A NOVEL NO-REFERENCE QUALITY ASSESMENT ADOPTING HISTOGRAM SHAPE ANALYSIS

G.RAJENDER(M.tech, Assistant professor)[1]

HAFSA TAMKEEN (PG scholar.) [2]

Dr. B.R.VIKRAM (M.E, Ph.D, LMISTE, MIEEE) [3]

[1]Assistant professor, Vijay Rural Engineering College, Nizamabad, Telangana, 503003, INDIA

[2]Department of ECE, Vijay Rural Engineering College, Nizamabad, Telangana, 503003, INDIA

[3]PRINCIPAL, Vijay Rural Engineering College, Nizamabad, Telangana, 503003, INDIA

graj.247@gmail.com[1] hafsafaruqi1@gmail.com[2] vikramom@gmail.com[3]

Abstract

Digital image processing (DIP) itself a constituent of signal processing but without DIP we cannot perceive the statistical analysis of signal processing and hence concludes that both are inter-dependent on each other. Although image processing domain reaches new heights in recent years because of new technologies but still assessment of image quality is concerned area and perception of total information in 2-D view in not possible, this situation forces to develop new approaches. Additional views is possible if exploitation of pixel depth information is done by using Multi-view videos plus depth (MVD) representation and MVD provides ultimate 3-Dimensional view. MVD based depth information is used by histogram shape analysis to exploit the statistics of depth images and the proposed work relies on no-references mechanism which takes compression sensitive pixels of depth images into account to achieve high performance. High correlation of proposed work shows its supremacy over traditional state-of-art methods.

Keywords: High correlation, Multi-view videos plus depth, No-references system, Compression sensitive pixels (CSP).

1. INTRODUCTION

Multi-view imaging has attracted increasing attention, thanks to the rapidly dropping cost of digital cameras. This opens a wide variety of interesting research topics and applications, such as virtual view synthesis, high-performance imaging, image/video segmentation, object tracking/recognition, environmental surveillance, remote education, industrial inspection and 3DTV. While some of these tasks can be handled with conventional single view images/video, the availability of multiple views of the scene significantly broadens the field of applications, while enhancing performance and user experience.

The interest in Three-Dimensional Video (3DV) technologies has grown considerably in both the

225

academic and industrial worlds in the recent years. A simple and flexible 3DV representation is the so-called Multi-view Video-plus-Depth (MVD), in which depth maps are provided together with multi-view video. Depth maps are typically used to synthesize the desired output views, and the performance of view synthesis algorithms strongly depends on the accuracy of depth information. Several quality evaluation studies have been performed for video plus-depth coding systems. In these studies, however, the distortions in the synthesized views have been quantified in experimental setups where both the texture and depth videos are compressed. [4] proposed a principle in which the division is the urgent stage in iris acknowledgment. We have utilized the worldwide limit an incentive for division. In the above calculation we have not considered the eyelid and eyelashes relics, which corrupt the execution of iris acknowledgment framework. The framework gives sufficient execution likewise the outcomes are attractive. Assist advancement of this technique is under way and the outcomes will be accounted for sooner rather than later. Based on the reasonable peculiarity of the iris designs we can anticipate that iris acknowledgment framework will turn into the main innovation in personality verification.In this paper, iris acknowledgment calculation is depicted. As innovation advances and data and scholarly properties are needed by numerous unapproved work force. Therefore numerous associations have being scanning routes for more secure confirmation strategies for the client get to. The framework steps are catching iris designs; deciding the area of iris

limits; changing over the iris limit to the binarized picture; The framework has been actualized and tried utilizing dataset of number of tests of iris information with various complexity quality.

