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3D Image Generation from Textured Digital Images Using Improved Linear Algorithm Based On Depth Map Estimation and Resolution Enhancement

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***Abstract*: *Multimedia applications have gone through wide advancements in the recent years with the development of portable digital devices. With the advancements in multimedia application the demand for 3D technology has also increased. The most important issue in two dimension to three dimension image conversion is the poor image quality and its increased time complexity. The visual perception of the image can be improved by using pre-processing techniques on the noisy, blurred texture image with low resolution to remove spectral and spatial problems. The paper, explains the enhancement schemes using Discrete Wavelets and Stationery Wavelet Transforms with various interpolation techniques used as preprocessing technique. For the 3D conversion an Improved Simple Linear Iterative Clustering (ISLIC) method with Statistical Region Merging (SRM) is proposed. To retain the image quality Gaussian smoothing is performed with color uniformity principle. Here in the proposed work to reduce the time complexity a Depth Image Based Rendering (DIBR) method is applied to construct a 3D image from the given input. The performance analysis of this work has been compared with that of the existing methodologies and found to be more efficient*.

***Key Words*:** 2D to 3D conversion, Resolution Enhancement, Interpolation techniques, Iterative, Clustering, Region Merging

I. INTRODUCTION

3D imaging techniques are widely used in the field of orthodontic and dentofacial orthopedics for various diagnoses [1] to precisely depict, the physiological and anatomic realities for proper investigation. The size and type of craniofacial structure are obtained using imaging techniques [2]. 2D images are widely used for various orthodontic diagnoses but in 2D imaging the profundity of structures cannot be properly obtained. From as early as 1990's, research developments in 3D imaging [3] has started. Using 3D imaging, anatomical information can be obtained using mechanical gear, controlled by a PC. The actual motivation [4] in using three dimensional imaging is to obtain subjective and quantitative data of an object using the images obtained using techniques like ultrasonic, computer radiology, or Magnetic resonance imaging.

The most important issue in 2D to 3D image conversion [8[[9] is the poor image quality and its increased time complexity. The visual perception of the image can be improved by using pre-processing techniques on the noisy, blurred texture image with low resolution to remove spectral and spatial problems. Usually the input image is obtained from low cost imaging sensors which produce low resolution images. Since Digital images are a discrete values of continuous signals perceived through any imaging sensor, it requires a preprocessing mechanism to improve its perception. So enhancement of images has become a major challenge in image processing area of research. The highlight aspect of an image is the resolution value which indicates the number of pixels it contains in it to present the information. The preprocessing techniques involved are Discrete Wavelet and Stationery Wavelet Transform with various interpolation methods

II. LITERATURE SURVEY

[13] KeGu, VinitJakhetiya et al Introduced a novel reference less quality metric of DIBR-synthesized images using the auto regression based local image description. It was discovered that, after the AR expectation, the reproduced mistake between a DIBR-integrated picture and its AR-anticipated picture can precisely catch the geometry mutilation. The visual saliency is then utilized to change the proposed daze quality metric to a sizable edge. This takes reasonable time to finish the process but lacks in an image quality.

[14] Jiasong Zhu, Jie Hu, proposed a different 3-D feature combination system (M3DF3) for hyper spectral picture characterization. The 2-D Gabor surface feature had been extended into 3-D domains to agree to the spatial–otherworldly structure of the picture, which is directly applied on the first picture instead of the Gabor features. The proposed 3DSF separately describe the hyper spectral picture from three different edges, i.e., morphology, nearby dependence, and shape smoothness. This system maintains the quality of an input image but time complexity is high.

