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2D to 3D Conversion of Dental Images Using Deep Neural Network

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ABSTRACT

Dental implantation needs to be done in an accurate way. Radiographic examination is used to assist dental implantation practice. Computed Tomography (CT) has the added advantage of providing the information in three-dimensional than X-ray. High radiation dose and the affordability of CT image are the drawbacks of Computed Tomography. This reason makes to identify a novel based approach to convert a 2D dental image into a 3D dental image for dentistry that will be very useful in diagnosis and surgery planning. Conversion method can be semi-automatic or fully automatic. Semi-automatic methods involve supervision which provides efficient result but time consuming process. On the other hand fully automatic methods work on assumption based prediction. Thus it is very difficult to construct the entire information in the 3D image from 2D image. Analysis shows that semi-automatic methods provide better result than automatic methods. Thus, in this paper, a novel approach using neural networks has been used for conversion. First, depth analysis of the image was done. Secondly, color restoration was performed and finally, the 3D image has been obtained using neural networks. At last the data are validated using dental samples and patient data.

KEY WORDS: Dental Implantation, Computed Tomography, Conventional radiography, X-ray, 2D -3D Conversion, Deep Convolution.

1. INTRODUCTION

Human Tooth is the most distinctive and long-lasting features of mammal species. In dentistry, digital radiography has been available for more than 26 years, and it provides useful information to the diagnostic process. By using the digital system, information can be collected easily and specifically, which will improve the practice of diagnostic process.

Phan (2011), all say that many types of radiographic imaging have been recommended for treatment planning for implants such as Panoramic Radiograph, Periapical and occlusal radiographs, Conventional tomography and computed tomography (CT). X-ray imaging provides a more objective diagnosis, but repeated X-ray radiation may cause biological damage to human tissues. Dentists prefer 3D information than the 2D information because it provides sufficient information.

Singh (2007), states that CT imaging is used to view the 3D information about human body. However, CT scan is not preferred for continues assessment because high radiation and the cost affordability. Several researches are in progress to overcome this limitation. Due to the advancement in image processing tools like neural network and Computer vision researchers are carried out in the right path.

Herrera (2014), stated that there are many radiography techniques for 3D reconstruction of dental images, it emits lots of radiations and also very harmful to younger patients. Various methods have been proposed in the recent years to convert 2D dental images into 3D images.

Chenxi Zhang (2014), identified that most semiautomatic methods of stereo conversion use depth maps and depth-image-based rendering. There are automatic methods and does not require any human interference. Various approaches are presented under this category. It is possible to estimate depth using different types of motion automatically.

Huang (2015), proposed the technique Naturalistic 2D-to-3D. It is a Natural scene statistics (NSSs) model that outperformed several state-of-the-art 2D-to-3D conversion techniques. In this, depth information is estimated and Compensation processes are applied further to improve depth initialization. Gabor filter bank is applied and modeled using sub band of depth. The quality of the reconstructed model has been evaluated by generating 3D videos using both subjective and objective quality assessment methods.

Divya and Sneha Arun (2014), proposed a survey on 2D to 3D Image and Video Conversion Technique, states that most semiautomatic ways of stereo conversion use depth maps based rendering. The approach works tolerably just in case of scenes with static rigid objects like urban shots with buildings, interior shots, however has issues with non-rigid bodies and soft fuzzy edges. Abolfazl Mehranian (2013), proposed 3D Prior Image Constrained Projection states that a 3D MAR algorithm was proposed in the maximum posteriori completion of missing projections in a sequence of 2D CT slices and 3D cone-beam CT. In this algorithm, side information about missing projections was exploited, obtained from a tissue-classified prior CT image using a novel prior potential function. It was found that the proposed algorithm effectively reduces metal artifacts without introducing new ones owing to more accurate utilization of prior information in comparison with its state-of-the-art counterparts.

Uros Mitrovic (2013), proposed 3D-2D Registration of Cerebral Angiograms which is the novel method for 3D-2D rigid registration. Idea behind this algorithm is to identify the orientations with intensity matched gradient similarity. The Key success of this method is its adaptability to contrast variation and easiest registration process.
Janusz Konrad (2012), proposed Learning based automatic 2D-to-3D Image and Video Conversion. This approach is built upon a key observation and an assumption. The key observation is that among millions of 3D images available, there are less likely 3D contents that match the 2D input query.

Konrad (2012), proposed 2D-to-3D image conversion by learning depth from examples. It is a simplified and computationally efficient version of 2D-to-3D image conversion algorithm is developed. The validation was also limited to a database of indoor scenes on which Make3D was not trained. The generated images produce a comfortable 3D perception but are not completely void of distortions.

