

# PET/CT Image Denoising and Segmentation based on a Multi Observation and Multi Scale Markov Tree Model

Medical Sensors Project Presentation

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# Outline

- 1 Introduction
- 2 Registration
- 3 Denoising
- 4 Segmentation
- 5 Result and Discussion
- 6 Conclusion

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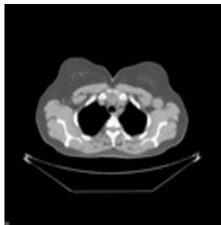
# Introduction

## Why PET/CT

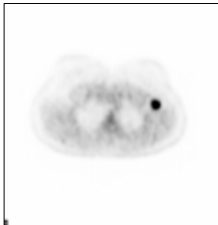
PET	CT
<ul style="list-style-type: none"><li>- High contrast</li><li>- For oncology</li></ul>	<ul style="list-style-type: none"><li>- High spatial resolution</li><li>- For anatomy</li></ul>
<b>Fuse PET/CT data to provide high quality anatomical correlations with radionuclide</b>	

# Introduction

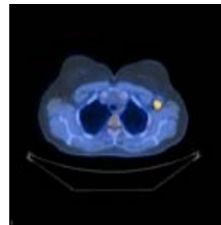
## Why PET/CT



CT



PET



Fused Image

**Fuse PET/CT data to provide high quality  
anatomical correlations with radionuclide**

# Introduction

## Flowchart

### STEP 1

Select PET and CT

### STEP 2

Register

### STEP 3

Denoise

### STEP 4

Fuse

### STEP 5

Segment

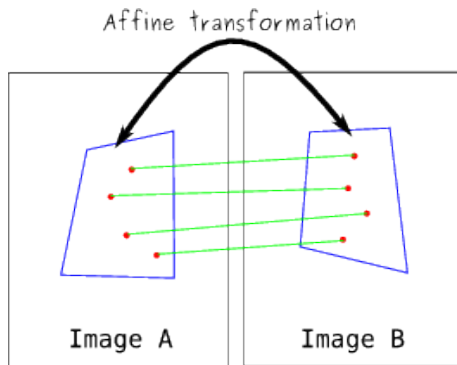
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# Registration PET/CT

PET/CT are acquired:

- With patient in different positions
- With different pixel sizes
- With different array sizes





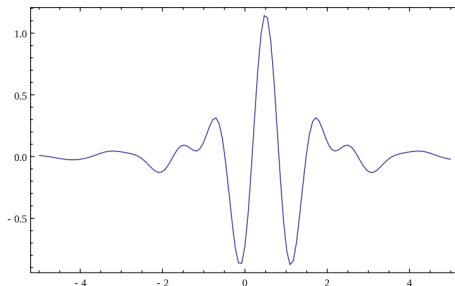
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# Wavelet Denoising

## What is Wavelet

A wavelet is a wave-like oscillation with an amplitude that begins at zero, increases, and then decreases back to zero .

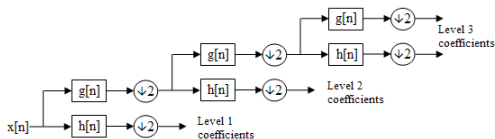


Meyer Wavelet

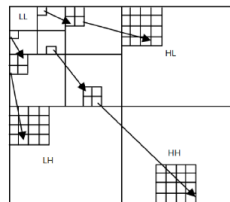
# Wavelet Denoising

## Wavelet Transform and Decomposition

Wavelet transform performs a correlation analysis, therefore the output is expected to be maximal when the input signal most resembles the mother wavelet



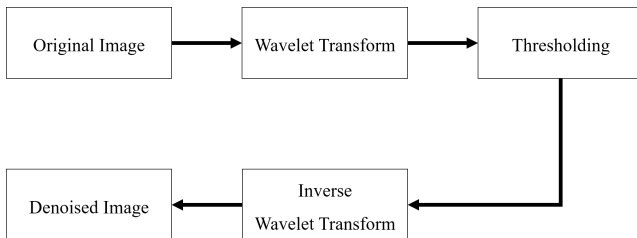
Three-level filter bank



Wavelet Coefficient Arrangement

# Wavelet Denoising

## Flowchart



**Optimal for isotropic structures**

# Contourlet Denoising

## Contourlet Transform

Contourlets form a multiresolution directional to separate smooth regions with smooth boundaries.