Many diverse representations of 3D scenes have been proposed in the literature. Each one presents different advantages and disadvantages, so the choice of one over the others depends on the requirements of the specific 3DV system. In general, 3D scene representation methods can be classified in relation to camera density, as proposed in the computer graphics literature. Two extremes are identified: image-based representations and geometry-based representations. On one hand image-based representations (including Ray-Space and light-field) typically require very dense camera settings in order to ensure good rendering performance. View generation is performed by means of interpolation from the available camera views without basing on any geometric model. In this approach complexity is a major issue as the amount of data to be processed is huge. On the other hand geometry based representations may require less dense camera settings but rely on complex image processing algorithms such as object segmentation and geometry estimation algorithms that are very sensible to noise and may require controlled environments to ensure acceptable results. Pure geometry-based models such as 3D meshes are used in applications like computer games, Internet and movies. The rendering quality can be very high when the scene is computer generated.

2. MOTIVATION

Three-Dimensional Video (3DV) is believed to be the next major development step in the evolution of motion picture formats towards a more natural and realistic visual experience. However, Three Dimensional Television (3DTV) is not a new concept at all. The invention of the first system enabling stereoscopic vision of still images dates back to 1838, when a mirror-based device able to fuse two different perspective images into one and give the viewer the impression of depth was invented. Later in the 1920's the first full-length 3D film was released and an experimental stereoscopic TV setup was demonstrated, thus showing that 3DTV is almost as old as its mono-scopic counterpart – also demonstrated in the 1920's. The interest in 3D movies had the first peak in the 1950's, when the cinema industry tried to react to the increasing popularity of television. However, due to the lack of experience with the new technology and the big limitations of the display equipments, the production of 3D movies significantly dropped in the late 1950's without showing a clear return before the 2000's.

Later in 2008 the successful H.264/MPEG-4 Advanced Video Coding (AVC) [5] standard was extended with the Multi-view Video Coding (MVC) extension featuring more efficient inter-view prediction schemes and higher compression gains. However, it was clear that in order to support the large number of views required by high-quality auto stereoscopic multi-view displays new solutions were needed: the size of an MVC bit stream is in fact proportional to the number of views in the multi-view

video. Motivated by this issue and other limitations of both MPEG-2 Multi-view Profile and MVC, a new approach to 3DTV that efficiently exploits the scene geometry was proposed. After a first exploration phase, the technology is being now standardized by the MPEG 3DV ad-hoc group, which recently joined the efforts with the International Telecommunication Union – Telecommunication Standardization Sector (ITU-T) Study Group (SG) 16 Working Party (WP) 3 to form the Joint Collaborative Team on 3D Video Coding Extension Development (JCT-3V). The idea is to represent a 3DV with a small number of views – typically 2 to 3 – and the corresponding depth map information.

An example of a view and the associated depth map is provided in Fig. 2.1. If depth data are available at the decoder side, any intermediate view between the 2 or 3 input views can be synthesized by means of Depth-Image-Based-Rendering (DIBR) algorithms according to the specific display requirements, and used for display. This format looks particularly attractive as it allows decoupling content creation and display requirements – a key feature for the success of 3DTV delivery – without introducing substantial bit rate increases, thus solving the central issue of MVC.

227

Fig. 2.1.: A color image (a) and the corresponding depth map (b) from the Ballet dataset

3. RELATED WORKS

3.1 Image Quality

Assessing the quality of digital image attains attention due to its application ability. Human visual system (HVS) is the basic parameter used to assess the quality of digital image but in most of the cases HVS fails to recognize the abnormal content because HVS mainly depends on content rather than its statistics. Image quality is a characteristic of an image that measures the perceived degradation of an image.

3.2 Image Quality Assessment (IQA)

As increase in the demand of the Image Processing Applications, the quality measure is the important concern.IQA is mainly developed to evaluate the image quality automatically in agreement with the Human Visual System (HVS).

3.3 Image Quality Assessment Techniques

There are two techniques of Image Quality Assessment:

1. Subjective Quality Assessment

We can say that human itself recognize the quality of image very well. In this type of method humans are involved and they have to recognize the quality of image. The scores evaluated by multiple subjects are averaged for each test image to obtain mean opinion score and difference mean opinion score. For this technique the answer is different for individual observer. Also the expenses are more as well it is not applicable to real time processing.