[16] Ming Xu and Zeyunyu introduced a tetrahedral work based approach for 3D picture division on a given picture volume. The 3d vigilant edge indicator is used to protect critical component limits in the produced tetrahedral work. Each bunch of voxels inside a tetrahedron is

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III. PROBLEM STATEMENT

While on dealing with the conventional 2D imaging strategies, it is difficult to understand the profundity of image structure or the texture . The most important issue in two dimension to three dimension image conversion is, the poor image quality of the input image. In recent days, depth map is analyzed during two dimension to three Dimension transformations. The traditional two dimension to three dimension image conversion strategies fails, due to the huge requirement of memory. Since the transformation results have heavy calculations, high cost is also another major hurdle while implementing the traditional 2D to 3D conversion methods. Simultaneously in some approaches, while trying to determine the depth map, an error might be occurred due to the presence of hole regions i.e., the region with no edge information or image boundary. Therefore the visual perception of the image has to be improved by using pre-processing techniques on the noisy, blurred texture image with low resolution to remove spectral and spatial problems. As well the time taken to convert a two Dimension image to three Dimension image is also high i.e., the processing time is high, which leads to increased time complexity.

IV. PROPOSED METHODOLOGY

In this current era, each and every multimedia device deals with 3D technology. But once there was time it was difficult to convert a 2-dimensional image into a 3D image. But in recent times it became possible with the advanced technologies, where the researchers converts 2D images into 3D images with some approaches using digital image processing. Though conversion or transformation is achieved, the time consumption is high for these process, as well the image quality is too poor. In addition, due to the confounded calculations, the memory requirement is also high. These are some common hurdles that made the existing approaches undeserving.

Thus to handle all such drawbacks, our proposed work uses a 2D texture image as input which is preprocessed to improve the image quality using SWT-ICBI .This preprocessed image is then given as the input of an improved SLIC . Here, super pixels are generated depending on the color similarities. Further it provides the information about the edges and the boundary pixels. Then segmentation or the foreground extraction process is carried out by means of Statistical Region Merging (SRM). It is then supposed to perform Gaussian smoothing results to analyze the initial depth of input image. Occurrence of noise will be detected and removed with this process. Incase if any hole region is detected, it is then filled using the color uniformity principle. Final depth map is estimated using the bottom-up model, by utilizing Depth based Rendering the left view and the right views of the image is retained with the integration of the depth map and the original 2D texture image, the resultant 3D texture will be obtained with high quality and at reduced time complexity. The proposed system architecture is described by the Fig .1

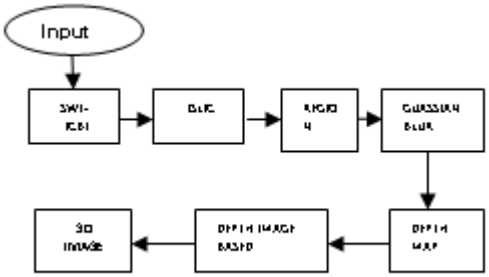

Fig .1. The Flow diagram of the proposed system

A. SWT-ICBI

The visual perception of the input image can be improved by using pre-processing techniques on the noisy, blurred input/ texture image with low resolution to remove spectral and spatial problems. SWT-ICBI (Iterative Curvature based interpolation) can be used for preprocessing, which has an improved quality of resolution along with the edges of the image. Initially, an adaptive algorithm is applied for interpolating local pixel values in the direction of the lower second image derivative. These values are updated using an iteration done for minimizing the differences in second order derivatives, maximizing second order derivative values and smoothing the curves of the image. Finally the same steps are adopted to get the high resolution image Fig.2 shows the flowcharts for generating high resolution from low resolution images using SWT-ICBI

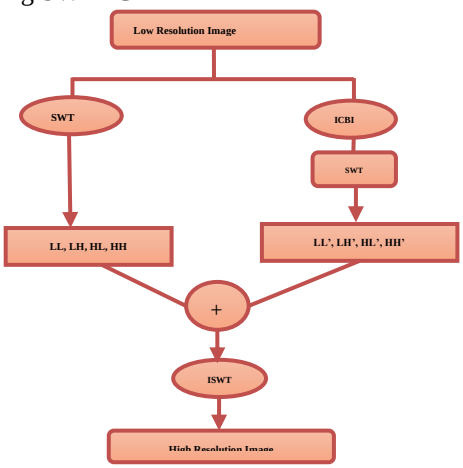

Fig.2. Flowcharts for generating high resolution image

B. IMPROVED SLIC

In this phase, the pixels of an image o would be partitioned into classes that efficiently compare with the objects in an image. In this work ISLIC is proposed to effectively carry out the segmentation process.

