Contrast Enhancement Technique using Discrete Wavelet Transform with Just Noticeable Difference Model for 3D Stereoscopic Degraded Video

Bhagya H K, Keshaveni N

***Abstract:** The Video Technologies for Medical, cultural, and social activities prefer 3D visual data rendering and processing. So 3D videos are captured by any capturing devices, like the digital cameras are not acceptable all the time due to the lack of capturing devices or indecent illumination or due to poor weather surroundings like Low light, rain, fog, mist, etc. reduces the contrast, thus the videos get degraded. 3D video contrast enhancement technique is an essential process for upgrading the quality and information content in the videos. The proposed work employs a discrete wavelet transform based enhancement technique with Jut noticeable difference model to improve the video frames and it is simple and computationally inexpensive. The application of DWT results in the Low and High-frequency sub-bands. The low-frequency components that contain the greatest amount of the information are improved using weighted threshold histogram equalization(WTHE) with the JND model algorithm while the high-frequency sub-bands are distortions and highly affected by noise. The Gaussian high pass filter is applied to each high-frequency sub-bands to remove the noise. Besides, enhancement gain control and luminance preservation are used to acquire the enhanced output video. At the end check the quality of the degraded video frame, the presented work is implemented in MATLAB 2018a and evaluated using objective parameters. Experimental results show that the proposed method can generate better and agreeable results than 2D videos.*

***Keywords:** WTHE, Just Noticeable difference model, discrete wavelet transform, Contrast enhancement, GHPF.*

I. INTRODUCTION

With the developing business sector in 3D imaging items, the 3D video has become a functioning zone of exploration as of late. The 3D video is the way to give more reasonable and vivid perceptual encounters than the current 2D partner. There are numerous uses of 3D Videos, for example, 3D TV, which is viewed as the principal drive of the current TV upheaval. The stereoscopic display is the momentum standard innovation for 3D TV, while the auto-stereoscopic presentation is all the more encouraging arrangement that requires more examination attempts to determine the related specialized challenges. The accomplishment of the 3D video industry depends on the specialized development of 3D video innovation, including its portrayal, catching, improvement, pressure, transmission, and delivery. 3D video upgrade is a provoking issue to be comprehended in video innovation. The significant period of stereoscopic 3D (S3D) will furnish onlookers with characteristic sensation and ideal submersion to binocular and monocular profundity sign.

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Nonetheless, there is a recognizable diminish in the appeal of S3D methods over the most recent couple of years. Because of the unpredictability of a substance and unfortunate impact that may deliver by a perceptual perspective. S3D specialized difficulties in the field of video processing connected to quality examination, improvement,and compression. [1-2]

The main strategy of differentiation improvement is Histogram adjustment to balance the dark levels to upgrading contrast in numerous applications like clinical picture preparing, discourse acknowledgment, object tracking, and so forth Histogram equalization based procedures can't keep up average brightness level; it might deliver in either under immersion or over immersion in obscurity district or exceptionally splendid locale separately. To keep away from these issues some serious histogram leveling like bi-histogram equalization (BHE), partially overlapped sub histogram adjustment, and dualistic sub-picture HE strategies have been proposed by utilizing disintegration of two sub histograms of 2D video frames. In some paper proposed a neighborhood Histogram balance technique is known as Adaptive Histogramequalization. Here a video outline is isolated into little squares; close to HE is applied to each sub-square. Toward the end, the improved squares are consolidated utilizing the interpolation method. The adjusted HE technique depends on the singular-value decomposition of the LL sub-band of the discrete wavelet transform (DWT). Regardless of the improved contrast of theframe, this strategy will, in general, contort picture subtleties in low-and high-intensity regions [3-4]. To accomplish this objective, we present a proficient contrast upgrade technique for corrupted videos utilizing discrete wavelet transform based on improvement with the JND model. All the more explicitly, the proposed contrast upgrade calculation initially plays out the DWT to break down the info video outline into a bunch of band-restricted parts, called HH, HL, LH, and LL subgroups. Since the LL sub-band has the enlightenment data, JND values are determined.Based On the threshold values, the weighted threshold histogram equalization enhancement technique is applied. The high recurrence segments LH, HL, and HH parts are exceptionally influenced by noise, to eliminate the noise and upgrades the edge region Gaussian high pass filter is applied. After the JND based Enhancement upgrade strategy and noise decrease in the transformed area, play out the inverse discrete wavelet transform to recreate the improved videos.

