

# **MEDICAL SENSORS**

PROJECT REPORT

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

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## **Chapter 1**

# **Introduction**

## **Chapter 2**

# **Literature Review**

## 2.1 HMT

### 2.1.1 General Introduction

Segmentation of an image into unknown number of distinct and in some way homogeneous regions has been a fundamental issue in low level image analysis. There are many direct application of the algorithm, for example, segmentation of Computed Tomography (CT), Positron Emission Tomography (PET), segmentation of Nuclear Magnetic Resonance (NMR) images, and other applications in radar, satellite and agriculture. Many types of approaches has been in practice and in this paper a probabilistic method of segmentation is employed, Hidden Markov Model (HMM) based.

### 2.1.2 Overview of Hidden Markov Model

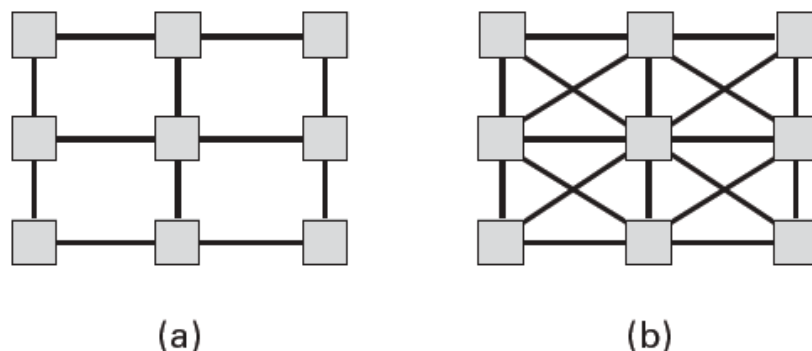
The Hidden Markov Tree (HMT) was introduced by Crouse, Nowak and Baraniuk (1998). The context of their work was the modeling of statistical dependencies between wavelet coefficients in signal processing, for which variables are organized in a natural tree structure. Applications of such a model are: image segmentation, signal classification, denoising and image document categorization [1].

A HMM is a statistical Markov model in which the system being modeled is assumed to be a Markov process with unobserved (hidden) states. In a hidden Markov model, the state is not directly visible, but the output, dependent on the state, is visible. Each state has a probability distribution over the possible output tokens. Therefore, the sequence of tokens generated by an HMM gives some information about the sequence of states. The adjective 'hidden' refers to the state sequence through which the model passes, not to the parameters of the model; the model is still referred to as a 'hidden' Markov model even if these parameters are known exactly [2].

The unifying ideas in using Markov Random Fields for vision are the following:

- Images are dissected into an assembly of nodes that may correspond to pixels.
- Hidden variables associated with the nodes are introduced into a model designed to "explain" the values (colors) of all the pixels.
- A joint probabilistic model is built over the pixel values and the hidden variables
- The direct statistical dependencies between hidden variables are expressed by explicitly grouping hidden variables; these groups are often pairs depicted as edges in a graph.

These properties are illustrated in Figure 2.1 below:



**Figure 2.1:** Graphs for Markov models in vision. (a) Simple 4-connected grid of image pixels. (b) Grids with greater connectivity here with the 8-connected pixel grid.

The notation for image graphs is that the graph  $G = (V, E)$  consists of vertices  $V = (1, 2, \dots, i, \dots, N)$  corresponding, for example, to the pixels of the image, and a set of edges  $E$  where a typical edge is  $(i, j)$ ,  $i, j \in V$ , and edges are considered to be undirected, so that  $(i, j)$  and  $(j, i)$  refer to the same edge. In the pixel graph of figure 1, the nodes are pixels, and a pair of pixels forms an edge in  $E$  if the two pixels share a common boundary.

The motivation for constructing such a graph is to connect the hidden variables associated with the nodes. For example, for the task of segmenting an image into foreground and background, each node  $i$  (pixel) has an associated random variable  $X_i$  that may take the value 0 or 1, corresponding to foreground or background, respectively

may take the value 0 or 1, corresponding to foreground or background, respectively. In order to represent the tendency of matter to be coherent, neighboring sites are likely to have the same label. So where  $(i, j) \in E$ , some kind of probabilistic bias needs to be associated with the edge  $(i, j)$  such that  $X_i$  and  $X_j$  tend to have the same label—both 0 or both 1. In fact, any pixels that are nearby, not merely adjacent, are likely to have the same label. On the other hand, explicitly linking all the pixels in a typical image, whose foreground/background labels have correlations, would lead to a densely connected graph. That in turn would result in computationally expensive algorithms. Markov models explicitly represent only the associations between relatively few pairs of pixels—those pixels that are defined as neighbors because of sharing an edge in  $E$ . The great attraction of Markov Models is that they leverage a knock-on effect—that explicit short-range linkages give rise to implied long-range correlations. Thus correlations over long ranges, on the order of the diameters of typical objects, can be obtained without undue computational cost.[3]