While using Conventional SLIC algorithm to generate the super pixels, more number of small areas will be formed in the image surface that would significantly affect the segmentation result so we have underwent image normalization to make an improved SLIC

The normalization process converts the n-dimensional gray scale values with the intensity values in the range (Min, Max) into a new one

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$$I:\{Y \le R^n\} \rightarrow \{Min,.....,Max\}$$

Normalization is non-linear if there is not a linear relationship between O and O_N.

$$O_N = (newMax - newMin)\frac{1}{1+e^{-\frac{1-\beta}{\alpha}}} + newMin$$

Where α is width of the input intensity range, β is the value of intensity in which the range is centered.

Simple linear iterative clustering has one parameter, ie the number of equally sized super pixels to be generated. The image is converted to blocks. The center of each grid tile is then used to initialize a corresponding k-means value.

SLIC does not compare each pixel in any image. For a region of size m × m, the value of *d* is computed (where *d* is the distance) in a region 2m × 2m of the super pixel as its center, which reduces the frequency of computations. After the assignment of nearest cluster, the newly obtained cluster centers are updated for super pixels which represent the mean vector of all the pixels belonging to the super pixel. The error computed, will be the gap between previous center locations and newly computed center locations. Then iterations are carried out and are terminated when the error reaches the threshold of the initial value of iteration.

$$d = \sqrt{\left(\frac{d_c}{O}\right)^2 + \left(\frac{d_s}{S}\right)^2} \quad .....(1)$$

$$d_c = \sqrt{\sum_{S_b \in B}\left(P(u_i, v_i, s_b) - P(u_j, v_j, s_b)\right)^2} \quad .....(2)$$

$$d_s = \sqrt{(u_j - u_i)^2 + (v_j - v_i)^2} \quad .....(3)$$

Where *d* indicates the distance measurement which includes both distance of intensity proximity and distance of space proximity. The distance of color proximity would maintain the homogeneity of the superpixel and the distance of spatial proximity would maintain the superpixel compactness.

Indicates the color and spatial distance between pixels $P(u_i, v_i, s_b)$ and $P(u_j, v_j, s_b)$ in the spectral band S_b. B and O acts as an optimal parameter for managing the compactness of super pixels. Fig 3 shows the flowchart of an improved SLIC

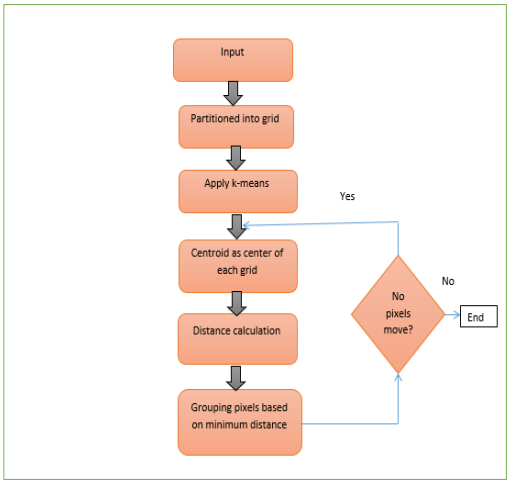

Fig. 3 Flow diagram of ISLIC

Algorithm for the Proposed Methodology:

Step 1: SLIC would commence by dividing an input image O into a rectangular grid with R*S tiles

Where $R = \left[\frac{width}{G}\right]$ .....(4)

$$S = \left[\frac{height}{G}\right] \quad .....(5)$$

Step 2: K means cluster would be initiated from each grid centre and calculate the average weighted

$$x_i = round \quad i\left[\frac{width}{G}\right] \quad .....(6)$$

$$y_i = round \quad j\left[\frac{Height}{G}\right] \quad .....(7)$$

Step 3: In order to prevent keeping these centres on worst portion of the image, the centres are moved in a 3*3 neighbourhood to reduce the edge strength

$$b|u| = g\sqrt{\frac{1}{2Q|u|}\ln\left(6|O|^2 U_{|U|}\right)} \quad edge=\{P(s+1,t)-I(s-1,t)+\{I(s,t+1)-I(s,t-1)\}..(8)$$

Step 4: Then the regions are obtained by running k-means clustering, started from the centres

$$C = \{\sum(x_i, y_i), i = 0,1,..,R-1, j = 0,1,..,S-1\}.....(9)$$

The output of this phase would be clustered form of an input image O

C. STATISTICAL REGION MERGING

After k-means had achieved better convergence, remerging is adapted to remove each clustered region whose region is small than the minimum region size.

