Slice Reconstruction on 3D Medical Image using Optical Flow Approach

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***Abstract*— High-resolution, high-quality imagery forms the basis of accurate 3D reconstructions. 3D reconstruction is obtained from a 3-dimensional stacking array or image sequence. In some cases the resulting slice image has a low resolution so that some parts miss information when reconstructed into 3D. The reconstruction of the new slice carried out by the researcher using the 3D interpolation technique has a disadvantage, namely that when the calculation is carried out using the structure similarity evaluation metrics, it is still unsatisfactory, therefore the following research will try to reconstruct a new slice using the optical flow approach to calculate the displacement vector field between the two adjacent slices and also we will evaluate the comparative suitability of various interpolation techniques using root mean square error (RMSE), peak signal-to-noise ratio (PSNR), structural similarity index (SSIM). experimental results shows that the use of the optical flow method in image reconstruction between I0 and I1 after interpolation has an increase in the similarity structure value of 0.002, a decrease in the NMSE value of 0.04, and an increase in the PSNR value of 2 leading to figure I0 rather than without using optical flow.**

Keywords— optical flow , reconstruction , DICOM , medical imaging , 3D

I. Introduction

High-quality, high-resolution imagery forms the basis of accurate 3D reconstructions. However, in certain cases, this *occurs in the case of MRI images obtained from alzemeir patients. MRI images are the main standard [1] for assessing the severity of alzemeir in the brain, but because the patient is a newborn, MRI images are taken at a low dose as a result of decreased axial resolution. To overcome this limitation, interpolation method between adjacent parts can be considered to increase its coronal spatial resolution.

Various techniques for image interpolation have been developed over the last few decades. These techniques play an important role in the development of analysis and visualization algorithms for two- and three-dimensional medical data [2]. In the field of medical imaging, it is very important to have a 3D view of the organ / tissue studied in several applications. Such 3D reconstruction is obtained from image sequences obtained through several types of sensors. In some cases the resulting slice image has a low resolution so that some parts miss information when reconstructed into 3D. Image interpolation methods combined with an optical flow approach are used which aim to estimate the direction of the displacement vector in one or more intermediate slices between two adjacent slices. [4].

The reconstruction of the new slice carried out by the researcher [3,13] using the triliniear interpolation technique has a disadvantage, namely that when the calculation is carried out using the structure similarity evaluation metrics, it is still unsatisfactory, therefore the following research will try to reconstruct a new slice using the optical flow approach to calculate the [14,15] displacement vector field between the two adjacent slices and also we will evaluate the comparative suitability of various interpolation techniques using root mean sqaured error (rmse), peak signal-to-noise ratio (psnr), structural similarity index (ssim).

II. LITERATURE REVIEW

Studies on the use of optical flow in estimating the direction of vector movement have been carried out. One of them is research [9]. This study examines the inaccurate part of the computed tomography when a 3D dimensional reconstruction process is carried out using a motion compensated frame interpolation. This method is inspired by the motion frame method in the video case study. The result of this research is a comparison between interpolation based on pixel base and patch base. From the experimental results, it was found that patch-based part reconstruction is superior to pixel-based reconstruction even though it is only small.

The performance of the proposed patch-based method gets a HOSI with a tolerance of = 0.04 on the contrary, a good HOSI result is with a tolerance value ranging from 0.001. Another study [5] on the proposed method also uses an optical flow approach to estimate the vector plane displacement between the slices. One of the studies [3] proposes an algorithm to construct medical image-based 3D image data with various metadata variations in the DICOM format using triliniear interpolation along with data resizing or 3D image resizing and annotation projection techniques. The technique of resizing or resizing 3D images is needed because the technology that we currently have cannot handle large 3D image data sizes. The results of this study indicate that the proposed method can handle multiple DICOM image data and project annotations onto resized images. However, in this study there was no evaluation metric when comparing the two images before and after resizing

III. METHODS

The following are the methods used in this study:

