently the most broadly used FR objective picture and video contortion quality assessment metric is MSE. The Equation of the MSE is:

$$\mathrm{MSE} = \frac{1}{N}\sum_{i=1}^{N}(xi - yi)^2 \qquad (1.5)$$

"Equation (1.5) respectively defines that N is the number of pixels in video signals or image signals, and x_i, y_i are the i-th pixels in the earliest and the contorted signals".

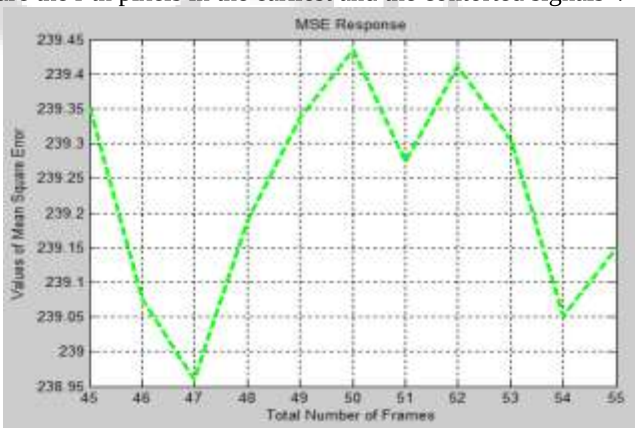

Fig. 3: Quality evaluation through MSE Metrics

Fig.3 shows the quality estimation of Noisy video frames on the basis of MSE (Mean square error) which is a quality assessment metrics.

3) RRED (Reduced Reference Entropic Difference) quality metric:

In this the ratio of the image is calculated by using the entropy information from other pictures. The complete value of the characteristics is to be estimated when the contortion process starts the enlargement and reduction in entropy. We have to estimate the significance of the difference to calculate quality. This shows that RRED ratios are regularly conclusive. So any improve image or video displays a variation in entropies and the variations should be explained as a development in quality. While penetrating the videos or images of adequate entropies in a sub band using rounded aperture of size b× b and examine by b in every domain. So the equation of RRED is where we put λ ϵ { 1, 2……Λ_k} indexing.

$$\mathrm{RRED}_k^{\Lambda_k} = \frac{1}{L_k}\sum_{\lambda=1}^{\Lambda_k}\left|g_{\lambda k}^{r} - g_{\lambda k}^{d}\right| \quad (1.6)$$

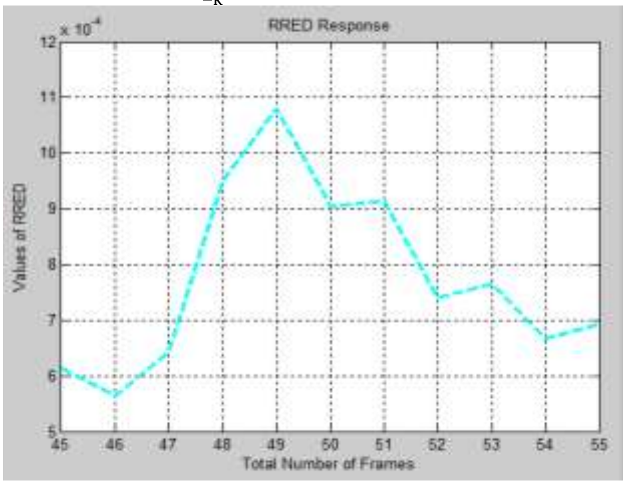

Fig. 4: Quality evaluation through RRED Metrics

Fig.4. shows the quality estimation of Noisy video frames on the basis of RRED (Reduced reference entropic difference) which is a quality assessment metrics.

4) *Correlation Metrics:*

It is defined as the metrics which is used to find the similarity of the frame. By this we find the bit information of frame or to measure the corresponding bits means in two frames we calculate how many bits are same. In this due to change in orientation and color shape the correlation values are not affected.

