



e-ISSN: 2319-8753 | p-ISSN: 2347-6710

IJRSET

International Journal of Innovative Research in
SCIENCE | ENGINEERING | TECHNOLOGY

INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN SCIENCE | ENGINEERING | TECHNOLOGY

Volume 12, Issue 4, April 2023

ISSN INTERNATIONAL
STANDARD
SERIAL
NUMBER
INDIA

Impact Factor: 8.423

9940 572 462

6381 907 438

ijirset@gmail.com

www.ijirset.com

A Novel Viewpoint Feature Enhancement Method Stereoscopic Image Saliency Detection and Quality Assessment using Disparity

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ABSTRACT: Current advancements in evolving 3D Display Technologies has created a great need for 3D Saliency based visual information modelling. The Conventional 3D Visual Saliency modelling methods are generally based on low level features and are not appropriate in exploring the 3D visual information for high level applications. In spite of many exertions devoted to this domain, the available 3D visual saliency methods do not excel in modelling the stereoscopic image saliency. In this project, we propose a visual saliency detection and quality assessment method for stereoscopic images based on adaptive viewpoint feature enhancement via binocular vision. The relationship among left and right perspectives is analyzed through a binocular stereoscopic saliency total module which empowers the generation of more run of the mill saliency highlights toward binocular vision. Thusly, we plan a dynamic consideration based saliency include pyramid extraction module to really incorporate the elements from top-level to down-even out and saliency maps are created for stereoscopic images by assessing the got saliency highlights. In addition to the Stereoscopic image quality defects detection and enhancement with saliency constraint, our work is also polarized to the quality assessment of the 3D Stereoscopic images and videos.

KEYWORDS: Stereo 3D Images, Videos, Quality Defects, Quality Enhancement, Quality Assessment, Binocular Disparity, Projection Features etc..

I. INTRODUCTION

As the accessibility of 3D video content has expanded lately, principally in 3D film, certain stereoscopic impacts that might confound the human visual system and adversely influence the 3D review experience have been explored. A drawn out openness to 3D video content showing quality issues can cause upsetting side effects, for example, eye strain, headaches and visual fatigue [1]. To manage these issues, 3D cinematographers have set cinematographic rules which, assuming definitively followed during the creation interaction, dispose of or moderate such issues. Especially, we manage the identification of the stereoscopic window violations (SWV), twisted window impacts, UFO items and profundity bounce cuts [2]. Besides, the proposed calculations attempt to portray the distinguished impacts, as indicated by the visual pressure they cause to the watcher.

The requirement for SIQA improvement originally got momentum in 2009, when Benoit et al. [3] recommended a procedure that joins two measurements. The contrast between the unadulterated sound system image difference map and the twisted ones is then processed. Another surprising FR-SIQA [4] metric has been introduced that beats the last option. The creators utilized a straight definition of cyclopean view that is influenced by binocular contest among left and right perspectives. Mama et al. [5] likewise introduced NR-SIQA, which utilizes binocular mix thought to direct Human Visual System (HVS) reproduction. AI draws near, specifically Deep Learning (DL) [6], empowered the programmed extraction of the best elements, permitting them to beat handwritten attributes. In the accompanying, we momentarily address the new recommended NR-SIQA measurements: In [7], saliency information [8] was utilized to choose remarkable and non-striking patches for neighborhood highlight extraction.

Stereoscopic image quality assessment (SIQA) is not quite the same as 2D image quality assessment (2D IQA) because of the lengthy profundity discernment aspect and binocular vision systems among left and right perspectives. Customarily, various NR-SIQA techniques [9]-[10] physically extricate a few hand-created highlights in light of the HVS qualities, natural scene statistics (NSS), and so on. The removed hand-created highlights are then taken care of into a relapse learning model like help vector relapse (SVR) [11] to foresee the perceptual quality of stereoscopic

images. These NR-SIQA techniques can be additionally partitioned into two classifications including contortion explicit NR-SIQA [12] and broadly useful NRSIQA [13]. In any case, it isn't adequately powerful to address stereoscopic image twists by involving hand-made highlights in learning the relapse model as per the pre-characterized HVS and NSS models.

In view of these perceptions, we investigate utilizing a start to finish double stream intuitive deep neural network (DNN) with multi-facet network collaboration to foresee stereoscopic image quality. As of late, deep learning strategies have been broadly utilized and made extraordinary progress in settling different image handling and PC vision issues [14].

II. LITERATURE SURVEY

Virtual Reality (VR) has become quite possibly of the most encouraging pattern in vivid media, which targets broadening the human visual experience and improving the feeling of authenticity and presence. With the help of business 5G technology [15], VR applications that call for ongoing correspondence and cooperation will be polished and advanced in a more extensive scope of fields. Image Quality Assessment (IQA) is of extraordinary importance in image procurement, pressure, transmission, storage and display [16]. SSIM is a milestone for interfacing the goal image quality with the Human Vision System (HVS), its variations further develop the quality expectation precision in many data sets. Besides, Liu et al. [17] proposed a variety of SSIM in the gradient space to quantify image distortion. Xue et al. [18] considered that the pixel-wise Gradient Magnitude Similarity (GMS) and its standard deviation could foresee the image quality with high expectation precision and productivity. Because of the restricted visual awareness of HVS, Liu et al. [8] investigated the image wise Simply Recognizable Contrast (JND) for packed images, which was anticipated by a perceptually lossy/lossless predictor utilizing deep learning model. Zhang et al. [9] used the stage congruency and image gradient magnitude as the estimation of element similarity. Additionally, Sun et al. [19] addressed the element similarity with the superpixel luminance/chrominance similarity and pixel gradient similarity, and then performed correlations of these highlights to quantify the image quality. Different powerful correlative elements of the image were extricated and a regressor was prepared by help vector relapse to decide the distorted degree of image [20]. Nonetheless, the exhibition acquired by straightforwardly applying these measurements to the VR contents was unsatisfactory, in light of the fact that the exceptional omnidirectional and stereoscopic attributes of VR image have not been thought of.