II. PROPOSED VIDEO ENHANCEMENT APPROACH

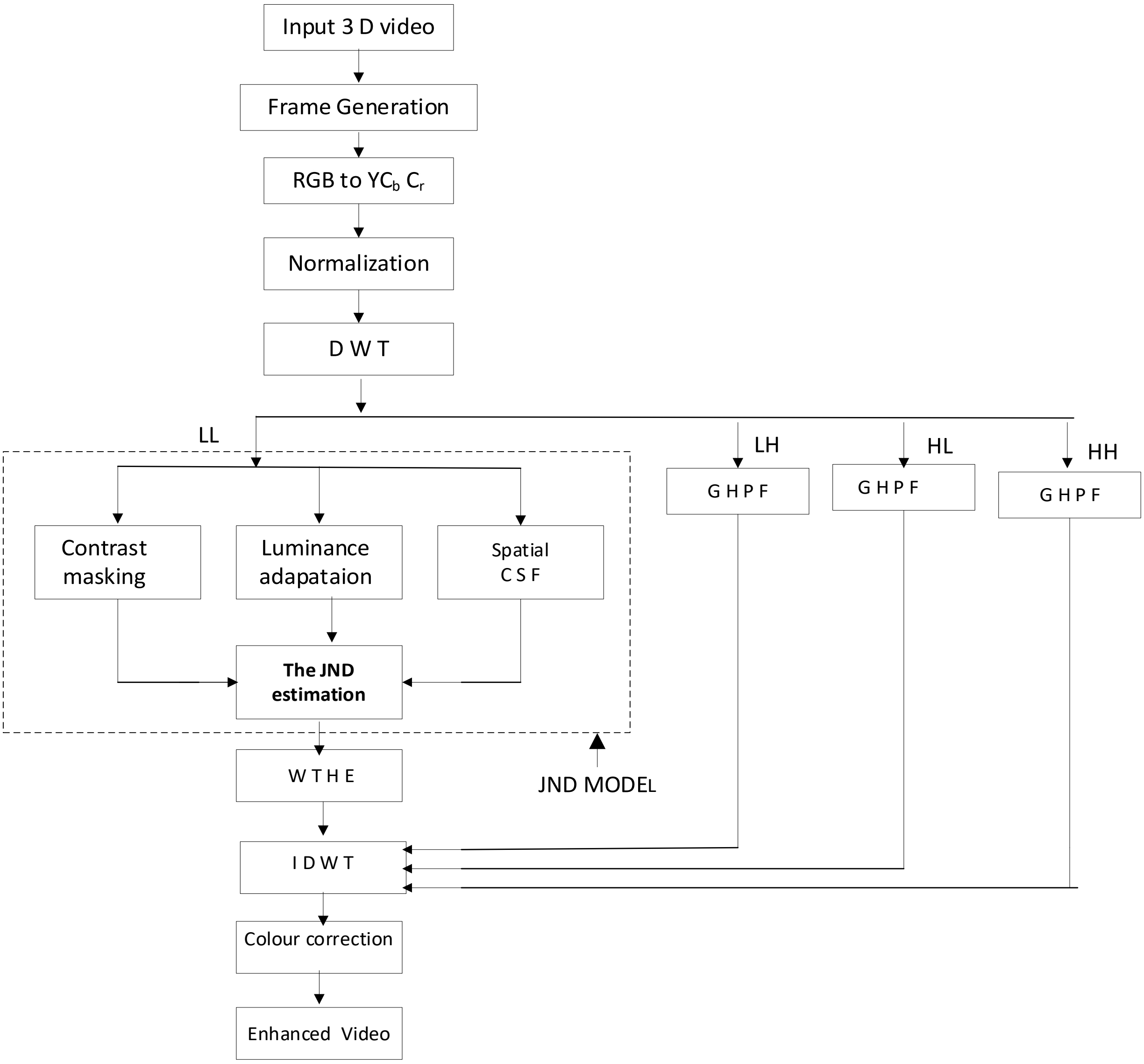

Figure 1: Proposed block diagram

1.1 Conversion of RGB to Y C_b C_r:

The Real-time videos are put away in color space since it relies upon affectability of shading location cells in the human visual framework. In advanced image processing,the Y $C_bC_r$color space is regularly used to utilize lower resolution capacities of the human visual framework for shading regarding luminance. Thusly, RGB to YC_bC_r transformation is regularly applied in image and video processing [5]

$$Y = 0.299 \times R + 0.589 \times G + \ 0.114 \times B \qquad (1)$$

1.2 Normalization

The dynamic scope of illuminationY isvery narrow, which doesn't use the dynamic scope ofdisplay tools. To utilize the dynamic reach totally, we utilized standardization dependent on an extending capacity as follows:

$$Y' = \frac{Y - Y_{min}}{Y_{max} - Y_{min}} \times 255 \qquad (2)$$

Here the maximum illumination components are $Y_{max}$and the minimum illumination component are Y_{min}.