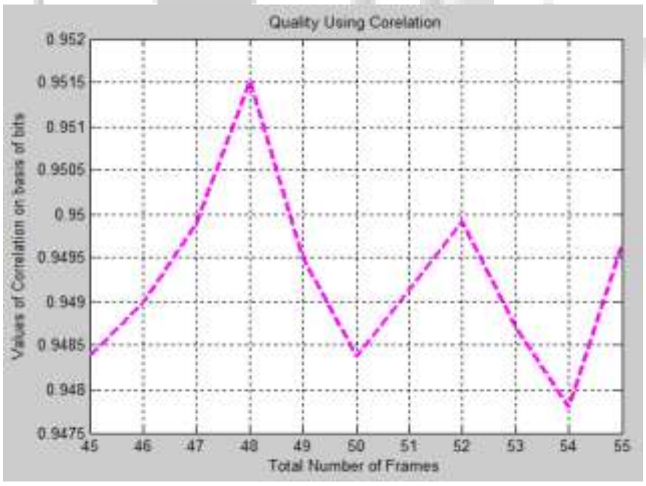

Fig 5: Quality evaluation through correlation Metrics

Fig.5 shows the quality estimation of Noisy video frames on the basis of Correlation.

5) *(EMM) Edge Entropy Motion Model Metrics:*

In this metrics we calculate the quality score on the basis of edges. So the edges are extracted on the basis of gradients. The image gradient is a directional change in intensity or color in an image. Gradients extract the edges on the basis of color RGB.

$$B(j,k) = /B_h(j,K) + B_V(j,K)/ \quad (1.4)$$

Where h & v is horizontal and vertical axis.

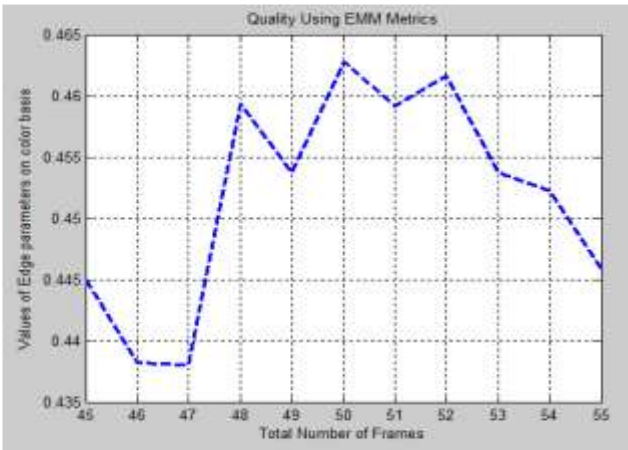

Fig. 6: Quality evaluation through EMM Metrics

Fig.6 shows the quality estimation of Noisy video frames on the basis of our purposed EMM (Edge Entropy Motion Model) which is a quality assessment metrics.

6) *BLIINDS Metrics:*

In this the Spatio-temporal statistical DCT technique is used. It is based on Gaussian density standard deviation. The aim of BLINDS model is to find the statistical or structural difference and quantify it for perceptual video quality score prediction.

$$f(x/\alpha,\beta,\gamma) = \alpha e^{-(\beta/x-\mu/)^{\gamma}} \quad (1.5)$$

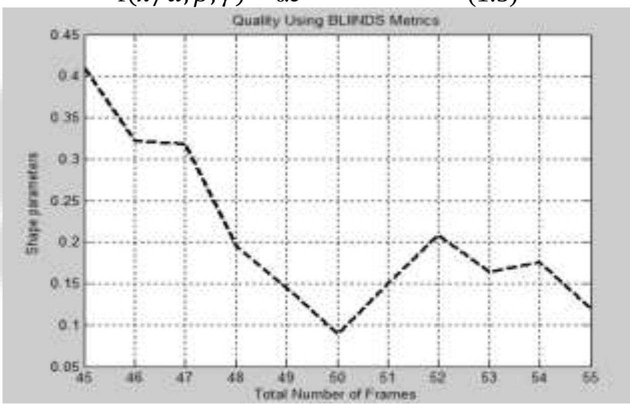

Fig. 7: Quality evaluation through BLIINDS Model Metrics

Fig.7 shows the quality estimation of Noisy video frames on the basis of BLIINDS Model which is a quality assessment metrics.

Quality estimation by all metrics like PSNR, RRED, Correlation, MSE, BLIINDS and EMM