Stereoscopic IQA (SIQA) draws specialists' consideration as of late since stereo images and videos become famous. Gorley and Holliman [21] estimated the stereo images with conventional 2D-IQA models and acquired a weighted normal score by applying the 2D-IQA models to the left-and right-view images. Wang et al. [22] presented an extra element of depth information to create the difference map as a weight map in working out the image quality scores. Different analysts examined the mind hypothesis and generative models to imitate the human cerebrum process instead of further developing SIQA-in light of the current 2D models. Hohwy et al. [23] introduced that prescient coding can analogize the cerebrum neural registering system and make sense of binocular contention while getting visual boosts. Zhu et al. accepted the "shock" from the image can make sense of the binocular competition and proposed a SIQA zeroing in on the binocular combination and contention component in stereo vision. Fan et al. [24] found that there exists a perceptual limit in the quality distinction between the stereo images.

These models are mostly intended for 2D images. With the fast improvement of 3D technology, numerous gadgets for stereoscopic catch have showed up. For instance, the Panasonic 3D camera catches the stereoscopic images and video for 3D films. The Kinect-1 gadget by Microsoft for the Xbox catches both the variety map and the depth map simultaneously, which can create the stereoscopic images (the depth map of the Kinect-1 might have openings that should be smoothed [25], which might cause noise). These gadgets make up various applications for 3D images or videos, for example, 3D delivering [26], 3D visual quality assessment [27], and 3D video identification. Bruce and Tsotsos broadened the 2D model, which utilizes a visual pyramid handling design [16], by adding neuronal units to demonstrate the stereo vision; in any case, they didn't propose a computational model in that review. In view of our insight, planning the stereo-vision model is undeniably challenging and we just track down two models in [27], in light of the fact that the systems of stereo vision actually represent a few examination challenges, for example, how to fabricate then apply the model for the stereoscopic vision component. Wang et al. [28] proposed a computational model that takes the depth factors as an extra visual aspect and furnishes a public information base with a ground reality of eye-following information. Tooth et al. proposed a visual consideration model for stereoscopic images in view of the



differentiation between low-level highlights. In any case, they didn't think about the attributes of human stereo vision, like the jump out impact or 3D fatigue.

Omnidirectional IQA (OIQA) is one more angle deeply examined in the field of VR. A few OIQA measurements were proposed to tackle the non-uniform examining issue delivered in circle to 2D plane transformations. Circular PSNR (S-PSNR) estimated the distortion by consistently inspecting on the circle. Weighted-to-Circularly uniform PSNR (WSPSNR) determined PSNR straightforwardly on the beginning round plane in view of the area ratio, and Hole Allegorical Projection PSNR (CPP-PSNR) determined PSNR by remapping the all encompassing image to the CPP plane. These bottom-up standards estimated pixel by pixel contrast among SOIs and assessed the image constancy from the signal viewpoint. Be that as it may, these ideal models actually could be worked on concerning the consistency with HVS. The image quality doesn't emphatically connect with pixel-wise contrasts, and the relationship between's image loyalty and image quality is low [29]. These days, there is a recent fad of creating OIQA that emulates the perceptual properties of HVS from the information driven point of view, which depends on the top-down psychophysiological instrument. WS-SSIM [26] was proposed by considering primary information as well as weight map of the omnidirectional image. Both the PSNR-based and the SSIM-based OIQA measurements have allotted suitable loads to remunerate the projection distortion. Taking into account the Field of View (FoV). Azevedo et al. proposed the OIQA metric in light of the viewport projected from circular image plane. Xu et al. resolved the issue of human's district of interest by the OIQA metric in light of saliency location. Gutiérrez et al. [29] also added the head development and eye development information to the data set for saliency identification in omnidirectional image.

III. PROPOSED WORK

A. BASIC IMPLEMENTATION:

In this project we proposed a quality assessment model based on the projection invariant feature and the visual saliency for Stereoscopic Omnidirectional Images. Initially the projection invariant monocular and binocular features of SOI are derived from the Scale-Invariant Feature Transform (SIFT) points to tackle the inconsistency between the stretched projection formats and the viewports. Then, the visual saliency model, which joins the chrominance and differentiation perceptual factors, is utilized to work with the expectation exactness. At last, as per the qualities of the all encompassing image, we create the weight map and use it as an area earlier, which can be adjusted to various projection designs.

A delayed openness to 3D video content displaying quality issues can cause upsetting symptoms, for example, eye strain, headaches and visual fatigue. 3D video quality issues that might upset the human visual system and adversely influence the 3D review experience are notable and become more pertinent as the accessibility of 3D video content increments, principally through 3D film, yet additionally through 3D television. To manage these issues, 3D cinematographers have set cinematographic rules which, assuming that unequivocally followed during the creation interaction, dispense with or moderate such issues. The current strategies involved the proper measure of defer in the singular frames of the 3D video. Image Quality Assessment (IQA) is of extraordinary importance in image securing.