A. Estimated Vector Displacement (DVF)

The vector displacement estimation aims to calculate the vector displacement value between two adjacent parts. These problems are solved by using an algorithm that is taken from the Optical Flow (OF) approach used. OF aims to estimate a dense vector plane of motion (one for each image pixel) which results in a prediction of a second image (target image) by applying it to pixels from one image (reference image). For example, the Horn & Schunck algorithm [7] can perform this task by minimizing the energy of prediction errors within the limits of the regularity.

$$E(u,v) = \int |I_2\,(p+w) - I_1\,(p)I^2 + \lambda(|\nabla u|^2 + |\nabla v|^2)dp \qquad (1)$$

Where ∇ gradient operator, λ weights, I_1 and I_2 are two interconnected slices

B. Bicubic Interpolation

Cubic convolution is an interpolation method that aims to resampling discrete data. Interpolation kernel:

$$u(s) = \begin{Bmatrix} (a+2)|s|^2+1 & (0<|s|\le 1) \\ -a|s|^2-5a|s|^2+8a|s|-4a & (1<|s|\le 2) \\ 0 & (2<|x|) \end{Bmatrix} \qquad (2)$$

Using 16 pixel values (x, y) indicates the pixel location:

$$(x,y) = \left(u(x_1)\,u(x_2)\,u(x_3)\,u(x_4)\right)\begin{pmatrix} f_{11} & f_{12} & f_{13} & f_{14} \\ f_{21} & f_{22} & f_{23} & f_{24} \\ f_{31} & f_{32} & f_{33} & f_{34} \\ f_{41} & f_{43} & f_{43} & f_{44} \end{pmatrix}\begin{pmatrix} u(y_1) \\ u(y_2) \\ u(y_3) \\ u(y_4) \end{pmatrix} \qquad (3)$$

C. Normalized Root Mean Square Error

Normalized Root Mean Square Error is a 2D evaluation metric defined as :

$$NRMSE = \sqrt{\frac{\sum_{m,n}(x_{true}[m,n]-x_{int}[m,n])^2}{\sum_{m,n}(x_{true}[m,n])^2}} \qquad (4)$$

where x_{int} is the interpolated image and x_{true} is the original image.

D. Peak Singnal Noise Ratio

PSNR [16] is used to calculate the ratio between the maximum possible signal power and the power of the distorting noise which affects the quality of its representation. This ratio between two images is computed in decibel form. The PSNR is usually calculated as the logarithm term of decibel scale because of the signals having a very wide dynamic range. This dynamic range varies between the largest and the smallest possible values which are changeable by their quality.The Peak signal-to-noise ratio is the most commonly used quality assessment technique to measure the quality of reconstruction of lossy image compression codecs. The signal is considered as the original data and the noise is the error yielded by the compression or distortion. The PSNR is the approximate estimation to human perception of reconstruction quality compared to the compression codecs. In image and video compression quality degradation, the PSNR value varies from 30 to 50 dB for 8-bit data representation and from 60 to 80 dB for 16-bit data.
PSNR is expressed as:

$$PSNR = 10\log 10\,(peakval_2)/MSE \qquad (5)$$

Here, peakval (Peak Value) is the maximal in the image data.

E. Structure Similarty Index

Structure Similarity index is an evaluation metric used to measure the similarity between two images by way of modeling any image distortion as a combination of three factors namely loss of correlation, lighting distortion and contrast distortion. SSIM is defined as:

$$SSIM\,(f,g) = l(f,g)c(f,g)s(f,g) \qquad (6)$$

Where :

$$\begin{cases} l(f,g) = \dfrac{2\mu_f \mu_g + C_1}{\mu_f^2 + \mu_g^2 + C_1} \\ c(f,g) = \dfrac{2\sigma_f \sigma_g + C_2}{\sigma_f^2 + \sigma_g^2 + C_2} \\ s(f,g) = \dfrac{\sigma_{fg} + C_3}{\sigma_f \sigma_g + C_3} \end{cases} \tag{7}$$

