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Comparison of PDE-based, Gaussian and Wavelet Approches for Enhancing PET Images

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Abstract-**The ability to diagnose many of the severe diseases, such as cancer and heart problems, is a challenge for physicians and radiologists. Recently, a wide range of technologies are being used to increase the accuracy of physicians' diagnoses. Positron Emission Tomography (PET) is an important nuclear medicine imaging technique which enhances the effectiveness of diagnosing many diseases. The raw-projection data, i.e. the sinogram, from which the PET is reconstructed, contains a very high level of Poisson noise. Radiologists face difficulties when reading and interpreting PET images because of the high noise level. The later may lead to erroneous diagnoses. Finding a suitable de-noising technique for PET images has attracted many researchers in the last two decades as this can significantly alleviate the problem. In this work, we compare and investigate four filtering schemes for enhancing PET image post-reconstruction: The Perona and Malik, construction curvature motion, Gaussian filter and wavelet filler. The PET images are reconstructed using two well-known reconstruction algorithms: the filtered back projection (FBP) and the ordered subset expectation maximization (OSEM).**

Keywords-PET, post-reconstruction enhancement, PDE based filter, Wavelet, Gaussian.

I. INTRODUCTION

PET image is a type of nuclear medicine scan, that's need very sensitive instrument called a PET camera, which shows internal body organ function [1]. It's commonly used to diagnosis number of diseases such as cancer, hard disease, Alzheimer disease, epilepsy, heart disease, brain disease. The PET is a functional imaging approach used to study the metabolism and physiology of the brain, furthermore, this technology used to analyze alcohol's effects on various neurotransmitter systems. . Figure 1 shows an example for a real PET image. PET images contain a high level of noise due to radioactive decay and the constraints on the injected radioactivity dose. This noise makes the PET image difficult to interpret and understand resulting in false negative and false positive diagnoses. Various enhancement algorithms are used to reduce image noise and increase the contrast of structures of interests in literature. In this study, we investigate and compare several types of post-reconstruction filters for enhancing PET images. The results for the applied filters are compared quantatively and visually.

II. FILTERING APPROCHES

In this work, we apply four well-known filtering schemes [1,2,3,4,5] for PET image post-reconstruction. The used filters are described briefly in this section.

A. Anistropic Diffusion Filter

Anisotropic Diffusion Filter [2]which introduced by Perona and Malik in 1987 is a numerical technique for de-noising digital image noise without removing significant of the image content, like edges, line, or any important information of the image. The idea behind the use of the diffusion equation in image processing the use of Gaussian filters in multi-scale image analysis.

B. Curvature Motion

One way of introducing smoothness in the curve is to let it evolve under its Euclidean curvature [3]. Mean curvature motion (MCM) is considered as the standard curvature evolution. MCM allows diffusion solely along the level-lines. The constraint curvature motion (CCM) is a variant of the mean curvature motion in which an edge-stopping function is introduced. The main goal is preventing further shrinking of the level-lines once they have reached the important image edges.

B. Gaussian Filter

A Gaussian smoothing [3] is the result of blurring an image by a Gaussian function. It is a widely used effect in graphics software, typically to reduce image noise and reduce detail. Smoothing an image according to the isotropic diffusion equation is equivalent to filtering the image with a Gaussian filter

C. . Wavelet Filter

Wavelet transform was developed from Fourier transform. Fourier transform represents a signal as a sum of cosine and sine functions, whereas wavelet transform represents a signal as a sum of translations and dilations of a band-pass function, called a wavelet. In other words, although the Fourier transform represents a signal in the frequency domain an alone, the wavelet transform provides a spatial-frequency representation of a signal.

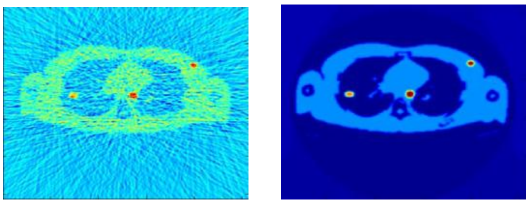
III Experiments

The goal of the conducted experiments consists of measuring the performance of the applied filtering methods, and studying their influence on the PET reconstruction. The validation of the applied filters employs simulated PET data of a slice of the thorax, which allows generating multiple realizations of the noisy data. The simulated PET contains three regions of interest (tumors). We generate 50 realizations with size 256x256 pixels.