Markov models are particularly useful as prior models for state variables  $X_i$  that are to be inferred from a corresponding set of measurements or observations  $z = (z_1, z_2, \dots, z_i, \dots, z_N)$ . The observations  $z$  are themselves considered to be instantiations of a random variable  $Z$  representing the full space of observations that can arise.[3]

## 2.2 2D DISCRETE WAVELET TRANSFORM

### 2.2.1 Overview

A wavelet is a wave-like oscillation with an amplitude that begins at zero, increases, and then decreases back to zero. It can typically be visualized as a "brief oscillation" like one recorded by a seismograph or heart monitor [3]. As a mathematical tool, wavelets can be used to extract information from many different kinds of data, including – but certainly not limited to – audio signals and images [4].

In numerical analysis and functional analysis, a Discrete Wavelet Transform (DWT) is any wavelet transform for which the wavelets are discretely sampled. As with other wavelet transforms, a key advantage it has over Fourier Transform (FT) is temporal resolution: it captures both frequency and location information (location in time) [5].

In signal processing, wavelets make it possible to recover weak signals from noise. This has proven useful especially in the processing of X-ray and magnetic-resonance images in medical applications. Images processed in this way can be "cleaned up" without blurring or muddling the details [6].

### 2.2.2 Definition

In 2-Dimensional dyadic multiresolution, a wavelet orthonormal basis in  $L^2(\mathbb{R}^2)$  is built up from (tensor) products involving:

- A scale function  $\varphi$  associated to a multiresolution  $\{V_j\}_j \in \mathbb{Z}$  of  $L^2(\mathbb{R})$
- An orthonormal wavelet  $\psi \in L^2(\mathbb{R})$  to define a complete orthonormal system, for the Hilbert space  $L^2(\mathbb{R})$  of square integrable functions.

The orthonormal wavelet  $\psi$  is constructed as the family of functions:

$$\psi_{jn}^k(x) = 2^{\frac{j}{2}} \psi^k(2^j x_1 - n_1, 2^j x_2 - n_2) \quad (2.1)$$

for integers  $j, k \in \mathbb{Z}$ .

For this purpose, one defines three wavelets:

$$\psi^1(x_1, x_2) = \varphi(x_1)\psi(x_2) \quad (2.2a)$$

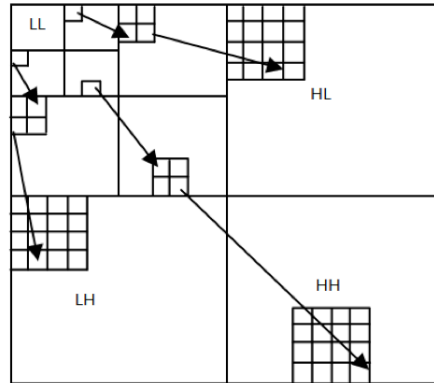
$$\psi^2(x_1, x_2) = \psi(x_1)\varphi(x_2) \quad (2.2b)$$

$$\psi^3(x_1, x_2) = \varphi(x_1)\varphi(x_2) \quad (2.2c)$$

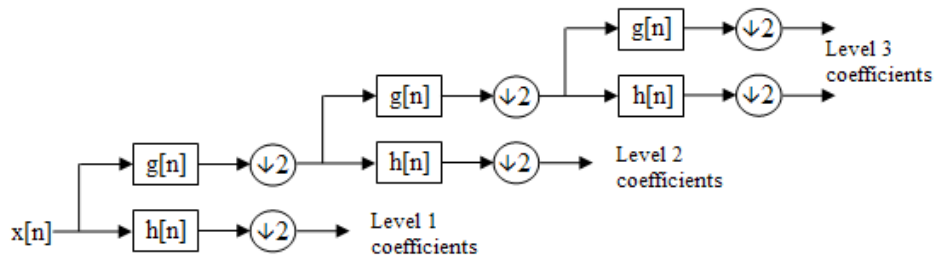
In the case of the discrete wavelet transform, the mother wavelet is shifted and scaled by powers of two:

$$\psi_{j,k}(t) = \frac{1}{\sqrt{2^j}} \psi\left(\frac{t - k2^j}{2^j}\right) \quad (2.3)$$

where  $j$  is the scale parameter and  $k$  is the shift parameter, both which are integers.



