Bilateral filtering on resliced images

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Abstract. This report compares two approaches for slicing and edge-preserving smoothing of oblique slices in medical imaging: 3D-bilateral filtering before re-slicing and 2D- bilateral filtering after re-slicing. This study qualitatively and quantitatively (using MSE, PSNR, SSIM) compares the two approaches and finds that the latter approach better preserves small or fine structures in the image. This study also illustrates that indeed bilateral filtering does not only depend on Euclidean distance of pixels, but also on the radiometric differences such as color intensity.

Keywords: Oblique slices · Bilateral filtering · Euclidean distance · radiometric differences.

1 Introduction

In biomedical imaging, filtering poses a tougher challenge since careful consideration must be done to ensure that important structures and details critical for medical diagnosis are preserved, while still removing unwanted features from the image. In addition to image filtering, visualizing medical images in a non-orthogonal orientation may provide a better view of a particular structure or visualize a specific pathology.

A bilateral filter, proposed by [1], is a noise-reducing smoothing filter designed to preserve the edges of an image. It replaces the intensity value of each pixel with an average value weighted by the geometric and photometric similarities between neighboring pixels within a spatial window [2]. This allows the filter to adjust to the image's local characteristics, retain edges, and at the same time, smooth out noise.

The aim of this project was to implement and apply a bilateral filtering method, described in [1], on either resampled 2D images or the entire 3D image. This report presents the implementation of a re-slicing algorithm that obtains an image slice in a non-orthogonal plane, the implementation of a bilateral filter for both 2D and 3D images, and a qualitative and quantitative comparison between *3D-filtering before re-slicing* and *2D-filtering after re-slicing.*

2 Methods

2.1 Bilateral filtering

The core idea behind bilateral filtering is that two pixels are considered to be near each other if they are not only located in adjacent spatial positions, but also if they share some similarity in their radiometric range such as color intensity or depth distance. Therefore, 2D bilateral filtering was implemented as described in [1,3] as:

$I^{filtered}(x) = \frac{1}{W_p} \sum_{x_i \in \Omega} I(x_i) f_r(||I(x_i) - I(x)||) g_s((x_i) - (x))$,

where $I^{filtered}$ is the *filtered image*, I is the *original image*, x represents the coordinates of the pixel being filtered, Ω is the window centered in x, f_r represents a range kernel and g_s represents a spatial kernel.

W_p,referred to as the normalization term is defined as: $W_p = \sum_{x_i \in \Omega} f_r(||I(x_i) - I(x)||) g_s((x_i) - (x))$.

In this work, both the spatial and range kernels were considered to be *Gaussian kernels* such that f_r was a range Gaussian σ_r that decreased the influence of pixels with disparate intensity values and g_s was a spatial Gaussian σ_s that decreased the influence of distant pixels. Then, considering a 2D slice, the weight assigned for pixel (k,l) with intensity $I(k,l)$ to denoise pixel (i,j) with intensity $I(i,j)$ was given by

$w(i,j,k,l) = exp(-\frac{(i-k)^2+(j-l)^2}{2\sigma_d^2} - \frac{||I(i,j)-I(k,l)||^2}{2\sigma_r^2})$

The denoised intensity I_D of pixel (i,j) was then obtained by normalizing the previously calculated weights as:

$I_D(i,j) = \frac{\sum_{k,l} I(k,l)w(i,j,k,l)}{\sum_{k,l} w(i,j,k,l)}$ Similarly, a 3D bilateral filter was implemented, incorporating a third plane (z-axis), with the rest of the parameters i.e a window size of Ω, range parameter of σ_r, and spatial parameter of σ_s, being similar to a 2D bilateral filter.

2.2 Re-slicing algorithm

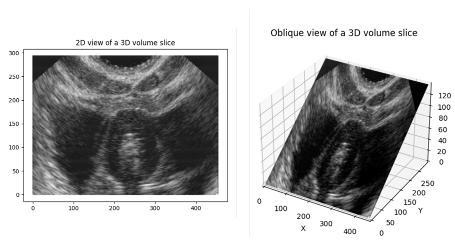

Fig. 1. Results of the re-slicing algorithm

Medical images often use non-orthogonal planes to improve visualization and image-guided interventions accuracy, particularly when orthogonal planes do not provide sufficient information. The implemented algorithm for obtaining and visualizing oblique slices of a 3D volume takes a 3D data volume, the slice index along the z-axis that needs to be visualized, and the desired orientation of the slice with respect to the x-y plane which is defined by two rotation angles: θ for horizontal rotation about z-axis and ϕ for vertical rotation about the x-axis. The algorithm calculates a transformation matrix $T = R_z(\theta).R_y(\phi)$ using these angles and applies it to the original slice's coordinates to obtain the coordinates of the transformed slice. The transformed slice values are then resampled using linear interpolation to obtain the desired resolution of the oblique slice. Finally, the algorithm outputs the coordinates and intensity values of the extracted slice for visualization.