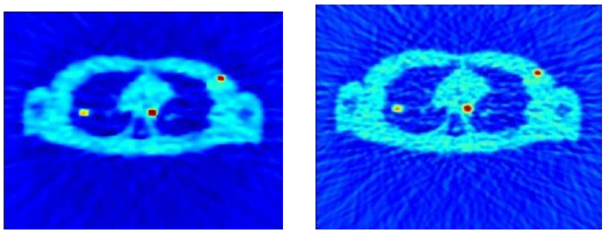
We are measured the performance of each filter based on the quality of the image. The latter can be easily achieved because of the presence of its noise-free counterpart. In [1], several approaches for measuring the closeness to the noise-free image were analyzed. In this work, we adopt following measures for evaluating the quality of the diffused PET:
The Peak Signal to Noise Raito (PSNR), the correlation between the noise –free and the filtered image and variance of the noise (NV) describes the remaining noise level [1]. In this work, we are interested in comparing the proposed filters: Perona and Malik, Gaussian, Wavelet and CCM. We apply the adopted filters on 50 realizations reconstructed PET image. Table 1 and Table 2 show the de-noising results for the reconstructed PET by FBP and OSEM respectively. The best performing filtering method per measure is displayed in bold. Figure 1 and Figure 2 show an example for the filtered PET by the four filters.

Table1 : De-noising result for PET by FBP.

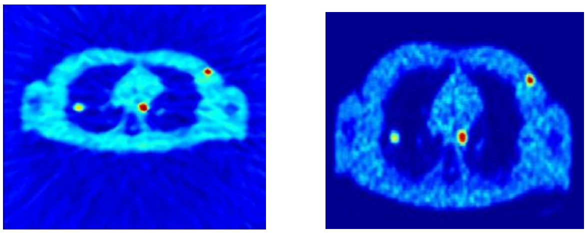
	Noise osem	Perona & Malik	Gussian	Wavelet	Curvature
PSNR	22.9196	32.5611	21.5641	18.6044	27.4822
Correleion	0.7948	o.9805	0.9777	0.9591	0.9701
NV	0.0652	0.0216	0.0758	0.0850	0.0367



(a) Noise image (b) Original image



(c) after perona (d) after gaussian

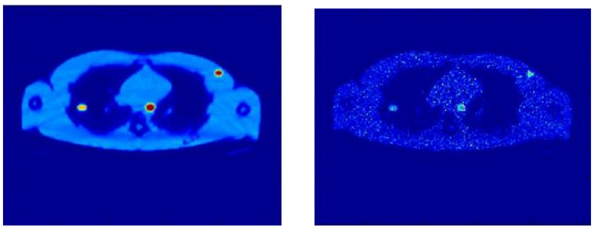


(e) after curvature (d) after wavelet

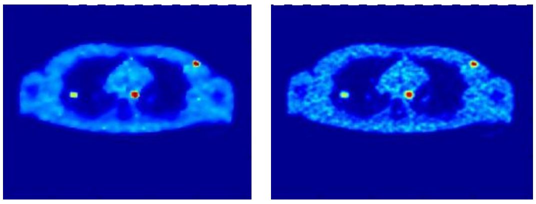
Figure 1: The filtered PET by the used filtering schemes (FBP).

Table2 : De-noising result for PET by OSEM.

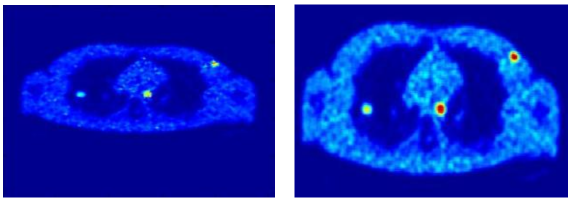
	Noise osem	Perona & Malik	Gussian	Wavelet	Curvature
PSNR	22.9196	32.5611	21.5641	21.7255	27.4822
Correleion	0.7948	o.9805	0.9777	0.9786	0.9701
NV	0.0652	0.0216	0.0758	0.0734	0.0367



(a) Noise image (b) Original image



(c) after perona (d) after gaussian



(d) after curvature (e) after wavelet

Figure 2: The filtered PET by the used filtering schemes (OSEM).

IV. CONCLUSION

In this work, we compared four filtering approaches for enhancing PET image that reconstructed by FBP and OSEM. The comparison is achieved by measuring the quality of the filtered PET images and visually. The experiment results showed that the PDE-based filters (Perona & Malik and CCM) are better enhancing PET images and keep the important features.

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