The functionality is to begin with one locale for each pixel and after that applying a factual test on neighboring areas (in rising request of force contrasts) regardless of whether the mean powers are adequately sufficiently comparative to be combined.

Let *O* be an image having $|O|$ pixels, in which, every pixel comprises of Red, Green and blue color channel values from the set {0, 1, . . . , g − 1}where g is having the values from 0 to 255. *O**, be the observation of a true image and the pixel of *O* are impeccably symbolized. *O** has been acquired from *O* by means of sampling each and every statistical pixel for observed RGB bit slice. The color channel values for every pixel in *O** are replaced by a set of Q independent random variables, which take on values from [0, g/Q]. It is to be renowned that the Q parameter specifies statistical complexity of *O**. Higher the values of Q , better segmentation results obtained. Region merging using statistical data holds two components first one is a merging predicate and the second one is the order in examining the predicate, which is as given below,

$$P(U, U') = \begin{cases} true & if \quad \forall a \in \{R,G,B\}, \left|U'_a - U_a\right| \le \left|\sqrt{b^2(U) + b^2 U'}\right| \end{cases} \quad ....(9)$$

Here u and u' indicates the regions to be tested. u_a

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Indicates the color channel average in the location is the set of locations with pixels. The order of the merging region is indicated by invariant, which states that when the test is performed between the two locations which is inside a real location, additional tests are not needed.

u and u' be pixels of an image M , and $R(U)$ be the present region in which a pixel U fit in.

Initially the SRM algorithm sorts the pairs in increasing order with respect to the function $f(U, U')$. After sorting, the merging test is carried out $P(R(u), R(u'))$ for any pair of pixels (U, U') for which $R(u) \neq R(u')$ and merging $R(U)$ and $R(U')$ if it returns true. Thus with SRM, the boundary pixels are identified to perform modification in the edges so as to generate better convergence

D. GAUSSIAN SMOOTHING

The image O which is effectively and equally clustered would be subjected to depth calculation.

Representing images as matrices of numbers $R = (r_{i,j})$ each number indicates the intensity of a pixel and Gaussian matrix as $S = (s_{i,j})$

Using defined function

$$G(x, y) = \frac{1}{2\pi\sigma^2} e^{-(x^2+y^2)/2\sigma^2} \quad (10)$$

$$S = \begin{bmatrix} S_{1,1} & S_{1,2} & S_{1,3} \\ S_{2,1} & S_{2,2} & S_{2,3} \\ S_{3,1} & S_{3,2} & S_{3,3} \end{bmatrix} = \begin{bmatrix} g(-1-1) & g(-1,0) & g(-1,1) \\ g(0,-1) & g(0,0) & g(0,1) \\ g(1,-1) & g(1,0) & g(1,1) \end{bmatrix}$$

Blurring R with S

$$C_{k,l} = \sum_{i=1}^{1} \sum_{j=1}^{1} r_{k+i,l+j} \, s_{1+i,1+j} \quad \ldots\ldots\ldots\ldots\ldots \quad (11)$$

$$C = \begin{bmatrix} R_{1,1} & R_{1,2} & R_{1,3} \\ R_{2,1} & R_{2,2} & R_{2,3} \\ R_{3,1} & R_{3,2} & R_{3,3} \end{bmatrix} (\&) \begin{bmatrix} S_{1,1} & S_{1,2} & S_{1,n} \\ S_{2,1} & S_{2,2} & S_{2,3} \\ S_{3,1} & S_{3,2} & S_{3,3} \end{bmatrix}$$

The output of this process would be blur (O). With this method, the presence of noise is detected and is removed. As well along with this Gaussian smoothing, the color uniformity principle is used to detect the hole regions. Here by smoothing the image the number of big holes is reduced. The blur image is then assigned to estimate the final depth map.