2. MATERIALS AND METHODS

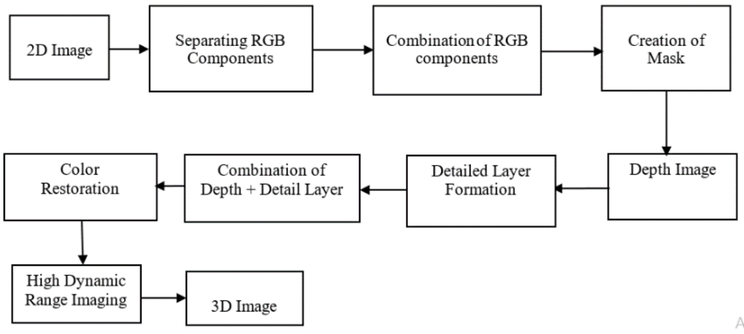


Figure.1. Block Diagram

The input 2D image is converted into separate R, G, B components. Tarun (2010) all suggested that If only the brightness information is needed, color images can be transformed to gray scale images. The transformation formula for calculating intensity is;

$$I_y=0.333R+0.5G+0.1666B$$

Intensity value of red, green, blue channel can be obtained by accessing the pixel value of the image. In image analysis, masking refers to the act of hiding or enhancing the color of certain areas of a image, or conversion of these areas into another background. In a similar way, we can mask images when certain objects in the photography should not be visible. Since a simple removal of the object would leave a gap in the picture, the area of the object has to be masked, first. This method works easily with a monochrome background.

Depth estimation or extraction refers to the set of techniques and algorithms aiming to obtain a representation of the spatial structure of a scene. Depth Map methods are divided into active and passive. An active method uses information in the image like illumination and processing, passively, the reflected energy.

The only approach that provides an absolute measurement of distance with monocular information is based in the focus properties of the image. This approach estimates the distance of every point in the image by computing the defocusing level of such points, following the human visual focusing system. This defocusing measurement is mainly done with Laplacian operators, which computes the second spatial derivative for every point in a neighborhood of N pixels in each direction. Focused pixels provide an exact measurement of the distance, if the camera optical properties are known.

Color Restoration is used to enlighten the view of an image. The Image is corrected using different adaptive histogram equalization technique to make the easiest analysis process. CLAHE operates on narrow regions than the full image. It has the advantage of noise susceptibility.

In most imaging devices, the degree of exposure to light applied to the active element (be it film or CCD) can be altered in one of two ways; by either increasing/decreasing the size of the aperture or by increasing/decreasing the time of each exposure. Exposure variation in an HDR set is only done by altering the exposure time and NOT the aperture size; this is because altering the aperture size also affects the depth of field and so the resultant multiple images would be quite different, preventing their final combination into a single HDR image.

3. RESULTS AND DISCUSSION

Patient data have been collected in order to perform to 3D conversion. Fifty samples have been taken and each sample has undergone step by step procedure in order to obtain the required result. For each 3D image thus generated, IEF and SSIM values have been calculated in order to increase the performance measure of the system. The proposed approach was successful in providing appropriate results. The step by step processes and their results are as follows: X-Ray images have been taken and are given as an input to the system. Now the coordinates of the input image like position, axes properties, resolution, and pixel range have been taken into consideration. Fig 4.1 shows patient X- ray image as an input.

Given input image is separated into red, green and blue components and the output is shown in the figure. When the R, G and B components have been separated, we find that the pixel resolution is very less and thus the

images lack clarity. Thus, we combine all the components to form a combination of three components. The Figure shows the combination of R, G, and B components.