2.3Discrete Wavelet Transform

DWT is a straightforward and effective cycle for the development of wavelets. Wavelets are fundamentally the waves which are restricted in both time and recurrence area. DWT investigates the signal andvideo frames into continuously better octave groups. Break down the signal at various frequencies with various goals. The proposed calculation utilizes Haar wavelet because of its straightforward and effectiveness in improving boundaries of differentiation for recordings. This strategy is simpler to execute and comprehend as wavelets are developed in the recurrence area [5]. DWT is considered as a filter bank that contains two filters, for example, low-pass and high-pass channels, and decays the information outline into four sub-groups including LL, LH, HL, and HH. Since videos are two-dimensional signals, wavelet decomposition in the horizontal level and vertical levels, separately, and afterward, down-sampling is performed on the yields of filters so each filter yield is 50% of the first size input. The working of DWT is as appeared in the figure. 2. In the first level of decomposition, four sub-bands LL, LH, HL, and HH represent the approximation details, vertical detail, horizontal detail, and diagonal details respectively [6-7].

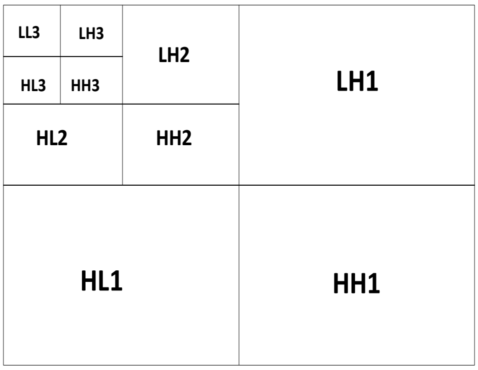

Figure 2. Three-level two-dimensional discrete wavelet transform

2.4The overall Just Noticeable Difference Model

In image and video processing technology, the Just noticeable difference model dependent on the human visual framework is generally utilized, which gives an essential visual perception model that relies upon the visual constraints and the qualities of the picture. The proposed JND model is a blend of three perspectives such as luminanceadaption, Contrast sensitivity function, and contrast masking [8].

2.4.1The JND Estimation

$JNDt(\lambda, \theta, i, j) = SF(\lambda, \theta, i, j)L(\lambda, \theta, i, j)T(\lambda, \theta, i, j)$(3)

The three elements of$SF(\lambda, \theta, i, j)$, $L(\lambda, \theta, i, j)$ and $T(\lambda, \theta, i, j)$ represents the spatial contrast sensitivity function (CSF), luminance adaption masking, and contrast masking respectively and i and j are spatial coordinates [9].

2.4.2Contrast sensitivity function

The most essential visual hypothesis model is Contrast affectability work. The substance of video outlines has no part in this model though it relies upon the eye to notice the video point of view. In the spatial recurrence space, the natural eye has band-pass highlights.

Mathematically this model is represented as the correlative of the essentialdistortion limit that each Discrete Wavelet Transform coefficient can deal with. The base limit can be figured utilizing the accompanying condition [10].

$$SF(\lambda, \theta, i, j) = \begin{pmatrix} \sqrt{2}, if \ \ \theta = HH; \\ 1, \ \ \ otherwise \end{pmatrix} \frac{1}{H(t)(\lambda, \theta)} (4)$$

Where $H(t)(\lambda, \theta)$ represents CSF and $\frac{1}{H(t)(\lambda, \theta)}$ is the just perceptual weighting depending on the frequency of the spatial coordinates and represents minimally noticeable sensitivity. Wavelet decomposition level is λ and wavelet co-efficient direction is θ. H(f) is a widely adopted model for the C0ntrast sensitivity function and is given by the equation

$H(t) = 2.6(0.0192 + 0.0114t)e^{[-(0.0114)^{1.1}]}$ (5)

2.4.3. Masking of luminance

Properties of the natural eye, for example, less affectability to the hazier area of the video frame over the lighter district and the location of a more brilliant locale of comparable power of commotion and obliviousness of more obscure district mutilations are clarified by luminance covering impact. It relies just upon the nearby highlights of the video frame, which is utilized to compute the impact of bending recognition under the condition of fixed pixel esteem as the foundation.