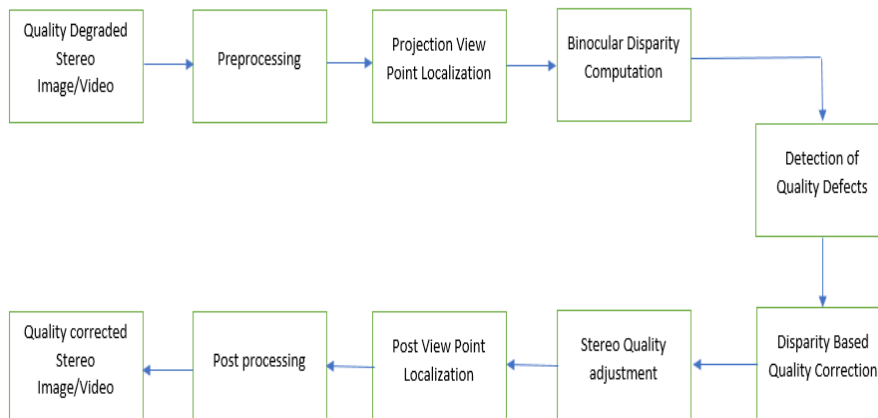


Fig.1: Schematic Block diagram of the basic stereoscopic image/video quality defects detection system.

As of late, as the relating equipment, for example, Head Mounted Display (HMD) and catch gadgets are opening up to customers, VR contents have involved the rising extent of sight and sound information. Stereoscopic Omnidirectional Image (SOI) is a fundamental sort of VR contents since it permits clients to encounter 360 degree scene intuitively and vividly. Contrasted and conventional 2D image, SOI needs further examinations regarding quality control. Image quality is a significant indicator for looking at the exhibition of different image handling calculation and system because of various items display gadgets and visual experience.

B. ADVANCED IMPLEMENTATION:

In this project, we propose a visual saliency detection and quality assessment method for stereoscopic images grounded on adaptive viewpoint feature enhancement via binocular vision. A major component in 3D scene translation is depth information. In a stereoscopic image pair, made out of a left and a right channel, a thick divergence map that doles out a depth related difference worth to each image pixel can be assessed from recognized pixel correspondences between the two channels. In this article, we propose a Projection INvariantT element and visual Saliency-based SOIQA (PINTS-SOIQA) to evaluate the perceptual quality of SOI. Our commitments are mostly threefolds. Both the monocular and binocular highlights of SOI are gotten from projection invariant element, which can tackle the irregularity between designated images in emotional and objective evaluations. A visual saliency model is proposed for SOI, which is taken on as perceptual loads for SOIQA. A weighted map is created as an area earlier in view of the qualities of omnidirectional image and client social inclination, which can adjust to SOIs with different projection designs.

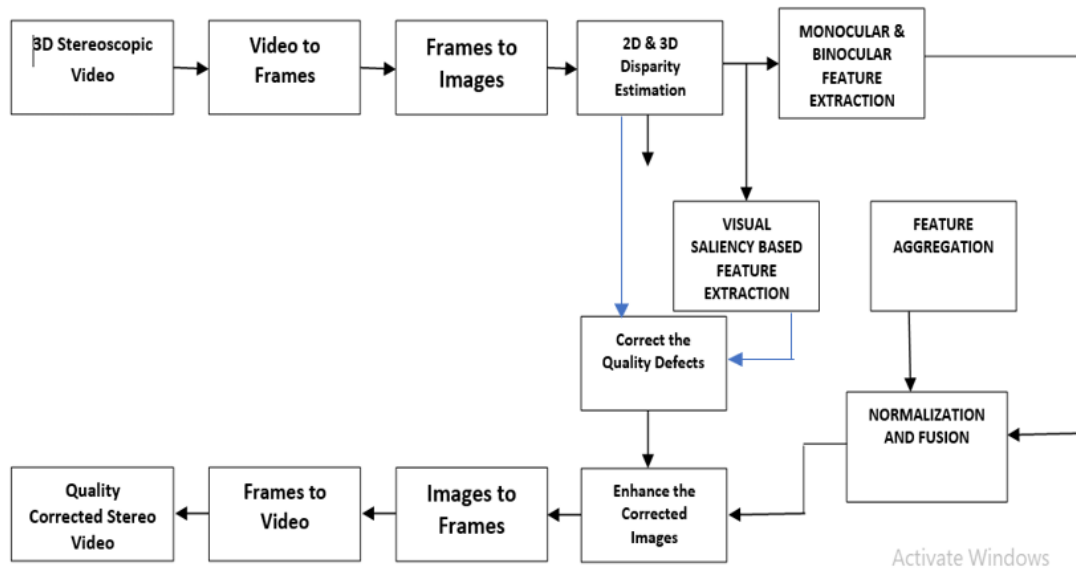


Fig. 2: Schematic Block Overview of the proposed system.

In any case, in 3DTV and 3D film, the stereo-matches are regularly handled in after creation, to permit an apparent situation of imaged objects, during video display, both in front of and behind the screen plane. In this way, the divergence maps assessed from post-handled 3DTV substance commonly contain both positive and negative difference values. Pixels related with adverse left difference are to be displayed in front of the screen, pixels with positive left divergence are to be displayed behind the screen and pixels with zero uniqueness will be displayed on the screen plane itself. The proposed system gauges the underlying highlights of the singular frames of the 3D video and finds their fleeting similarity. Thus the proposed method will work out the versatile defer worth to lessen the dissimilarity in the 3D images in view of the frame image structures.