E. DEPTH ESTIMATION

After determining the initial depth map from the un-shaped image generated by the Gaussian blur, have to calculate the value of depth for each pixel in the texture. Here in the proposed work, bottom-up mode taken to calculate the depth map. The bottom-to-up mode is defined by Eq. (12)

$$Depth = White - i \times \left(\frac{White}{Height}\right) \quad \ldots\ldots\ldots(12)$$

Where, 1 < slope, i=1, 2, 3,…, height. Height is the said to be the height of the texture image.

F. 3D CONSTRUCTION USING DIBR

Here to construct a 3D textured image, the DIBR method is used. In DIBR method, we have to calculate the *Shift value* using Eq. (13).

$$Shift\_value = abs[Depth - Zc]/(255) \quad \ldots\ldots\ldots(13)$$

where, *Depth* be the Depth value obtained from Eq. (13) and *Zc* be the convergence Distance.

Here the *Shift_value* is used to shift the original pixels with its depth values to calculate the left view and the right view and is calculated the formulas defined by Eq. (14) and Eq. (15).

$$Xrv(x, y) = pic(Xc + Shift\_value) \quad \ldots\ldots\ldots\ldots(14)$$

$$Xlv(x, y) = pic(Xc - Shift\_value) \quad \ldots\ldots\ldots\ldots(15)$$

Where, Xlv be the left view of image and Xrv be the right view of the image respectively. With this DIBR, the real 3D recording camera setup is formulated with a virtual camera configuration formula. Finally based on that configuration formula, both the views of the images is calculated and are integrated with the depth map. It would results with affine 3D texture image retaining high quality and at reduced time complexity. This approach is also implemented on MATLAB.

V. EXPERIMENTAL ANALYSIS AND RESULT

This section shows the results obtained with our proposed work. The whole setup is implemented in MATLAB. The simulation results obtained for different MRI images with our proposed work is shown below.

Fig. 3 - 6 represents the experimental results explaining the process of image transformation from 2D to 3D. That the original 2D Brain image is given as input to our proposed work. The input image is assigned to the ISLIC method, where the super pixels are generated to find the edge information. It is segmented and the foreground is extracted from the image. Further Gaussian smoothing is carried out to blur the image, so as to detect and remove in case of the occurrence of noise is present. Finally the depth map is determined and is integrated with the original 2D input image to develop a required 3D texture image as output

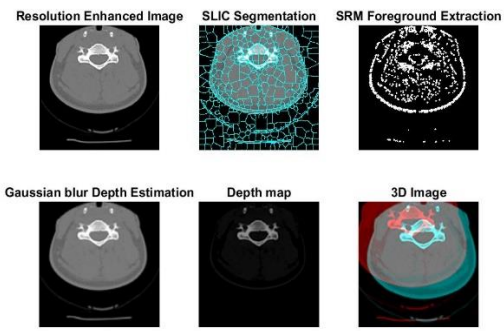

Fig 3 Image 1 Through the Proposed method

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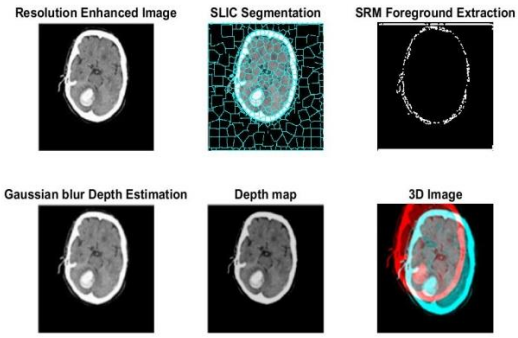