In a caught video frame natural eyes are less touchy to extraordinary brighteror darkerareas, and based on this numerous models are utilized. In a DWT based model, we utilized the low-recurrence bit of the video casing to represent the nearby splendor. It is to propose another model [11], which is inferred in the sub-band for a given level, thinking about the degree of the estimate of remaking and neighborhoodsplendor appraisal. It can be shown below

$L(\lambda, \theta, i, j) = 1 + L'(\lambda, \theta, i, j)$(6)

$$L'(\lambda, \theta, i, j) = \begin{cases} 1 - x(\lambda, LL, i, j), \ \ if \ x(\lambda, LL, i, j) < 0.5, \\ \quad x(\lambda, LL, i, j), \quad otherwise \end{cases} (7)$$

Where $x(\lambda, LL, i, j)$ is the wavelet coefficient value of the discrete wavelet transform at the level λ, (i, j) position of the sub-band LL. The local brightness factor will be the maximum if the video frame area is very high light or very dark.

2.4.4. Masking of contrast

In the edge locales, the natural eye has less resilience to contortion and generally insensitive in the surface areas. This procedure is identified with the level of appearance of one signal within the sight of another signal. That is the permeability of the principle segment in the casing will change with the presence of different parts. The difference covering impact is most grounded when the direction, positions, and spatial frequencies of the two segments are equivalent. Similar clamor or examples put in a to a great extent finished locales, is hard to track down looked at an even region. That implies the casing surface can veil or conceal another bit of the example. The veiling of difference impact can be composed as [12].

$T(\lambda, \theta, i, j) = T_{self}(\lambda, \theta, i, j)T_{neig}(\lambda, \theta, i, j)$(8)

Here $T_{self}(\lambda, \theta, i, j)$ represents the self –masking adjustment factor of contrast at the location (λ, θ, i, j), $T_{neig}(\lambda, \theta, i, j)$describes the neighborhood masking adjustment factor of contrast at the location(λ, θ, i, j).The model for $T_{self}(\lambda, \theta, i, j)$ is given by [13-14].

$$T_{self}(\lambda, \theta, i, j) = max\left\{1, \left(\frac{|v(\lambda, \theta, i, j)|}{SF(\lambda, \theta)L(\lambda, \theta, i, j)}\right)^{\emptyset}\right\}(9)$$

Where $v(\lambda, \theta, i, j)$ represents the discrete wavelet transform coefficient in position(λ, θ, i, j). In the LL sub-band Ø= 0, The model for $T_{neig}(\lambda, \theta, i, j)$ can be written as

$$T_{neig}(\lambda, \theta, i, j) = max\left\{1, \ \frac{\sum_{k\in \text{neighbors of } (\lambda, \theta, i, j)} \left|\frac{v_k}{SF(\lambda, \theta)L(\lambda, \theta, i, j)}\right|^{\delta}}{N_{i,j}}\right\}$$

(10)

Where the area is made out of neighborhood coefficients in a similar sub-band inside the window focused at the area (i, j), N i,j is the number of coefficients of the area, v_k is the estimation of every local coefficient, and δ is consistent and controls the level of every neighborhood coefficient.

2.5 Histogram equalization

The customary histogram equalization strategy is portrayed as shows: By taking avideo frame,F (i, j) in Low-frequency components (LL), with a sum number of picture elements and a dark level range of black to white that is [0, K-1]. The probability density function (PDF) of the video frame can be written as

$P(K) = \frac{n_k}{N}$ where $k = 0,1 \ldots., k-1$(11)

N = Sum of all pixels in the frame F(i, j)
n_k= Sum number of pixels in the frame that have gray level k.