Here, we propose a projection invariant component and visual saliencybased SOIQA as displayed in Fig. 1. Given the first image and the distorted image for the two perspectives, the monocular and binocular highlights are gotten from the projection invariant element for left-and right-view images. Then, two perspectives are re-organized into a total image for concurrent handling by means of the adjusted visual saliency model, which thinks about the SOI's



textural saliency, likewise, projection transformation is created by considering the scope weighting factors and examining distinction in projections. At last, the projection invariant and visual saliency-based highlights are standardized and totaled into definite quality score. The proposed quality assessment model can be stretched out to adjust different projection designs.

B. Monocular and Binocular Quality Feature Extraction

We model the quality expectation cycle of SOI from all encompassing and stereoscopic characteristics mutually. Both the monocular and binocular elements are intended to evaluate the apparent quality debasement by forcing them on leftand right-view images. In this work, we attempt to catch invariant elements steadily existed in both viewports and 2D projection designs. Then, at that point, statistics of invariant highlights are used to uncover the debasement of the image quality.

Also, the stereoscopic trademark ought to be estimated with respect to the all encompassing trademark, as opposed to changing over the SOIQA into straightforward expansion of SIQA and OIQA. Projection invariant element is developed with the component focuses identified by Scale-Invariant Element Change (SIFT) calculation in our work. The reasons are: 1) Component points of an entire image are created with the Distinction-of-Gaussian which is a guess of Laplacian-of GaussianThe objective quality estimation of every individual view, noted as monocular score, is processed through applying the log10(·) operator as a remapping capability to the ratio, which can be introduced as

$$Q_M = \left| \log_{10} \frac{T(S(F(I_D^V)))}{T(S(F(I_O^V)))} \right|,$$

where F(·) means the component focuses location operation, S(·) is the operation of holding the most steady element focuses by the position, T signifies the total number of element focuses in the saved component focuses set, V ∈ {L, R} means the left view or the right view. QM is the quality record as far as the monocular trademark. Objective quality estimation on binocular attributes, noted as binocular score, is characterized as

$$Q_B = \left| \log_{10} \frac{T(S'(M(I_D^L, I_D^R) \cap M(I_O^L, I_O^R)))}{T(S'(M(I_O^L, I_O^R)))} \right|,$$

where M(·) means the component point match operation among left-and right-view images, S(·) is the operation of holding the stable matched matches by RANSAC. QB is the depth quality file with regards to the binocular trademark.

The quantity of matched matches is not exactly the quantity of SIFT highlight focuses in a solitary view, suggesting a fragile estimation of depth prompts. It likewise keeps a diminishing pattern as distortion prompted to the two perspectives increments. In addition, these SIFT highlight focuses can likewise be recognized in viewports and other projection organizes as opposed to ERP. Exploiting invariant highlights as well as their statistics can not only fill the gap between subjective and objective evaluation, but also reveal the degradation of the image quality with HVS

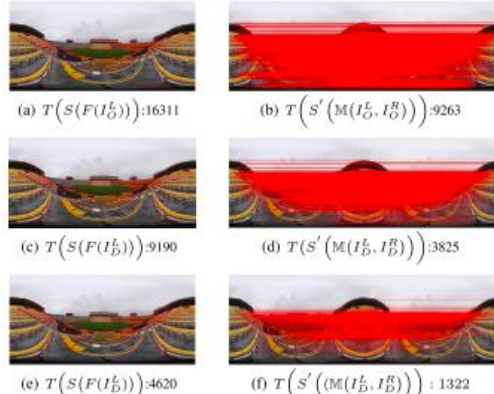


Fig. 3. Conveyance of element focuses and coordinated sets of images from NBU-SOID with various bpp boundaries in JPEG2000.

Dispersions of monocular highlight focuses on left-view image in SOI and binocular matched matches are introduced in Fig. 2 independently. Exploiting invariant highlights too as their statistics can not just fill the hole among emotional and objective assessment, yet in addition uncover the debasement of the image quality with HVS.

C. Visual Saliency-Based Quality Feature Extraction

Albeit the SIFT highlight focuses can mean the predominant aspect of SOI, it for the most part figures scale space extrema, which is shy of other conventional visual information in HVS. Saliency of an image is firmly connected with the abstract apparent quality of the image, in this manner it's vital to acquaint saliency model with SOIQA. For omnidirectional images, there might exist a case that a spectator doesn't investigate each piece of the image, yet specific locales went into their FoV. Hence fractional of the image gives more prominent effect while different locales offer less.

significance of saliency is likewise confirmed from the quick improvement of abstract IQA data sets. These data sets contained the extra saliency related information other than the actual image. Likewise, saliency map isn't possibly used as a component while processing the nearby quality yet in addition a weighting capability to mirror the significance of neighborhood locales. With this consideration, we bulid a compelling computational saliency model as per the qualities of SOI, and apply it to the SOIQA. In this we follow the Saliency Recognition by joining Basic Priors (SDSP) metric, and further develop the saliency identification model to make it more reasonable for SOI.

Rather than utilizing SDSP straightforwardly, we take on a scope factor as additional area earlier for all encompassing image quality estimation. As projection will get extending and upsampling distortions, it isn't relevant to treat each piece of the image similarly. Likewise, subjectives are constantly drawn in by the equatorial region and ignore the bipolar district, which is brought about by the VR seeing circumstances and the conduct inclinations as review a SOI. We present a circular scope earlier in regards to client conduct. Thus, we consider the visual sailiency diminishes with the rising scope and utilize the cosine bend to describe this property.