In this paper [16], there is an advanced version of SSIM called the Multi-Scale Structural Similarity Index Method (MS-SSIM) which evaluates various structural similarities of images at different image scales [17]. In MS-SSIM, two images are compared at the same size and resolution scale. As with SSIM, changes in luminance, contrast, and structure were considered to account for the multi-scale structural similarity between two images [10]. Sometimes it provides better performance than SSIM on different subjective image and video databases. Another version of SSIM, the so-called three-component SSIM (3-SSIM) fits the fact: the human visual system observes differences more accurately in textured areas than in smooth areas. This 3-component SSIM model was proposed by Ran and Farvardin [18] where an image is broken down into three important properties such as edges, texture and smooth areas. The resulting metric is calculated as a weighted average of structural similarity for these three categories. The estimated weight measurement proposed is 0.5 for edges, 0.25 for texture and 0.25 for smooth areas. It can also be said that the 1/0/0 weight measurement influenced the results to be closer to subjective judgments. It can be implied that, no texture or subtle areas rather than edge areas play a dominant role in the perception of image quality [18].

IV. EXPERIMENTAL

Experiments were carried out by taking two slices from each dataset, namely I_0 and I_1. The dataset used is in the form of a dicom with 1 color channel on the coronal part with dimensions of 256 x 256 x 156.

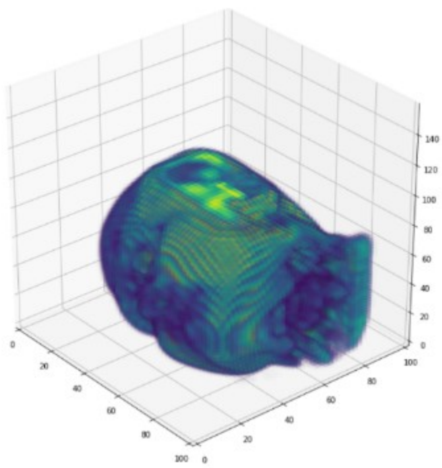

Fig 1. 3D Reconstruction DICOM

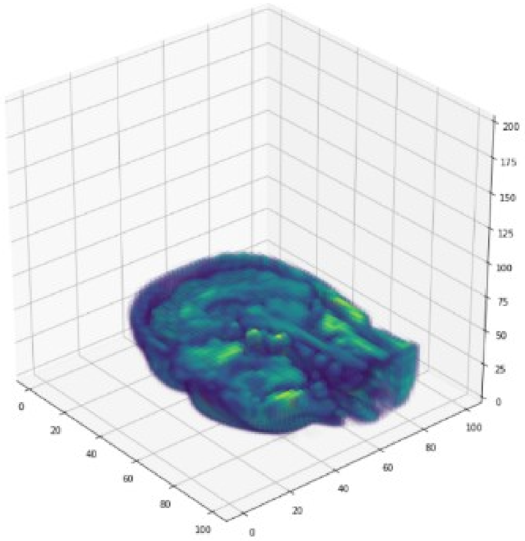

Fig 2. appears in the coronal brain organs

After that, the process of estimating the value of the vector displacement uses the optical flow approach with the Horn Schuck algorithm. After the estimation process, the vector value is denoted by the variable u, v.

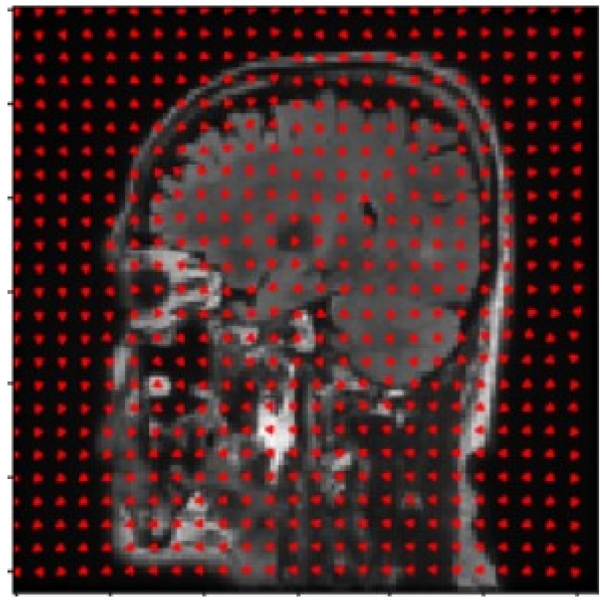

Figure 3. Vector Displacement

After obtaining the Iα value, the next step is to interpolate using bicubic and bilinear. the following is the algorithm process carried out :

```
Input : I0 (image reference) & I1 (image target)

Output : Iα
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1:Resize image I0 & I1 to half
2:Create mesh grid depends on I0 & I1 dimension
3:Calculate displacement vector field
Horn Schunck(I0, I1, alpha=1.0, Niter=100)
4:Warp (I0 , mesgrid(vector horizontal , vector vertical)
5:Iα = Interpolate to real dimension using bicubic or biliniear
```