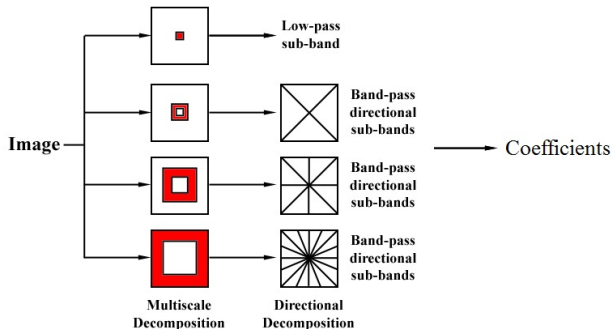
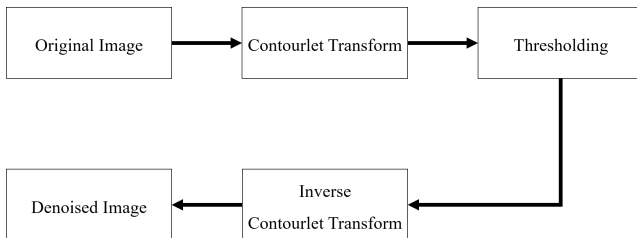


Figure: Contourlet Transform

# Contourlet Denoising

## Flowchart



**Optimal for directional information**

# Wavelet-Contourlet Denoising

Isotropic structures of **Wavelet**



Directional information of **Contourlet**



Isotropic structures of **Wavelet**  
Directional information of **Contourlet**

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# PET-CT Image Segmentation

## What is Segmentation?

Segmentation is the process of splitting an observed image into its homogeneous regions

- Extract **features** from the input image
- Define the set of **labels** for each pixel/features
- **Hidden Markov Model**



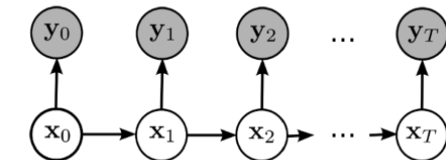
# PET-CT Image Segmentation

## What is Hidden Markov Model?

A Hidden Markov Model (HMM) is a statistical model in which the system being modeled is assumed to be a Markov process.

- Observed and Hidden States
- Hidden Markov Model: Segmentation

Observed States



Hidden States

Figure: Hidden Markov model

# PET-CT Image Segmentation

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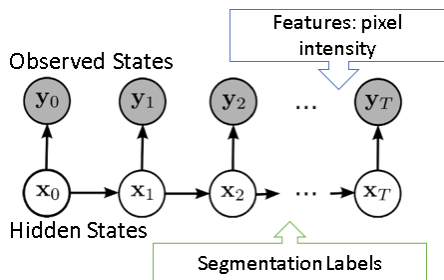


Figure: Hidden Markov model in Image Segmentation

# PET-CT Image Segmentation

## HMT based Segmentation

- Given an image  $Y$   $M \times N$  lattice  $\Omega$ , indexed by a pair  $(i, j)$  so that  $\Omega = (i, j); 1 \leq i \leq M \text{ and } 1 \leq j \leq N$
- Labeling  $X$  same size as  $Y$
- The relationship between gray scale values and labels: Bayesian Likelihood function.
- According to the MAP criterion ‘

$$X^* = \underset{x}{\operatorname{argmax}} \{P(Y | X, \Theta)P(X)\} \quad (1)$$

Where  $\Theta = \{\theta_l | l \in L\}$  is the parameter set

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# PET-CT Image Segmentation

## HMT based Segmentation: Model Parameters

Gaussian distribution function with parameters  $\theta_l = (\mu_l, \sigma_l)$ :

$$G(z; \theta_l) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{(z - \mu_l)^2}{2\sigma^2}\right) \quad (2)$$