Figure.2.1 Input Image

Figure.2.2 Red Component

Figure.2.3 Green Component

Figure.2.4 Blue Component

Figure.2.5 Combination Of R, G, B Components

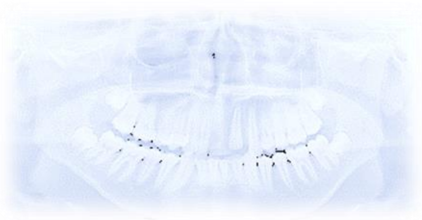


Figure.2.6 Mask Image

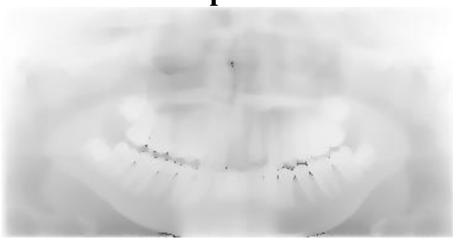


Figure.2.7 Depth Image

Figure.2.8 Base + Detail Compressed Image

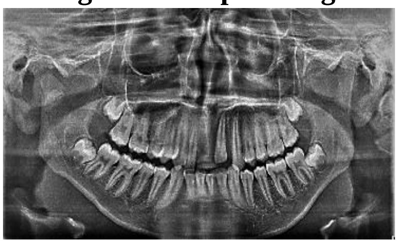


Figure.2.9 Hdr Image

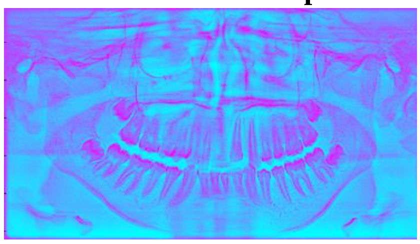


Figure.2.10 Output Image

Figure.2. Simulation Results

Masking image is generated and it is shown in the figure. The Figure shows the mask of the combination image. Now mask is applied to the color images and the next stage is the estimation of the depth images and it is shown in the figure.

The depth image is combined along with the detail layer component image to get the compressed image of the above. Fig shows the combination of base and detail compresses the image. Color Restoration deals with improving the appearance of an image. The Image is corrected using different with improving the appearance of an image. The Image is corrected using bilateral filtering in order to restore an image to its original forms. Figure 2.5 shows the color restored image. High-dynamic-range images are obtained by combining base image with the compressed image. Figure 2.9 shows the HDR image.

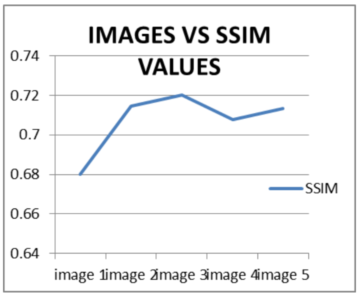
The HDR converted image is then converted into the 3D image. Deep Neural networks have been used to convert 2D image into 3D image. It is designed as a Feed forward network. It consists of three layers and four hidden nodes. Fig shows the output 3D image. The IEF value and SSIM value for the above image are 1.9810e+30 and 0.6800 respectively.

Performance Analysis: SSIM and IEF values of each image has been obtained after conversion and is as shown in Table.1.

Table.1. Performance based on SSIM and IEF

Images	SSIM	IEF
Image #1	0.6800	1.9810e+30
Image #2	0.7144	8.8127e+29
Image #3	0.7203	3.5251e+30
Image #4	0.7076	6.4748e+29
Image #5	0.7132	1.9829e+30

SSIM values have been noted and plotted against images in the following graph as shown in fig 3.1



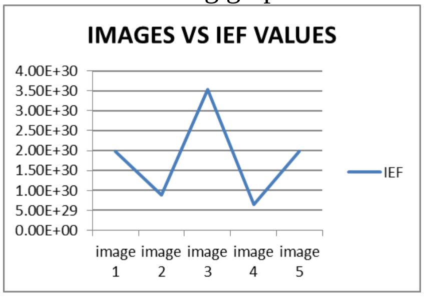


Figure.3. Performance analysis

IEF values have been obtained after conversion and each value have been plotted against images in the following graph as shown in fig.3.

4. CONCLUSION

This paper presents a novel approach using neural networks for converting 2D X- Ray images into 3D images. Dentistry requires an accurate three-dimensional (3-D) representation of the teeth and jaws for diagnosis, surgery and treatment planning. Initially, parameters like shape, motion, color, texture, edges have been taken into consideration. Depth cues have to be found to generate depth maps. Semi- automatic method with little human intervention have been used to perform the simulation. X – ray images from 50 patients have been collected and they have been used as input image. The images shown a nominal response after conversion but the pixel resolution have been very less so in the final step after filtering, color restoration and high dynamic ranging to obtain the required image. Finally deep neural networks have been used to convert high dynamic ranging image into 3D image. Performance analysis has been done by taking image parameters, SSIM values and IEF values. The graphical analysis has been done and the results have been obtained.

The simulated result shows that conversion produces better accuracy, with less processing time consumption rather than existing methods except of the challenges in the unconstrained environment. This method can not only be used for dental images but can also be extended to 3D view of other parts of the body like human brain, lungs, bones, and other imaging techniques.

The present system can be extended into future work by converting 2D videos into 3D videos and further improvisation can be done by collecting more parameters from the 2D image.

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