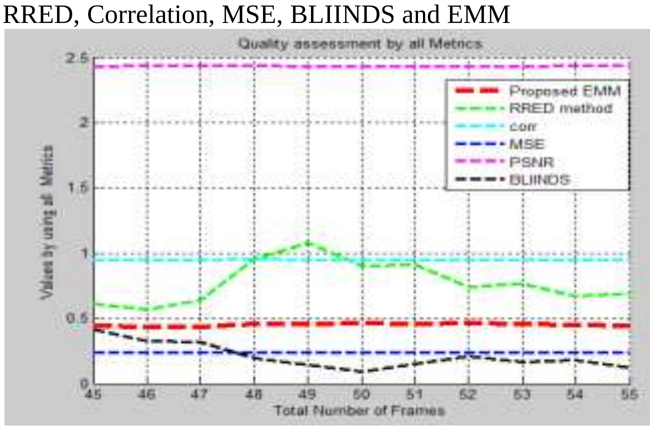

Fig. 8: Quality evaluation through all Metrics

Fig.8 shows the quality estimation of Noisy video frames on the basis of all quality assessment metrics At last we shows the quality assessment by all metrics in tabulation form and estimate their values. In this we compare our purposed metrics Edge entropy motion model with our base metrics BLIINDS model metrics. And by this comparison we checked the working of our purposed metrics. In this the results comes from Edge entropy motion metric is more close to PSNR metrics results. We compare our purposed method EMM metrics with Bllinds metrics and according to PSNR, the fluctuations in the frames of EMM give more accurate results as compare it to BLIINDS. We compare it to PSNR metrics because this metrics gives the overall information of noise and signal for the distorted video frames.

Frames	45	46	47	48	49	50	51
EMM	0.4450	0.4382	0.4380	0.4594	0.4537	0.4628	0.4592
RRED	0.6134	0.5645	0.642	0.9520	1.0803	0.904	0.913
Corr.	0.9483	0.9489	0.9498	0.9515	0.9495	0.9483	0.9491
MSE	0.2393	0.2390	0.2389	0.2391	0.2393	0.2394	0.2392
PSNR	24.3404	24.3454	24.3475	24.3433	24.3407	24.3389	24.3418
BLIINDS	0.4094	0.3217	0.3185	0.1950	0.1453	0.0892	0.1496

Table 1.Values of all metric

Table.1 shows all quality assessment metrics values of distorted video frames. In this we clearly evaluate the change in PSNR values from one to another frame, so according to this the change in EMM metrics is quite closer as the BLIINDS metrics. In BLIINDS the change in fluctuations is more as compare to PSNR.

B. When we apply Pixelize blur on video then the quality of video is being assessed by using quality metrics. In this we take 20 -40 frames of video:

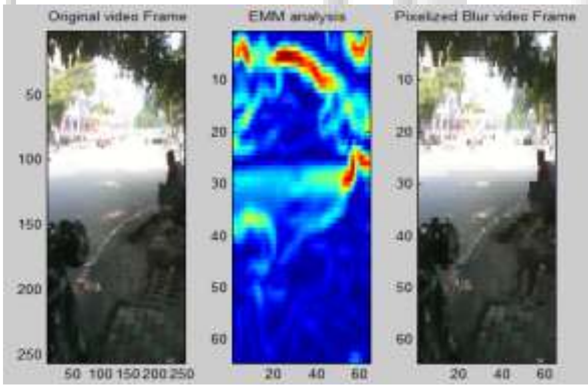

Fig. 9: Original and distorted frame

In Fig.9 the left sided frame is original video frame or the right sided frame is blurred video frame and the middle frame shows EMM (Edge entropy motion model) analysis of blur frame on the basis of edges

1) PSNR (Peak Signal to Noise Ratio) of Pixelized Blurred video frames

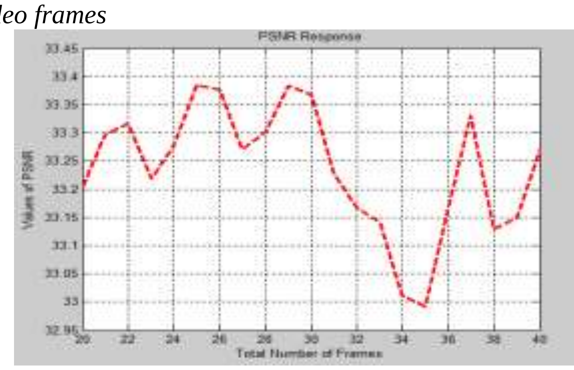

Fig. 10: Quality evaluation through PSNR Metrics

Fig.10 shows the quality estimation of blurred video frames on the basis of PSNR (Peak signal to noise ratio) which is a quality assessment metrics