# PET-CT Image Segmentation

## Expectation Maximization(EM): Iterative Process

- 1 Estimation Step: Labels known, estimate parameters

$$\begin{aligned}\mu_l^{(t+1)} &= \frac{\sum_i P^{(t)}(l | y_i) y_i}{\sum_i P^{(t)}(l | y_i)} \\ (\sigma_l^{(t+1)})^2 &= \frac{\sum_i P^{(t)}(l | y_i) (y_i - \mu_l^{t+1})^2}{\sum_i P^{(t)}(l | y_i)}\end{aligned}\tag{3}$$

- 2 Maximization Step

- Knowing parameters assign labels: Optimization problem

$$X_i^{(k+1)} = \underset{l \in L}{\operatorname{argmin}} \{ U(y_i | l) + \sum_{j \in N_i} V_c(l, x_j^k) \} \tag{4}$$

Where  $U(x)$  is prior energy function and  $V_c(X)$  is the clique potential and  $C$  is the set of all possible cliques

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# Result and Discussion

## Graphical User Interface

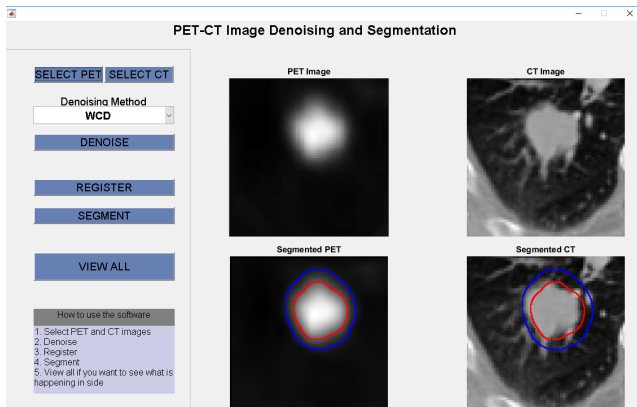


Figure: Wavelet-Countroulet denoised image. PET Image

# Result and Discussion

## PET Denoising

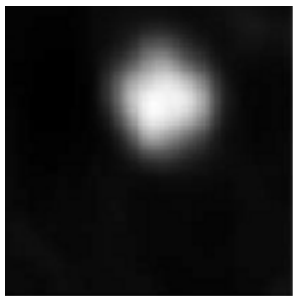


Figure: Wavelet denoised image.

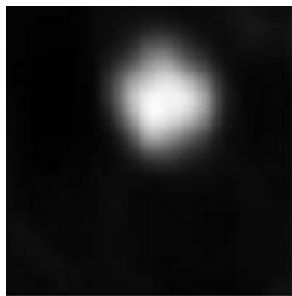


Figure: Countroulet denoised image. PET Image

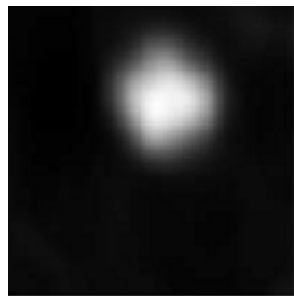


Figure: Wavelet-Countroulet denoised image

# Result and Discussion

## Segmentation Result

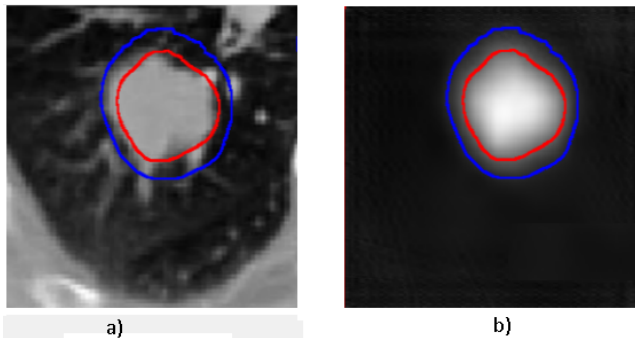


Figure: Segmented CT and Pet Images

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# Conclusion

- Wavelet and Contourlet transforms based denoising
- HMT based Image Segmentation
- Future Work
  - Extending our algorithm to PET-MRI
  - Enhancing the segmentation algorithm

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Thank you for listening