3 Experiments

This study compared two approaches for oblique slice filtering and re-slicing, namely, "3D-filtering before re-slicing" and "2D-filtering after re-slicing". For varying values of range parameter σ_r, spatial parameter σ_d, and diameter/window of each pixel neighborhood Ω, a visual comparison was performed between the two approaches and the differences quantified using three metrics: *Mean Squared Error (MSE)*, *Peak Signal-to-Noise Ratio (PSNR)*[4], and *Structural Similarity Index (SSIM)*[5]. By using these three metrics together, we can obtain a comprehensive understanding of the quality of the filtering and re-slicing process. A higher MSE value and a lower PSNR value suggest a greater degree of distortion or loss of information in the resulting image, while a lower SSIM value indicates a lower degree of similarity between the two images. Thus, these metrics can help in evaluating the degree to which the filtering and re-slicing process has preserved the structural and intensity information of the original slice. This is vital if any of the approaches are to be translated to clinical use.

Table 1. Results: Effects of varying range parameter σ_r

Filter Parameters		MSE		PSNR		SSIM	
σ_{color}	$\sigma_{spatial}$	re-slice2D	3Dre-slice	re-slice2D	3Dre-slice	re-slice2D	3Dre-slice
5	5	1284.09	1276.86	17.0448	17.0694	0.2344	0.2267
20	5	1193.66	1217.41	17.3620	17.2764	0.2779	0.2409
80	5	1133.29	1152.22	17.5874	17.5155	0.2917	0.2595
120	5	1090.29	1095.47	17.7554	17.7347	0.2976	0.2839
240	5	1127.97	1083.26	17.6078	17.7834	0.2921	0.3002

4 Results

Comparing the two approaches, 3D-filtering before re-slicing produces smoother slices than 2D-filtering after re-slicing. Quantitative metrics (*Table 1, 2*) confirm this, as 3D filtering results in slices with *higher MSE*, *lower PSNR*, and *lower SSIM* compared to 2D filtering.

These results suggest that 3D filtering may be removing important image features, resulting in a less accurate reconstruction of the original slice, and also introduce more noise. As expected, both 2D and 3D bilateral filters preserve the edges of the slices, with the 3D filter being more computationally expensive, taking 90 minutes for a window size of 6 pixels. Increasing the window size Ω results in more smoothing of the image but increases the computational complexity of the filter. Increasing the range parameter σ_r improves the reconstruction of the original slice, but this trend starts to reverse at $\sigma_r = 240$ due to the range Gaussian becoming nearly constant over the image intensity interval.

Finally as illustrated in *Table 2*, a large spatial Gaussian σ_s coupled with a narrow range Gaussian σ_r only achieves limited smoothing despite having a large spatial extent alluding that the contribution of distant pixels is reduced by the range Gaussian filter.

Table 2. Results: Effects of varying spatial parameter σ_s

Filter Parameters		MSE		PSNR		SSIM	
σ_{color}	$\sigma_{spatial}$	re-slice2D	3Dre-slice	re-slice2D	3Dre-slice	re-slice2D	3Dre-slice
5	20	1283.53	1284.38	17.0468	17.0304	0.2347	0.2268
5	120	1282.69	1283.55	17.0585	17.0454	0.2359	0.2276
5	240	1281.79	1276.57	17.0588	17.0459	0.2359	0.2279

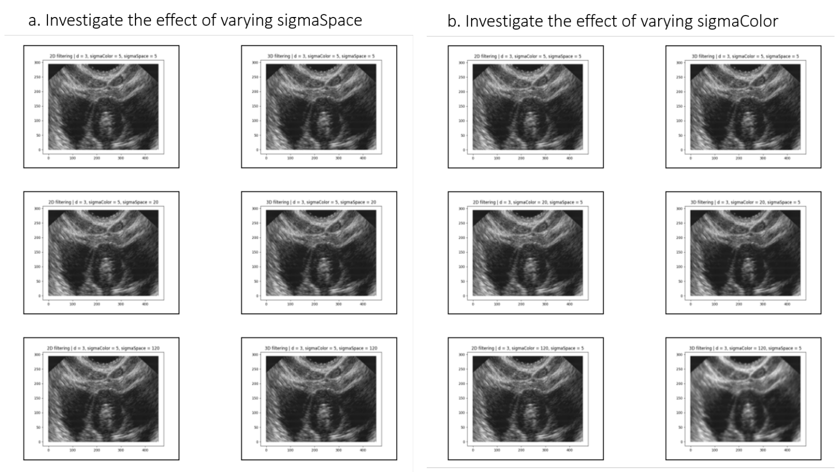

Fig. 2. The effect of varying the parameters of a bilateral filter

5 Discussion

These subtle differences can be attributed by the fact that these two approaches apply the filters in different ways, resulting in different levels of smoothing and noise reduction. In 3D filtering before re-slicing, the filter is applied to the entire volume before a slice is extracted, which results in the blurring or smoothing of fine structures that were present in the oblique slice. The oblique slice is then resampled from the filtered volume, resulting in more loss of information. In contrast, 2D-filtering after re-slicing applies filtering to only the oblique slice, hence the filtering process can be more focused and precise, preserving more of the important features of the image.

6 Conclusion

This study compared 3D-filtering before re-slicing and 2D-filtering after re-slicing quantitatively and qualitatively, both achieving edge-preserving smoothing critical for clinical applications. The latter approach better preserves the fine structures in oblique slices. Investigating the filter parameters showed that the range parameter σ_r weight strongly preserves image edges. However, the implemented 2D and 3D bilateral filtering algorithms are time-consuming, and more efficient implementations can be developed in the future based on [6][7]. The clinical choice between these approaches will depend on factors such as the need to preserve the overall 3D structure of the image, whether slices will be used independently, and the desired computational times.

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