2) MSE (Mean Square Error) of Pixelized Blurred video frames

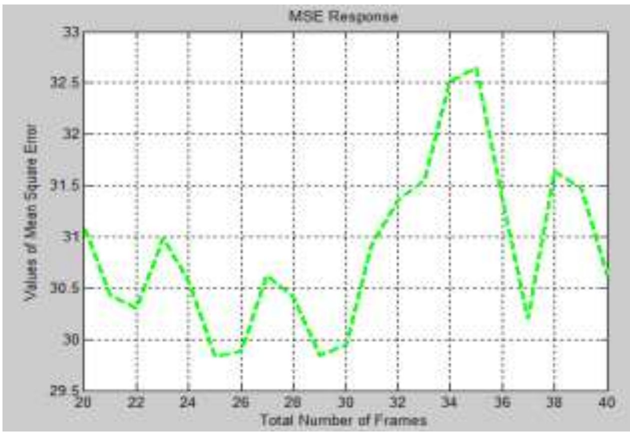

Fig. 11: Quality evaluation through MSE Metrics

Fig.11 shows the quality estimation of blurred video frames on the basis of MSE (Mean square error) which is a quality assessment metrics.

3) RRED (Reduced Reference Entropic difference) of Pixelized Blurred video frames

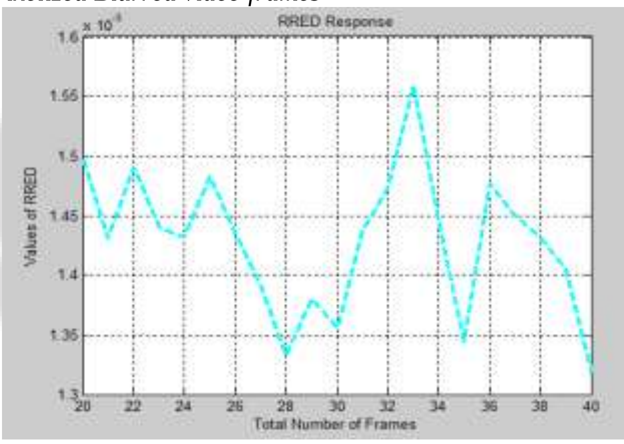

Fig. 12: Quality evaluation through RRED Metrics

Fig.12. shows the quality estimation of blurred video frames on the basis of RRED (Reduced reference entropic difference) which is a quality assessment metrics

4) Correlation metrics evaluation of Pixelized Blurred video frames

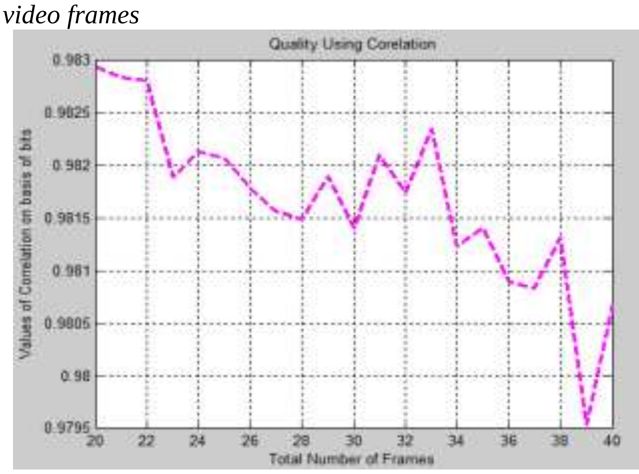

Fig. 13: Quality evaluation through correlation Metrics

Fig.13 shows the quality estimation of Blurred video frames on the basis of Correlation.

5) EMM (Edge Entropy Motion Model) of Pixelized Blurred video frames.

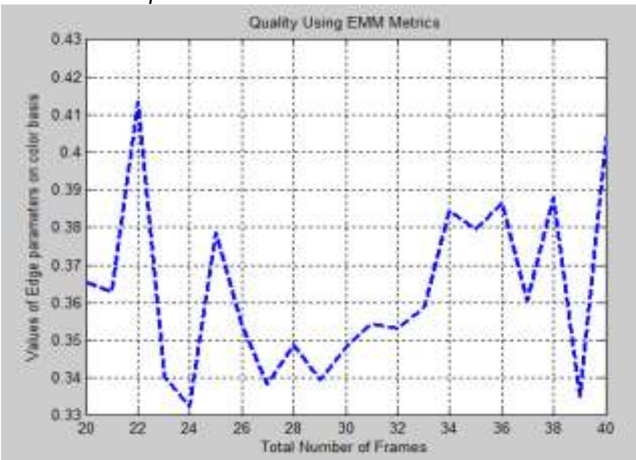

Fig. 14: Quality evaluation through EMM Metrics

Fig.14 shows the quality estimation of Blurred video frames on the basis of our purposed EMM (Edge Entropy Motion Model) which is a quality assessment metrics.