Fig 4. Optical Flow Algorithm

Optical flow algorithm on fig 4 is done by resizing I0 and I1 dimensions from 256 x 256 to half dimensions or 128 x 128 using bicubic [12] or bilinear interpolation techniques [11]. After that, create a mesh grid based on the image dimensions after resizing, which is 128 x 128.

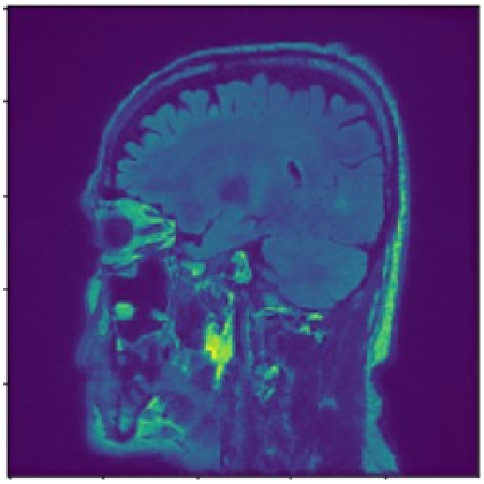

Fig 5. Slice I_1

After step 1 and stage 2, the next step is to calculate the displacement vector field between two adjacent slices, usually I0 (even slice) and I1 (odd slice) using the Horn Schunck algorithm. After that, the warping process continues between I0 and the resulting value of the horizontal vector (u) and the vertical vector (v) then interpolated back into the original 256 x 256 dimensions.

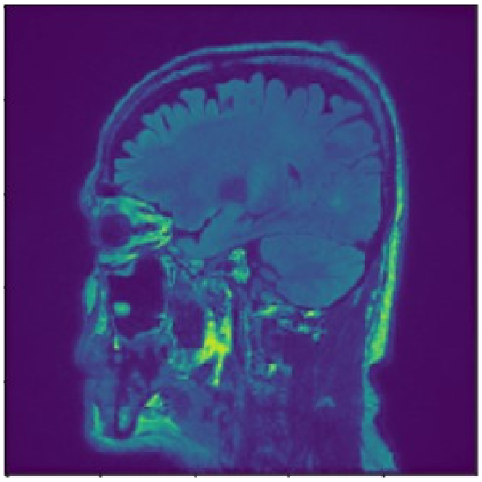

Fig 6. Slice I_2

The evaluation scenario is carried out by resizing the initial image, namely from 256 x 256 to half of the resolution 128 x 128, then interpolated and then compared the results of the evaluation value between Iα and I0 and I1.

TABLE I. COMPARISON RESULTS

Interpolate	I_α					
	SSIM I_0	SSIM I_1	NMSE I_0	NMSE I_1	PSNR I_0	PSNR I_1
Bilinear	0.99632	0.99622	0.15730	0.15898	49.075	49.002
Bicubic	0.99647	0.99638	0.15408	0.15561	49.254	49.188
Bilinear + OF	0.99798	0.99153	0.12168	0.23214	51.305	45.714
Bicubic + OF	0.99813	0.99155	0.11725	0.23216	51.627	45.713

From the table 1 above shows that the use of the optical flow method in image reconstruction between I_0 and I_1 after interpolation has an increase in the similarty structure value of 0.002, a decrease in the NMSE value of 0.04, and an increase in the PSNR value of 2 leading to figure I_0 rather than without using optical flow.

V. CONCLUSION

From the experiment we can conclude use of the optical flow method in image reconstruction between I_0 and I_1 after interpolation has an increase in the similarty structure value of 0.002, a decrease in the NMSE value of 0.04, and an increase in the PSNR value of 2 leading to figure I_0 rather than without using optical flow

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