The cumulative distribution function of frame F (i j) is given by

$C(k) = \sum_{m=0}^{k} P(m)$where $k = 0,1 \ldots., k-1$ (12)

Taking the CDF values and histogram equalization maps an input level k into an output level $H_k$using the equation as shown below:

$H_k = (K-1) \times C(k)$(13)

Traditional HE explained above, the increment level $H_k$can be seen easily is

$\Delta H_k = H_k - H_{k-1} = (K-1).P(k)$(14)

In other words, the addition levelH_k is relative to the probability of its corresponding level k in the input video frame. In principle, for frames with continuous illumination levels and PDFs, such a mapping method would consummately equalize out the histogram. Nonetheless, by and by, the force levels and PDF of a computerized frame are discrete. In such a case, the conventional HE technique is not, at this point ideal. All things being equal, it brings about unwanted impacts where force levels with high probabilities regularly become over-improved, and the levels with low probabilities get less upgraded, their numbers diminished or even disposed of in the resultant picture. HE regularly brings two sorts of antiquities into the upgraded picture: over-improvement for the more-successive levels and loss of difference for the less-continuous levels. In this manner, HE frequently over-improves the foundation of the video frame and causes level immersion (cutting) impacts in little however outwardly significant territories. To beat the visual antiquities of the HE technique and add greater adaptability to it, numerous specialists proposed distinctive improvementtechniques.

2.5.1 Weighted Threshold Histogram equalization

The proposed WTHE technique performs histogram leveling dependent on an altered histogram. Every probability density value P(k) in condition (14) is supplanted by a weighted and threshold PDF esteem $P_{wt}(k)$, yielding

$\Delta H_k = (K-1).P_{wt}(k)$(15)

$P_{wt}(k)$ = Weighted and thresholded PDF

The level-mapping technique shown in (15), by applying a transformation function T(.) to P(k),

$$P_{wt}(k) = T(P(k)) = \begin{cases} P_u & if\ P(k) > P_u \\ (\frac{P(k)-P_l}{P_u-P_l})^r \times P_u & if\ P_l \leq P(k) \leq P_u \\ 0 & if\ P(k) < P_l \end{cases} (16)$$

Where P_u is the Upper threshold and P_l is the Lower threshold. The change work T(.) clasps the first PDF at an upper edge threshold $P_u$and a lower threshold P_l, and changes the qualities between the upper and lower limits utilizing a standardized power law function with record r>0. when r<1, the Power-lawfunction will give a higherweight to the low probabilities and less-likely levels are "secured" and over-upgrade is diminished.

Likewise, in condition (16), the weighted Pwt(k) is limited at the furthest breaking point, P_u. Thus, all levels whose PDF values are higher than P_u will have their addition braced at a most extreme worth Δ_{max}=(K-1). P_u (given (15) and (16)). Such upper cinching further maintains a strategic distance from the predominance of the levels with high probabilities while distributing the yield dynamic reach. From our calculation, the estimation of P_u is chosen by

$$P_u = v.P_{max}\ ,\ \ 0 \leq v \leq 1 \qquad (17)$$

P_{max} is the Peak estimation of the first PDF, the real number v characterizes the upper limit standardized to P_{max}. In our proposed calculation, the standardized upper limit v is utilized as another boundary that controls the impact of improvement.

The lower edge P_l in condition (16), then again, is simply used to remove the levels whose probabilities are excessively low, to more readily use the full unique reach. The estimation of P_l is less significant in controlling the upgrade and is set an exceptionally minimum fixedvalue that is 0.01% in our calculation. It very well may be seen from condition (16) when r=1, P_u=1, and P_l=0 the technique WTHE reduces to the conventional Histogram Equalization.

In the proposed strategy, the power index is the primary parameter that controls the level of upgrade. With r<1, more unique reach is dispensed to the less likely levels, along these lines saving significant visual subtleties. At the point when the estimation of r continuously ways to deal with 1, the impact of the proposed work moves toward the customary HE. When r>1, more weight is moved to the higher-probability levels, and WTHE gives a much more grounded impact than the conventional HE. Utilizing r>1 is more uncommon because of its higher probability to result in over-upgrade, yet it is as yet helpful in explicit applications where the levels with higher probabilities should be improved with additional energy. The proposed change work (condition (16)) introduces thresholding with the histogram.In the proposed WTHE strategy, the upper limit P_u adjusts to P_{max}, the most probability observed in the frame. Such a system successfully mitigates the need for physically appropriatesetting thresholds, bringing about predictable upgrade impact for various sorts of video without physically changing the parameters.