Fig 4 Image 2 Through the Proposed method

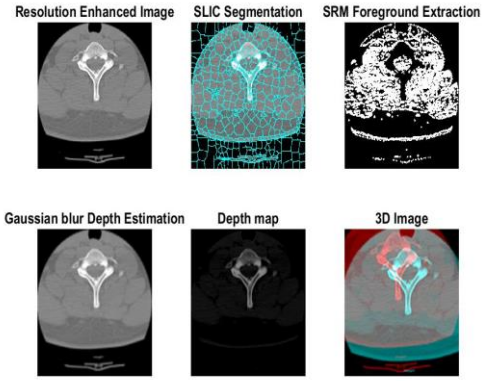

Fig 5. Image 3 Through the Proposed method

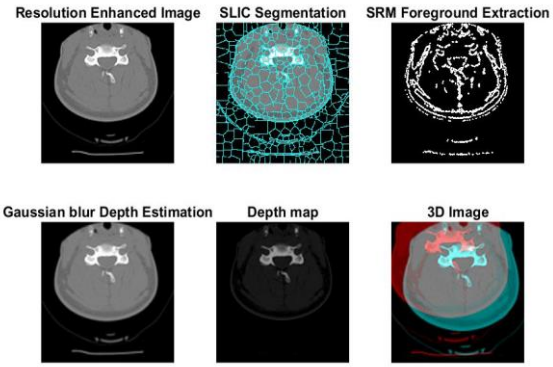

Fig 6 Image4 through the Proposed method

As part of the performance analysis of the proposed system, following metrics are taken into account. The PSNR and structural similarity index , which are shown in the performance analysis table 1.

G. Structural Similarity Index (SSIM)

SSIM indicates similarity between two intensity values in an image. The calculations are based on Eq (17) as mentioned below. It compares the two grids , a and b of size s*s

$$SSIM(x,y) = \frac{(2\mu_x\mu_y + c_1)(2\sigma_{xy} + c_2)}{(\mu_x^2 + \mu_y^2 + c_1)(\sigma_x^2 + \sigma_y^2 + c_2)} \qquad (17)$$

B. PSNR and MSE

The PSNR block computes the actual signal strength of the image intensity for better quality assurance.

The MSE values indicates the image compression quality. The lower the value of MSE, the lower the error. For Computing PSNR, the block first calculates the mean-squared error using the following equation:

$$MSE = \sum_{S,T}\left[\frac{I_1(s,t) - I_2(s,t)}{S*T}\right]^2 \qquad (18)$$

where S denotes the horizontal information and T denotes vertical information of input image. The computations are as per the Eq (19)

$$PSNR = 10\log_{10}\left(\frac{R^2}{MSE}\right) \qquad (19)$$

The performance of the proposed work is examined with the above equation and the resultant performance values are described in terms of graphical representations by Fig 7 and 8.

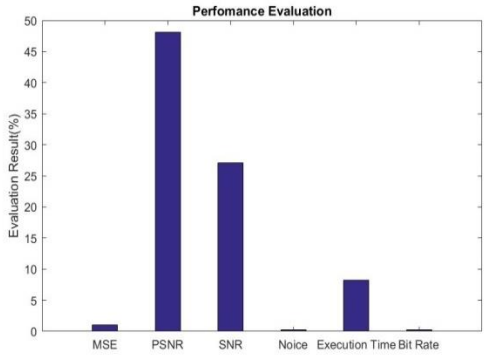

Fig. 7 Performance analysis of proposed method (MSE, PSNR, SNR, noise, execution time and bit rate)

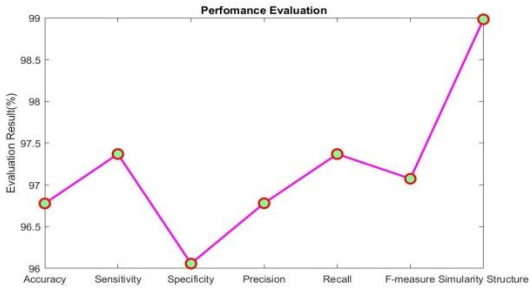

Fig. 8 Performance analysis of proposed method in terms of accuracy, sensitivity, specificity, precision

Thus the resultant performance analysis shows better outputs for our proposed work in terms of several metrics such as accuracy, sensitivity, specificity, precision etc. here the execution time is low, thus reduced the time complexity face by the prior methodologies.

C. Performance comparison

For the purpose of comparison with the proposed system following methodologies are taken into an account such as relative height interface, time coherent depth maps and saliency detection.