Visual saliency model is utilized as a weighting capability to correspond human visual obsession with nearby quality element between unique image and distorted image. A model in Fig. 3 delineates the proficiency of the adjusted VSI. The exploratory outcomes exhibit above factors can well catch the distortion, particularly the GM. In synopsis, the adjusted VSI is a combination of the over three factors for VR image quality discernment, which can work with the expectation precision. ERP has turned into the most usually utilized projection design because of its effortlessness and accommodation. Contrasted and CMP, OHP and ISP contain triangle faces which bring greater intermittence between adjoining faces.

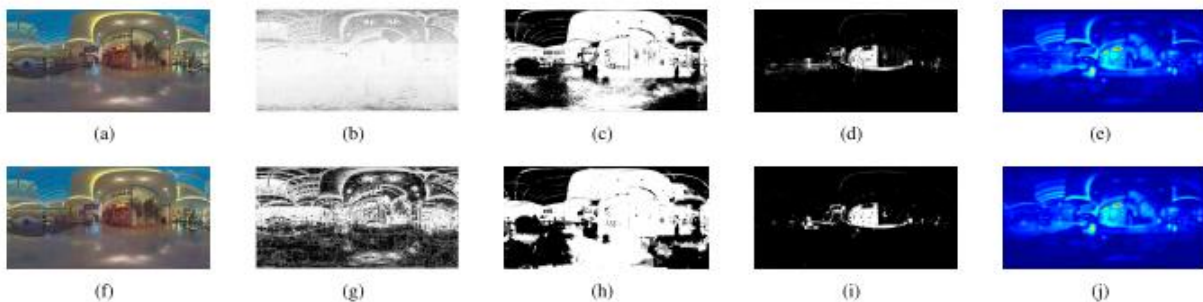


Fig. 4. Illustrations of the parts of the adjusted VSI of images from Strong

limit will bring about visual quality downfall since they break the image honesty. Turned Circle Projection (RSP) involves different projection strategies for bipolar and equator, so shape distortion is sensibly circulated. Shortened Square Pyramid (TSP) considers the client conduct, embracing the first goal in equatorial district and downsampling in different locales, which produce serious distortion in low goal regions. Projection between various arrangements will bring about distortions, for example, objects and other visual structures that seem extended, twisted or sheared, as well as changes in distance, bearing, shape and region of the articles. The goal of each organization is appointed practically equivalent to the first ERP design size for better examination.

The projection consequences of one example image in Strong [40] are displayed in Fig. 4. We can see that CMP has just a single broken limit, OHP has 8 triangle countenances and 6 vertices, ISP has 20 appearances and 12

vertices, RSP parts the circle into two equivalent estimated portions and puts them on the 2D projection plane in two columns, TSP uses the shape calculation and twists six block faces into a minimal frame with various goals. Regardless of how convoluted the arrangement becomes after projection, there is as yet weighting factor brought about by circle and human conduct inclinations.

IV. IMPLEMENTATION RESULTS

In this part, we present the data sets for genuine quality assessment and criterias for execution assessment of IQA measurements. The exhibition of the proposed PINTSSOIQA technique is contrasted and those of the best in class IQA measurements on every data set. Additionally, execution of the proposed PINTS-SOIQA on various projection designs are likewise assessed. The stereoscopic Left Reference Image and its Saliency Map is shown in Fig.5.

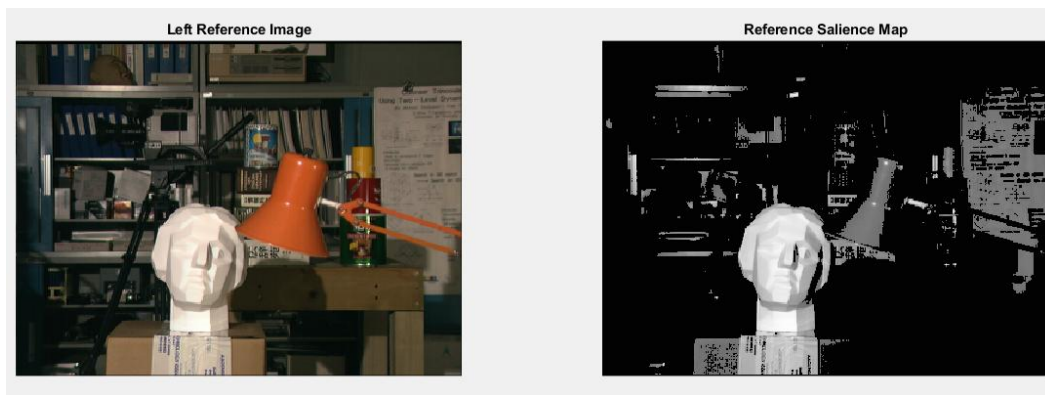


Fig. 5: Stereoscopic Left Reference Image and its Saliency Map.

This stereoscopic omnidirectional image quality assessment information base incorporates 276 distorted images with two distortion types and three depth levels got from 6 top notch reference images. All images are stored with ERP design. Also the Edge Maps of Stereoscopic Left, Ground Truth and Disparity Map images are illustrated in Fig.6, Fig.7 and Fig. 8 respectively.