From equation (16), the CDF is acquired by

$$C_{wt}(k) = \sum_{m=0}^{k} P_{wt}(m),\ for\ k = 0,1, \ldots \ldots K-1 \qquad (18)$$

$C_{wt}(k)$= Cumulative Distribution function (CDF) and the level mapping is

$\tilde{F}(i,j) = W_{out} \times C_{wt}(F(i,j)) + M_{adj}$ (19)

$\tilde{F}(i,j)$is the Mean of the enhanced frame, W_{out} is the dynamic range of the output frame and M_{adj} is the Mean adjustment factor.From our video tests, the proposed WTHE upgrade technique on the luminance part leaving the chrominance components unaltered. In condition (19) W_{out} can be composed as

$W_{out} = \min(255, G_{max} \times W_{in})$(20)

Where W_{in} is the dynamic range of the input video frame and G_{max} is a pre-set maximum gain of dynamic range and it can be used enhancement gain control mechanism.From equation (19), M_{adj} is the mean adjustment quantity that reduces the luminance changes after enhancement. From equation (19), Assuming M_{adj} =0, At that point, the distinction between it and the mean of the degraded frame isdetermined. Put Madj is equal to the value closures to this average difference such that it does not create any level of serious saturation.

Finally, we have to verify the improved video frames based on JND threshold values and the corresponding amplified contrast results are not distinguishable to human eyes. Therefore, the evaluation function represented in the following form

$$F(i\,j) = \begin{cases} 1 - \tilde{F}(i,j) & if \quad \mathrm{JNDt}(\boldsymbol{\lambda}, \theta, \mathrm{i}, \mathrm{j}) \le 0.5 \\ \tilde{F}(i,j)\ otherwise & \end{cases} \qquad (21)$$

Where $F(i\,j)$ enhanced videos based on weighted threshold histogram equalization $\tilde{F}(i,j)$and the final JND estimated values$\mathrm{JNDt}(\boldsymbol{\lambda}, \theta, \mathrm{i}, \mathrm{j})$.

2.6 Gaussian High pass filters

Wavelet transform isdecomposing the original frame into four frequency sub-groups. The unwanted signal appears in high pass coefficients, Edges and sharp changes in grayscale values in a frame that contributes essentially to high-frequency content are to be distinguished appropriately and Low-frequency content is to be attenuated.The filter order increases, less ringing impact is noticed. The edges which are high-frequency components can be seen in the improved frame and hence sharpening of the frame has been accomplished to each high-frequency subgroup. Here the filter n=2and the cut-off frequency is D_o= 24.

$$H(u,v) = 1 - e^{-D^{2(u,v)/2D_0{}^2}} \quad (22)$$

Where D_0 is the cutoff frequency at a distance D_0 (nonnegative quantity), and D (u, v) is the distance from the point (u, v) to the frequency rectangle [15]. If the frame size M x N, then

$$D(u,v) = \sqrt{(u - \tfrac{M}{2})^2 + (v - \tfrac{N}{2})^2} \quad (23)$$

2.7Color correction

The DWT based enhancement with JND threshold and noise decrease in the frequency domain and, play out the converse discrete wavelet transform to remake the luminance frame as output frame, Ye. Correction of color is the technique for matching and compensating the color in the frame. To play out the color frame by the proportion of the RGB components as follows.

$$\begin{bmatrix} R'' \\ G'' \\ B'' \end{bmatrix} = \begin{bmatrix} Ye/Yo & 0 & 0 \\ 0 & Ye/Yo & 0 \\ 0 & 0 & Ye/Yo \end{bmatrix} \begin{bmatrix} R' \\ G' \\ B' \end{bmatrix} \quad (24)$$

Here [R'', G'', B''] and [R', G', B'] shows the color channels of the output and input color videos, respectively.

III. Results And Performance Analysis

We conducted the proposed JND based Enhancement technique for 3D stereoscopic video sequences. The experiments wereconducted on an Intel Core i3 - 2.30 GHz CPU and 4.00 GB RAM. We have taken foggy, rainy, and Low light 3D stereoscopic, 2 to 5 sec. video sequences are downloaded from the internet sources like Videezy.com and Shutter.com. The performance parameters viz, Signal to noise ratio, Peak signal to noise ratio, and Structural similarity index module values are calculated and tabulated in table 1. The original and enhanced for low light, foggy, and rainy video frames are as shown in figure 3.