Table. 1 PSNR comparison of existing methods with proposed method

Methods	Image1	Image2	Image3	Image4
Relative Height Interface	10.275	12.2076	14.809	10.434
Time-coherent depth maps	10.535	11.2514	11.841	12.148
Saliency Detection	15.487	12.4473	12.362	13.247
Proposed System	17.42	16.257	15.32	17.25

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Table 1 describes about the performance comparison in terms of PSNR with our proposed work and the prior technologies such as Relative height Interface, Time coherent depth maps and saliency detection.

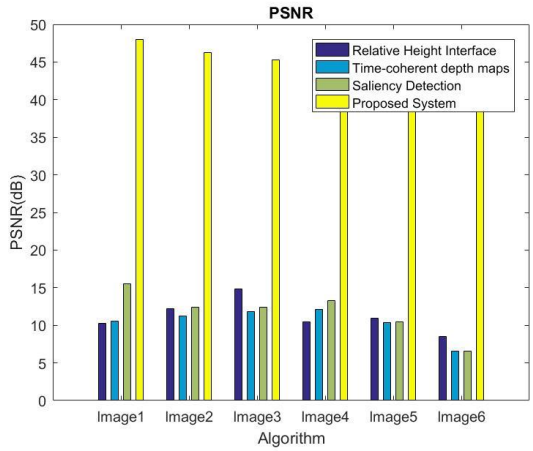

Fig.9 PSNR comparison of existing methods with proposed method

Fig 9 shows a better comparison result exhibiting high PSNR rate for our proposed work when compared it with the other prior methodologies. Thus the resultant texture image retains good quality and clarity than the existing methodologies.

Table. 2 SSIM comparisons of existing methods with proposed method

Methods	Image1	Image2	Image3	Image4
Relative Height Interface	0.5219	0.688	0.5591	0.6171
Time-coherent depth maps	0.4777	0.6744	0.5693	0.6772
Saliency Detection	0.5786	0.7065	0.6586	0.7061
Proposed system	**0.9438**	**0.9754**	**0.8712**	**0.9741**

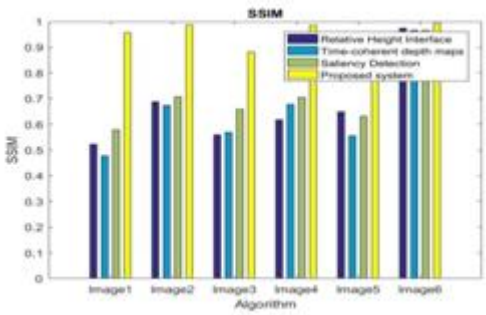

Fig. 10 SSIM comparison of existing methods with proposed method

Above comparison Table 2 for SSIM demonstrates about the comparison of our proposed work with some prior techniques in which the proposed work with ISLIC shows better results, yeild good image quality. The diagrametic representation for this comparison table is shown by the Fig 10. Thus the above tables and figures shows a better result for this proposed work, thereby it concludes that in our proposed framework using ISLIC, the drawbacks faced with the existing methodologies are successfully overwhelmed with reduced time complexities.

II. CONCLUSION

The conventional techniques for converting image from two dimensional to three dimensional had availed the parameters such as size of an image, edge, motion and texture for constructing stereo pairs. This leads to various problems such as distortion, lack of image quality, increased time complexity and so on. In order to deal with all those hurdles, our proposed framework is designed and implemented. In this proposed work, the given input is enhanced using SWT-ICBI and is fed to an improved SLIC with statistical region merging (SRM). With ISLIC, super pixels are generated and the foreground extraction is carried out by SRM. It is then followed by smoothing the image using Gaussian variables, thus the existence of noise will be reduced. Accordingly the depth is calculated with DIBR and the three Dimensional texture image is successfully generated from a 2D image, with improvised quality by the formula combining the depth map with the left vision and right vision of the texture image. Furthermore the time complexity issues faced with the prior methods are reduced here with DIBR. In Future, this system when implemented can be effectively utilized in the accurate diagnosis in orthodontic and dentofacial orthopedics.

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