2. Objective Quality Assessment

The goal of objective IQA is to design mathematical models that are able to predict the quality of an image accurately and automatically. An ideal objective IQA method should be able to mimic the quality predictions of an average human observer. This is quantitative approach which is used to estimate the number which shows the quality of image. The objective image quality is classified into following three types as full-reference, no- reference and reduced-reference. The following types are depending on the use of the reference image.

A. No-Reference Model

Evaluation of noise content or distortions present in an image is same as assessing the quality of an image. Measurement of such quality index is challenging in the absence of reference image. In this type of model we don't have any priori knowledge. This type of model is also called as 'Blind Model'. The main advantage of this type of model is we can use this type model in any application because they don't require any reference information. These models are easy for calculation and gives approximate estimation.

228

B. Full-Reference Model

In this type of algorithm we known the perfect version of image or video and we have to calculate the distortions present. The perfect version we can get by high quality acquisition device before the errors will take place like transmission error and compression artifacts.

C. Reduced-Reference Model

In this partial information about the 'perfect version' is available and we can compare this version with 'distorted version'. This information is used to decide the quality of distorted image by the RR QA algorithms.

4. PROPOSED METHOD

4.1 PROPOSED BLIND DEPTH IMAGE QUALITY METRIC

Conventional 2D quality metric such as SSIM are not giving good results for 3D images or videos. So there is need to implement this Blind Depth Quality Metric (BDQM) which is a no-reference algorithm to calculate the quality of compressed depth images. The proposed method having major steps as primarily it will propose a novel no-reference depth quality metric BDQM to know the blind depth quality artifacts in an image, after that we are going to consider the shape of the histogram for compression sensitive pixels for evaluation of the depth quality of an image. More is the compression ratio for a histogram is nothing but depth transition flattens because of the smoothing effect. Mostly the BDQM

is developed to calculate the quality of images which are undergone HEVC compression.

Depth information of a scene can be recovered from multiple close-by images using generalized stereo algorithms. These algorithms compute depth using the triangulation method based on image correspondences across multiple views.

Mainly in two steps this algorithm is divided as given below

First is we are going to calculate the compression sensitive map (CSM) of the pixels which are more susceptible for compression.

Second is we constructed and analyzed the Histogram of neighborhood for each CSP which will show the quality index.

BDQM mainly think that the histograms around the CSP are flattened when very huge amount of compression takes place, because the compression mostly affects the sharp discontinuities of the depth image. Hence the proposed algorithm is mainly focus on the development of the histogram shape, depending on the shape we can easily tell that the behavior of CSP's.

A. Evaluation of compression sensitive map

Compared with the homogeneous depth provided to an image, the boundary regions of the different depth levels are very easily can get compression artifacts. Compression sensitive map (CSM) of any depth image (I) having $M \times N$ pixels can be given as follow,

$$\text{CSM} = \sqrt{G_x^2 + G_y^2} \qquad (1)$$

Where, G_x and G_y are horizontal and vertical gradient components respectively and these can be calculated with the help of Sobel filter.

229

Mainly the compression sensitive pixels are used to calculate the quality of the image with the use of Gradient magnitude. Fig. 1a shows a depth image from Poznan Street sequence (View 5, 1st Frame) and its corresponding gradient representing the CSM (Fig. 1b). We can calculate the most sensitive pixels that is CSP's with the help of Thresholding by dropping the pixels having values CSM $\leq \tau$. These CSP's have positive side effects also which can reduce the computational cost also. All these are as shown below,
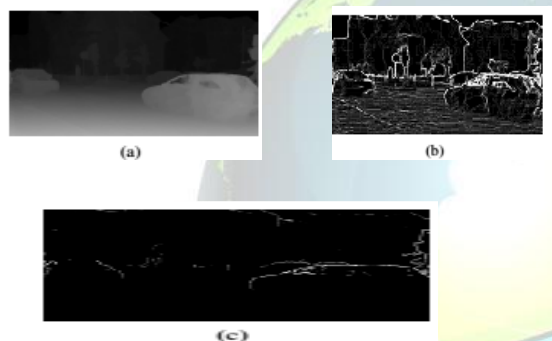
Fig. 4.1.: (a) A depth image (b) CSM of (a) (c) Threshold CSM ($at\ \tau = 4$)