Fig.3.1 Original lowlight 20th video frame

Fig.3.2. Enhanced lowlight 20th video frame

Fig.3.3. Original foggy 10th video frame

Fig.3.4. Enhanced foggy 10th video frame

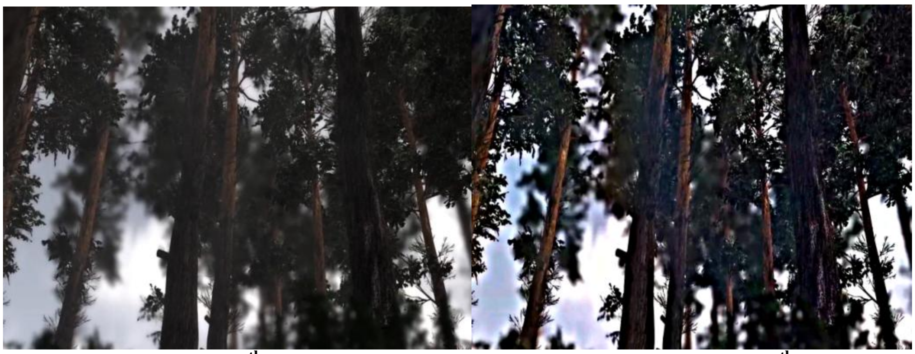

Fig.3.5. Original rainy 50th video frame **Fig.3.6. Enhanced rainy 50th video frame**

Figure 3. Examples of Original and Enhanced Videos frames with DWT based JND Model for different 3D Stereoscopic Videos.

Table 1.DWT-based Enhancement results without JND Model and with JND Model for different 3D Stereoscopic Videos

3D Videos	Enhancement without JND Model			Enhancement with JND Model		
	SNR	PSNR	SSIM	SNR	PSNR	SSIM
Foggy 1	22.8338	30.4726	0.8937	29.8787	34.3998	0.957
Foggy 2	22.9824	30.4378	0.6828	28.1654	34.4355	0.9559
Foggy 3	26.4774	29.5929	0.7304	27.4240	33.6167	0.9536
Rainy 1	24.7075	28.0458	0.7314	26.5252	30.2411	0.935
Rainy2	24.1194	27.0177	0.7024	24.8393	29.2811	0.8807
Rainy3	22.0714	27.0089	0.5897	24.4962	29.0153	0.8254
Low light1	19.9814	26.4916	0.5249	25.4513	28.9042	0.7722
Low light2	21.0745	24.3537	0.7895	23.1282	27.6646	0.7195
Low light3	22.9152	24.4055	0.7917	22.4068	26.8091	0.7154

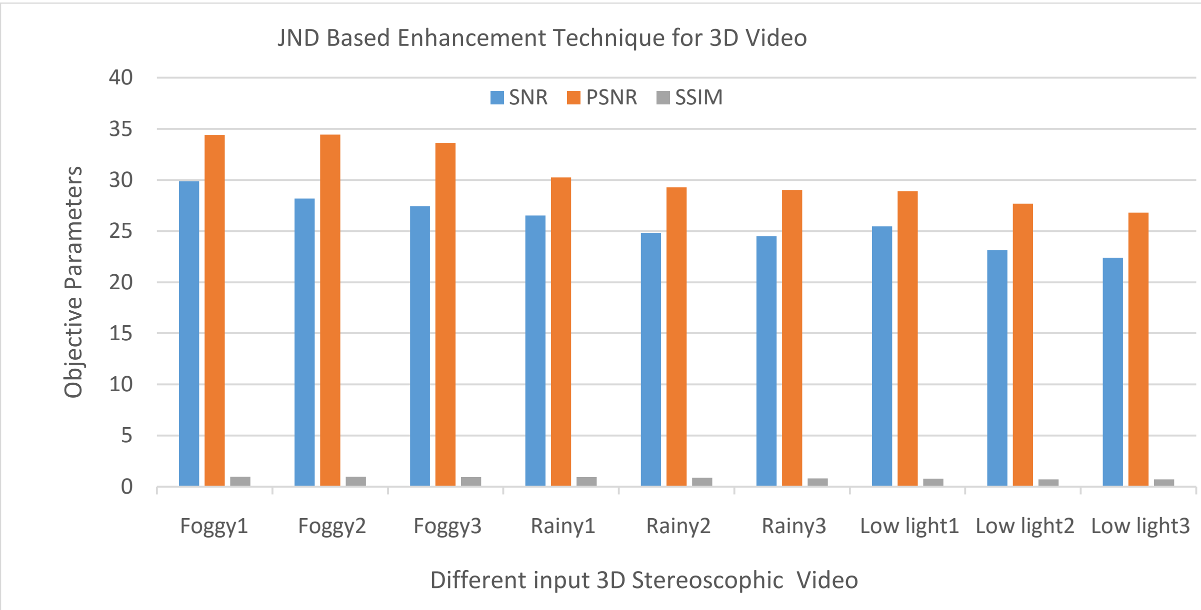

Figure 4. Analysis of the proposed technique with different degraded Stereoscopic 3D Videos