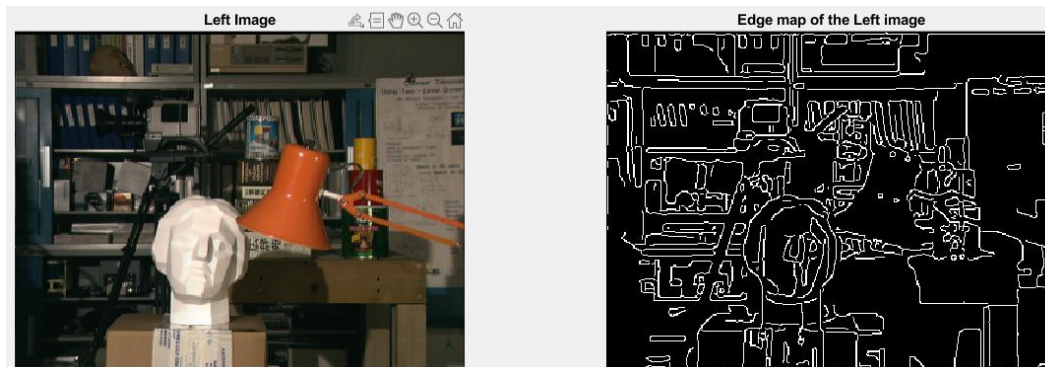


Fig.6 : Stereoscopic Left Image and its Edge Map.

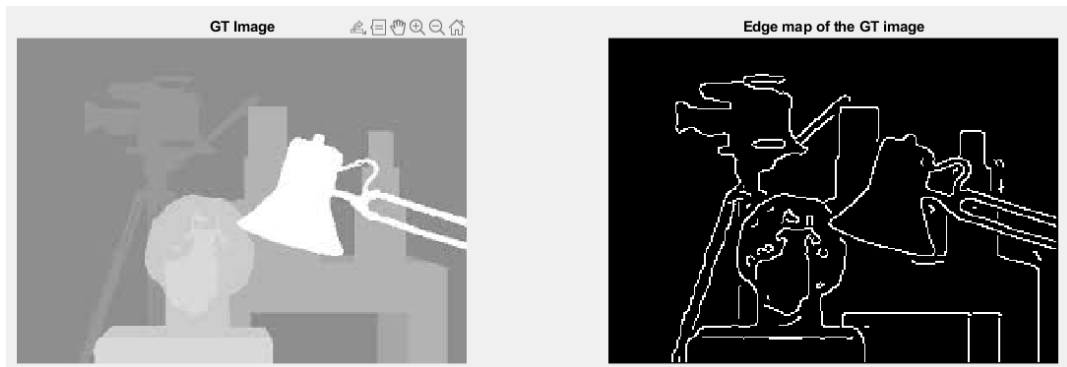


Fig.7 : Stereoscopic Ground Truth Image and its Edge Map.



Fig.8: Disparity Image and its Edge Map.

Abstract assessments of image quality, depth information and generally quality are gathered in the data set. The Gradient Map of GT Image is shown in Fig.9. Also the Saliency and Gradient Maps of Test and Reference Stereoscopic LEFT and RIGH images and also their Salient Edges and Depth(SED) maps are also presented in subsequent figures.



Fig.9: Gradient Map of the Ground Truth Image

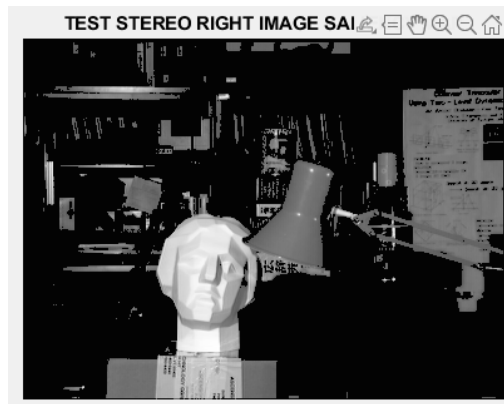


Fig.10: Test Stereoscopic Right Image Saliency Map.



Fig.11: Test Stereoscopic Left Image Gradient Map.

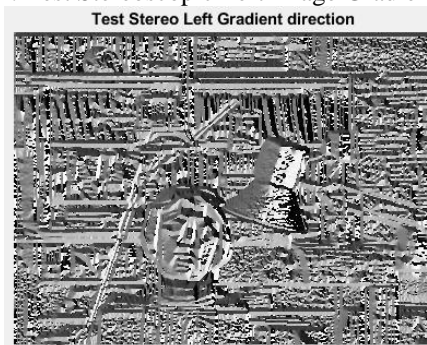


Fig.12: Test Stereoscopic Left Image Gradient Direction

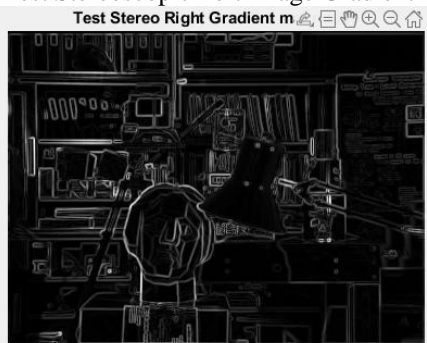


Fig.13: Test Stereoscopic Right Image Gradient Magnitude.



Fig.14: Reference Stereoscopic Right Image saliency map.