6) BLIINDS Model metrics of Pixelized blurred video frames.

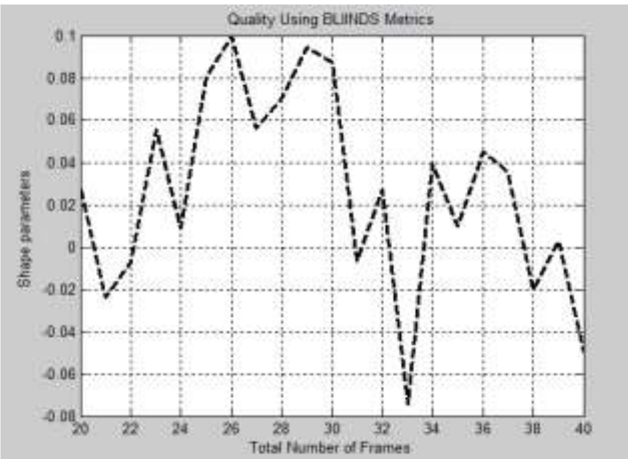

Fig. 15: Quality evaluation through BLIINDS Model Metrics

Fig.15 shows the quality estimation of Blurred video frames on the basis of BLIINDS Model which is a quality assessment metrics

7) Quality estimation by all metrics like PSNR, RRED, Correlation, MSE, BLIINDS and EMM

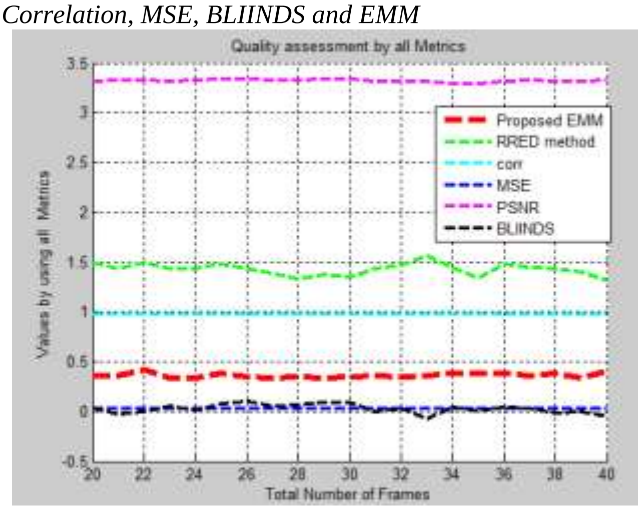

Fig. 16: Quality evaluation through all Metrics

Frames	20	21	22	23	24	25	26	27	28
EMM	0.3654	0.3628	0.4	0.3403	0.332	0.378	0.353	0.338	0.3407
RRED	1.496	1.4313	1.4910	1.4397	1.431	1.4833	1.43	1.392	1.3327
Corr	0.982	0.9828	0.9828	0.981	0.9821	0.982	0.981	0.981	0.981
MSE	0.031	0.03	0.030	0.030	0.0305	0.029	0.029	0.030	0.0304
PSNR	33.20	33.297	33.31	33.21	33.277	33.38	33.37	33.2	33.299
BLIINDS	0.027	-0.02	-0.007	0.05	0.098	0.080	0.099	0.05	0.0703

Table 2: Values of all metric

Table.1 shows all quality assessment metrics values of distorted video frames. In this we clearly evaluate the change in PSNR values from one to another frame, so according to this the change in EMM metrics is quite closer as the BLIINDS metrics. In BLIINDS the change in fluctuations is more as compare to PSNR.

VIII. CONCLUSION

In this paper we find the quality of videos on the basis of objective quality assessment. In this we use Quality metrics to access the quality of the distorted video. In this we works on EMM (Edge Entropy motion model) quality metrics which access the video on the basis of edges. And the extraction of edges on the basis of gradients which works on the basis of color. Then we compare the results of BLIINDS metrics and EMM metrics with PSNR. PSNR is a standard metric it defines the accurate values of signals and noise. So the results shows that the values of EMM is fluctuated acc. to PSNR as compare to BLIINDS fluctuations.

IX. FUTURE SCOPE

It there is a combined use of ICA (independent component analysis) and PCA (Principle Component Analysis) then by these the quality of video frames is more clearly estimated on the basis of Edges.

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