IV. CONCLUSION

We have proposed DWT based enhancement with and without JND model of different degraded stereoscopic 3D videos. Degrades videos are less dynamic domain, more noise as well as very weak in colors. Taking characteristics of degraded videos, it is developed into the three-level decomposition of input video frames into two sub-bands i.e. high- frequency information and low-frequency information. The DWT based JND model is applied to Low-frequency components. For improving the results, the weighted thresholded histogram equalization technique is applied according to the output of JND threshold values. The high-frequency components are highly affected by noise, to remove the noise and edge regions are improved by Gaussian high pass filter. Experimental analysis shows that the developed technique gives a good looking, informative, and enhanced forfoggy, rainy, and Low light 3D stereoscopic videos and very low performance for night videos.

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REFERENCES

1. P.Merkle, K Mueller, T Wiegand,” 3D Video: acquisition, coding, and display” IEEE Transaction, Consume. Electronics. 56(2) (2010) 946-950.
2. P.Merkle, K Mueller, T Wiegand, “ 3D Video representation using depth video”, In Proceedings of the IEEE, 99(4) (2011) 643-656.
3. J. A. Stark, “Adaptive Image Contrast Enhancement Using Generalizations of Histogram Equalization”, IEEE Trans. on Image Processing, Vol. 9, No. 5, pp. 889 – 896, May 2005.
4. J-Y. Kim, L-S. Kim, and S-H. Hwang, “An Advanced Contrast Enhancement Using Partially Overlapped Sub-Block Histogram Equalization”, IEEE Trans. on Circuits and Systems for Video Technology, Vol. 11, Issue 4, pp. 475 – 484, April 2001.
5. Lal, Shyam, and Mahesh Chandra. "Efficient algorithm for contrast enhancement of natural images." Int. Arab J. Inf. Technol. Vol.11, No.1, 2014.
6. Tingting Sun et al. “Readability Enhancement of Low Light Videos Based on Discrete Wavelet Transform.” 2017 IEEE International Symposium on Multimedia
7. Lu-Ting Ko et al. “Haar-Wavelet-Based Just Noticeable Distortion Model for transparent Watermark.” Hindawi Publishing Corporation Mathematical Problems in Engineering Volume 2012, Article ID 635738 doi:10.1155/2012/635738, Taiwan.
8. Chunxing Wang et al, “Visual Saliency Based Just Noticeable Difference Estimation in DWT Domain” Information 2018,9, 178, doi: 10.3390/info9070178.
9. Mannos, J.; Sakrison, D.J. The Effects of a Visual Fidelity Criterion on the Encoding of Images; IEEE Press: Piscataway, NJ, USA, 1974.
10. Xie, G.; Shen, H. Toward improved wavelet-based watermarking using the pixel-wise masking model. In Proceedings of the IEEE International Conference on Image Processing, Genova, Italy, 11–14 September 2005; p. I-689-92.
11. Liu, Z.; Karam, L.J.; Watson, A.B. JPEG2000 encoding with perceptual distortion control. In Proceedings of the 2003 International Conference on Image Processing (Cat. No. 03CH37429), Barcelona, Spain, 14–17 September 2003; Volume 1, p. I-637-40.
12. Teo, P.C.; Heeger, D.J. Perceptual image distortion. In Proceedings of the 1st International Conference onImage Processing, Austin, TX, USA, 13–16 November 1994; Volume 2179, pp. 127–141.
13. Hontsch, I.; Karam, L.J. Adaptive image coding with perceptual distortion control. IEEE Transaction, Image Processing. 2002, 11, 213–222.
14. Wang, Qing, and Rabab K. Ward. "Fast image/video contrast enhancement based on weighted thresholded histogram equalization." IEEE transactions on Consumer Electronics Vol.53, No.2, 2007.
15. Rafael C. Gonzalez, Richard E. Woods, “Digital Image processing” 3rd edition Pearson Education, ISBN 978-81-317-2695-2.

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