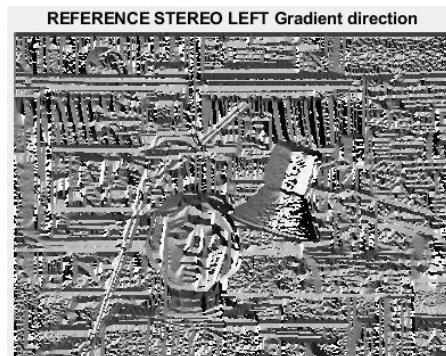


Fig.18: Reference Stereoscopic Left Image Gradient Direction.

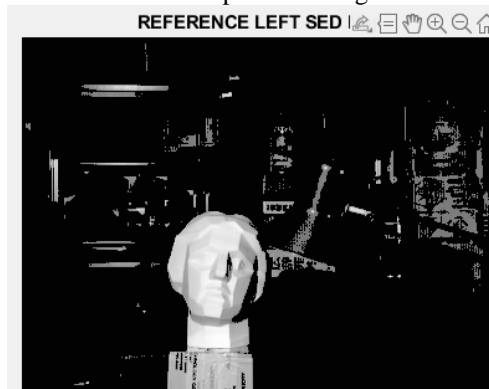


Fig.15: Stereoscopic Reference Left SED Map.

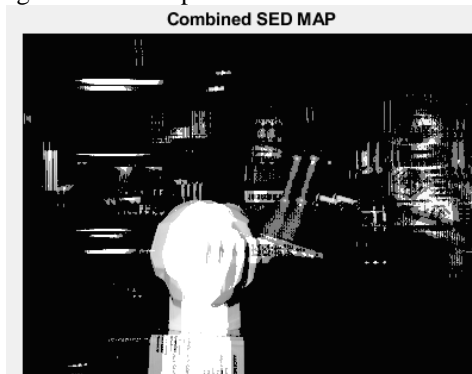


Fig.16: Stereoscopic Combined SED Map.

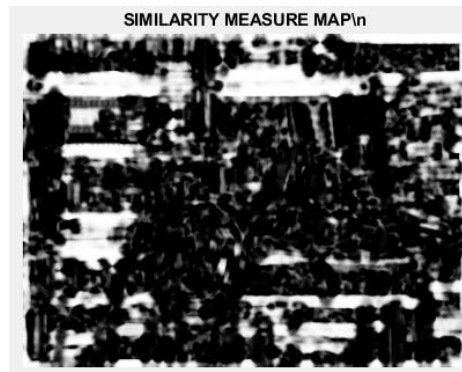


Fig.17 :Stereoscopic Structural Similarity Index Measure Map.

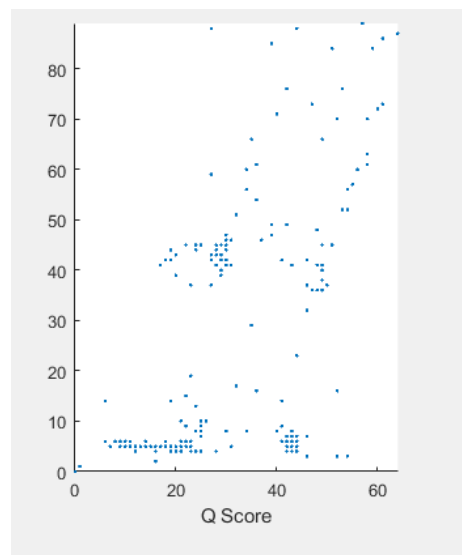


Fig. 19:Stereoscopic Image quality Enhancement score.

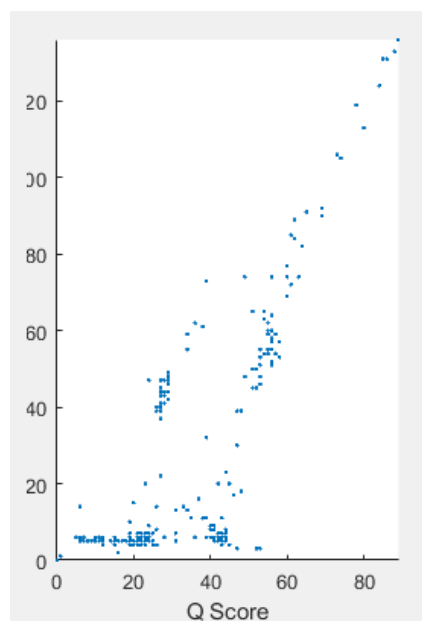


Fig.20:Stereoscopic video quality Enhancement score.

The relating Mean Assessment Scores (Greenery) are accommodated the reference image coordinates and distorted image matches. Reference images are compacted with three unique codecs, to be specific JPEG, JPEG2000, and HEVC intra. There are 180 evenly and 216 unevenly distorted images in it with two goals, i.e., 4096×2048 and 2560×1280. The Stereoscopic video quality defects detection and enhancement results are presented as under.

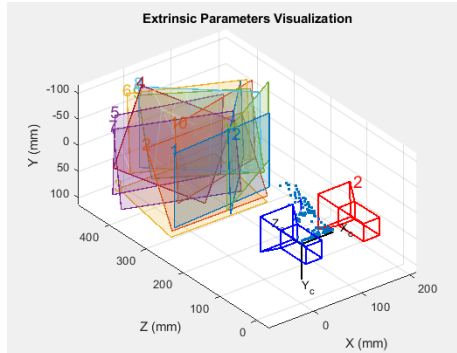


Fig.21: Stereoscopic 3D camera projection planes.



Fig.22: Rectified Stereoscopic 3D video frames.