B. Depth quality index

Evaluation of noise content or distortions present in an image is same as assessing the quality of an image. Measurement of such quality index is challenging in the absence of reference image. Above calculated compression sensitive map is used to calculate the quality of depth image. The CSP's present in the above image shows that the Sharpe discontinuities present between the boundaries of linearly changing regions of image having different depth levels. As there is very high change in the

colour map at the boundaries between two different depth levels, if Histogram calculated for these type of different colour map. Histogram for these types of images having different colour map is appears to be very high peaked at two bins of the histogram. Then we have to apply histogram equalization such that the levels of histogram are distributed equally to overall histogram.

Fig. 2   shows a sample bar chart of a CSP (neighborhood of size 15×15) from Poznan Street sequence compressed with HEVC with division parameter QP=30 (Fig. 2a) and QP=42 (Fig. 2b), severally. The bar chart is computed onto ten equal bins. Two terribly high peaks with values on top of eighty five can ascertained in Fig. 2a showing that the depth values area unit focused around two bins whereas the remainder of the bar chart is extremely sparse and nearly empty. In Fig. 2b it are often noted that the bar chart of constant region exhibits lower peaks and better depression between them once QP=42: a drop of thirty and fifteen are often ascertained in the two peaks severally beside accrued values of the bins intermediate. We are able to conclude that higher compression makes the bar chart flattered.

To determine the quality of an image we calculated histogram dispersion, the area under the curve is used. We the concluded that larger the area less compressed is the depth.
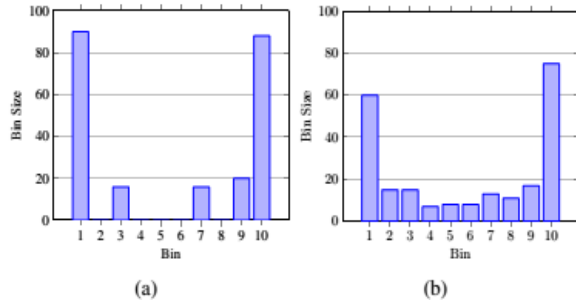
Fig. 4.2.: Histogram of a salient pixel from Poznan Street test sequence, view 5, frame 1 at QP=30 (a), and QP=42 (b).
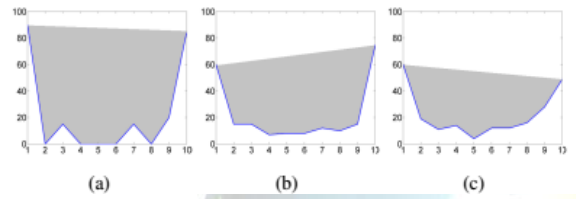

Fig. 4.3.: Predicting the quality index. (a) QP=30, Qi = 675, (b) QP=42, Qi = 525, (c) QP=46, Qi = 375.