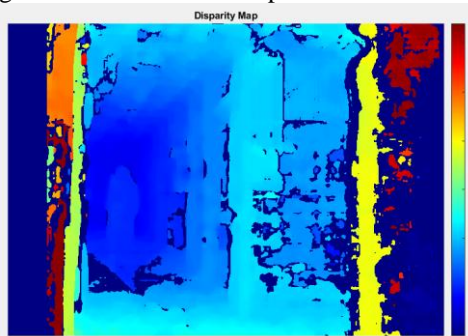


Fig.23: Estimated Stereoscopic Binocular Disparity Map.

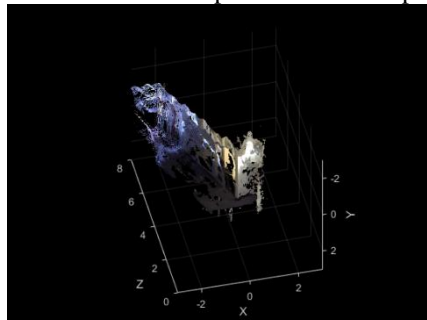


Fig.24: Estimated 3D Stereoscopic Binocular Disparity Map.

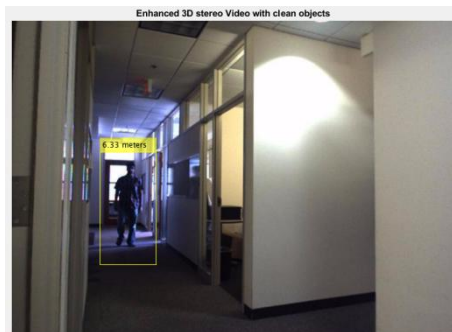


Fig.25: Enhanced 3D Stereoscopic video frames.

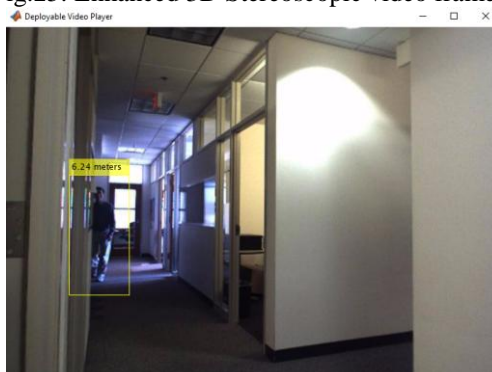


Fig.26: Final Enhanced 3D Stereoscopic video frames.

We contrasted the proposed PINTS-SOIQA and a few best in class objective quality assessment measurements on every data set, including eleven Full Reference (FR) IQA measurements and one No Reference (NR) IQA metric. These measurements were partitioned into four kinds. Right off the bat, we embraced five 2D IQA measurements (i.e., PSNR, SSIM, RFSIM [52], VIF, GSM [6]) from the regular IQA for correlation. Quality scores were processed through one re-organized image with left-view on the top and right-view on the bottom. Three OIQA measurements including S-PSNR, WS-PSNR and CPP-PSNR were used for estimating the exhibition of each view. Besides, SIQA measurements created to foresee the quality of stereo images, CHEN [55] and FI-PSNR [54], were acquainted with give a more complete presentation correlation.

SOI is produced and addressed in round structure, which can't be encoded with existing coding standards and is difficult to be stored or communicated. In this way, we should perform plane-to-circle mapping on the encoding side and reverse projection on the disentangling side. ERP has turned into the most generally utilized projection design because of its straightforwardness and accommodation. Shortened Square Pyramid (TSP) considers the client conduct, embracing the first goal in equatorial locale and downsampling in different districts, which produce serious distortion in low goal regions.

Projection between various configurations will bring about distortions, for example, objects and other visual structures that seem extended, bowed or sheared, as well as changes in distance, course, shape and region of the items . It is realized that no projection can hold more than one of these above properties, which adds challenges to IQA. To investigate the impacts of projection distortion on IQA, explicitly, the examining consistency and broken limit. We project ERP into a few other projection designs with 360Lib bundle [50] including CMP, OHP, ISP, RSP and TSP in this article. To limit brokenness among adjoining faces, we pick reduced pressing mode when experienced with different pressing modes. The goal of each arrangement is appointed practically equivalent to the first ERP design size for better examination.

V. CONCLUSIONS

In this project we proposed a quality assessment model based on the projection invariant feature and the visual saliency for Stereoscopic Omnidirectional Images. The Proposed system is designed to detect the quality defects and to carryout stereoscopic quality enhancement and assessment of both stereoscopic images and Videos. In this work, we propose an Image Quality Assessment (IQA) model consisting of projection invariant feature and visual saliency to

cope with the Stereoscopic Omnidirectional Images (SOIs). To the best of our knowledge, it is the first work to alleviate the inconsistency of evaluation objects via invariant feature rather than assessing on viewport through plane-to-sphere projection. There exists an equator bias in SOI, the latitude prior could be a guidance for saliency detection. Moreover, we make the projection adaptation through the converted saliency map. Overall, the proposed SOIQA model is in essence a versatile model that can be suitable for various projection formats. The proposed stereoscopic image and video quality assessment system is designed and implemented in the Matlab Environment and the simulation results adjudge that the

VI. FUTURE SCOPE

The proposed stereoscopic image and video quality assessment system is proved to be the best in performance and outperforms all the existing state of the art techniques and methods. Hence there is a huge scope to extend this work by physical realization to implement it on Hardware using the available state of the art VLSI Hardware Implementation Techniques.

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Impact Factor: 8.423



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