An average value of the CSP area associated are calculated to determine final quality index for a depth image I and let $P_i \in \mathcal{S}$ be the CSP with co-ordinate $(x,y)|\{1 \leq x \leq M ; 1 \leq y \leq N \}$. For each $P_i \in s$,we select patch of the size $w \times w$ centered at (x,y) and calculated the corresponding local histogram. Let $H_i^{\,k}$ denotes the histogram distribution of the patch P_i with k equally sized bins. The quality index Q_i for the calculated P_i is defined as given below,

$$Q_i = \sum_{t=1}^{k}\left[\max\!\left(H_i^{\,k}\right) - H_i^{\,k}(t)\right] \qquad (2)$$

Fig. 3 diagrammatically shows the planned quality index. The figure shows distribution curves of a sample CSP of the primary frame of Poznan Street check sequence coded by HEVC with totally different QP. The blue line represents the bar graph distribution whereas the area within the curve is

shaded in grey. One will note that, as we conjectured on top of, the bar graph space is decreasing once QP increases. Finally, the Q_i of all CSPs is averaged to get the quality of depth image I.

$$BDQM = \frac{1}{|\mathcal{S}|} \, \Sigma_{i=1}^{|\mathcal{S}|} \, Q_i \quad (3)$$

Where the $|\mathcal{S}|$ represents the size of $\mathcal{S}$. We performed same for the video then we applied all these single frame to calculate the overall quality of the depth video and all these values we averaged to get overall quality of the whole depth video. We can say that this calculated BDQM measures the quality and also we concluded that larger the value of the BDQM better is quality of the depth map.
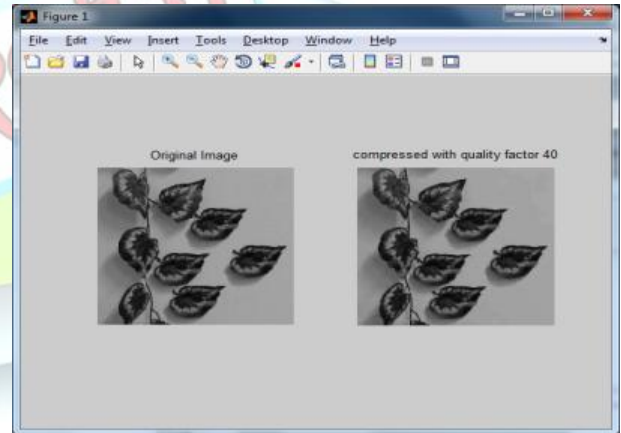
5. RESULTS

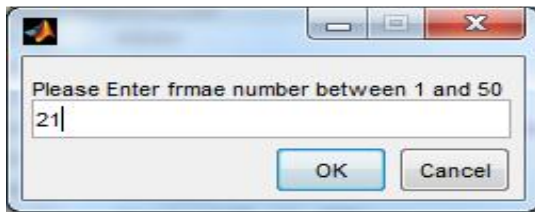Fig. 5.1: Original image compressed image (Leaf image)
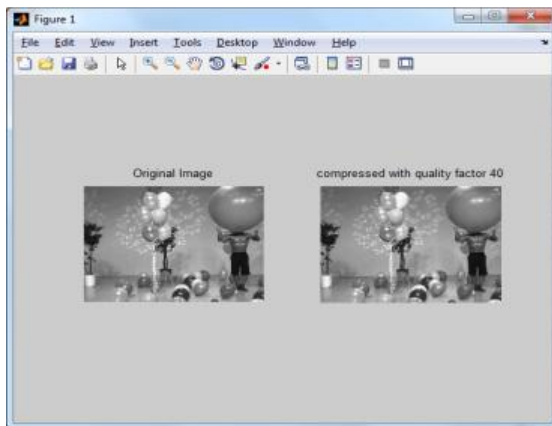
Fig. 5.2: Frame number

Fig. 5.3.: Original image compressed image (balloon image)

BDQ = 43.6947;

MSE1 = 5.6156;

PSNR1 = 40.6368;

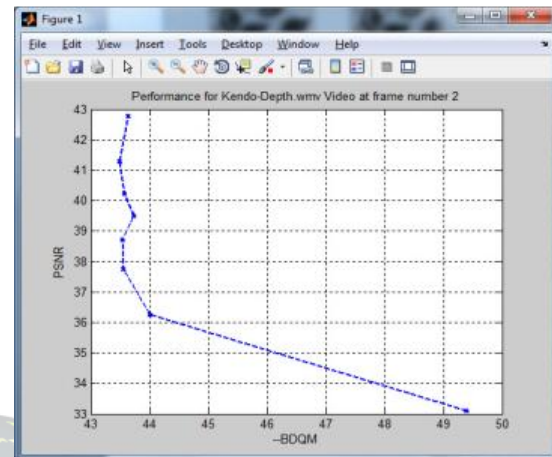RMSE = 2.3697;

MAE = 1.1126

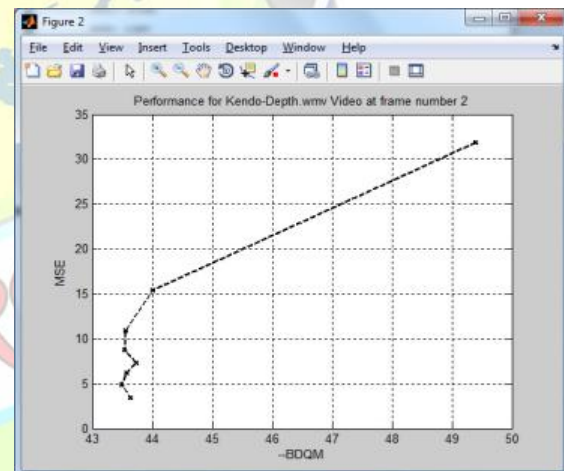Fig. 5.4.: performance for kendo-depth.wmv video for PSNR (Frame number =2)

Fig. 5.5.: performance for kendo-depth.wmv video for MSE (Frame number =2)

6. CONCLUSION

Three-Dimensional Video (3DV) is expected to be the next major step in the development of motion picture formats. Both the industry and academia are putting great efforts to overcome the challenges that the new technology brings, and significant results have already been achieved. Among the many issues

232

that need to be faced in the implementation of a 3DV communication system, data compression and transmission plays an important role. 3DV representations that enable the decoupling of content creation, transmission and display formats are of particular interest, and the Multi-view Video-plus-Depth (MVD) representation is currently the most widely adopted solution. In this paper a novel no-reference metric able to rank the compression artifacts of depth maps has been presented. The proposed algorithm leverages on the observation that depth images are characterized by flat regions with sharp boundaries that are potentially blurred after compression. The proposed algorithm estimates depth quality by measuring the blurriness of the compression sensitive regions of the depth image using a histogram based approach. The experimental results show that BDQM exhibits high prediction accuracy when compared to full reference PSNR metric.

REFERENCES

[1] M. Tanimoto, "FTV: Free-viewpoint Television," Signal Process.-Image Commun., vol. 27, no. 6, pp. 555 – 570, 2012.

[2] M.P. Tehrani et al., "Proposal to consider a new work item and its use case - rei : An ultra-multiview 3D display," ISO/IEC JTC1/SC29/WG11/m30022, July-Aug 2013.

[3] C. Fehn, "Depth-image-based rendering (DIBR), compression, and transmission for a new approach on 3D-TV" in SPIE Electron Imaging, 2004, pp. 93–104.

[4] Christo Ananth,"Iris Recognition Using Active Contours",International Journal of Advanced Research in Innovative Discoveries in Engineering and Applications[IJARIDEA],Volume 2,Issue 1,February 2017,pp:27-32..

[5] M.S. Farid et al., "Panorama view with spatiotemporal occlusion compensation for 3D video coding," IEEE Trans. Image Process., vol. 24, no. 1, pp. 205–219, Jan 2015.

[6] T. Maugey, A. Ortega, and P. Frossard, "Graph-based representation for multiview image geometry," IEEE Trans. Image Process., vol. 24, no. 5, pp. 1573–1586, May 2015.