**Figure 2.2:** Wavelet coefficients arrangement



**Figure 2.3:** A 3 level filter bank

Recall that the wavelet coefficient  $\gamma$  of a signal  $x(t)$  is the projection of  $x(t)$  onto a wavelet, and let  $x(t)$  be a signal of length  $2^N$ . In the case of a child wavelet in the discrete family above:

$$\gamma_{jk} = \int_{-\infty}^{\infty} x(t) \frac{1}{\sqrt{2^j}} \psi\left(\frac{t - k2^j}{2^j}\right) dt \quad (2.4)$$

This decomposition, which can be seen in Figure 2.2 [7], is repeated to further increase the frequency resolution and the approximation coefficients decomposed with high and low pass filters and then down-sampled. This is represented as a binary tree with nodes representing a sub-space with a different time-frequency localisation. The tree is known as a filter bank, see Figure 2.3.



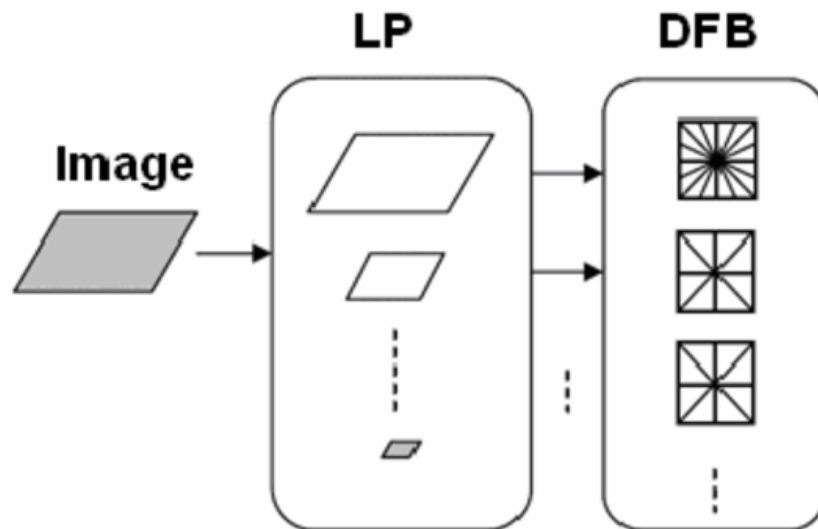
## 2.3 CONTOURLET TRANSFORM

### 2.3.1 Overview

In the field of Geometrical Image Transforms, there are many 1-D transforms designed for detecting or capturing the geometry of image information, such as the FT and Wavelet Transform (WT). However, the ability of 1-D transform processing of the intrinsic geometrical structures, such as smoothness of curves, is limited in one direction, then more powerful representations are required in higher dimensions. The Contourlet Transform (CT), which was proposed in [8], is a new two-dimensional transform method for image representations.

Contourlets form a multiresolution directional tight frame designed to efficiently approximate images made of smooth regions separated by smooth boundaries. The CT has a fast implementation based on a Laplacian Pyramid (LP) decomposition followed by Directional Filter Banks (DFBs) applied on each bandpass subband [9]. The new method as proposed in [10] uses a multiscale pyramid that can be adjusted by applying low pass or high pass filters for the different levels.

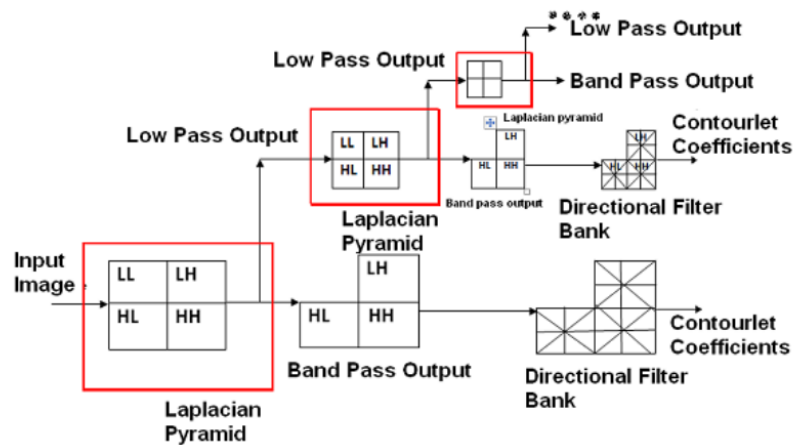
The LP decomposition only produce one bandpass image in a multidimensional signal processing, that can avoid frequency scrambling. And DFB is only fit for high frequency since it will leak the low frequency of signals in its directional subbands. This is the reason to combine DFB with LP, which is multiscale decomposition and remove the low frequency.



**Figure 2.4:** Contourlet Transform

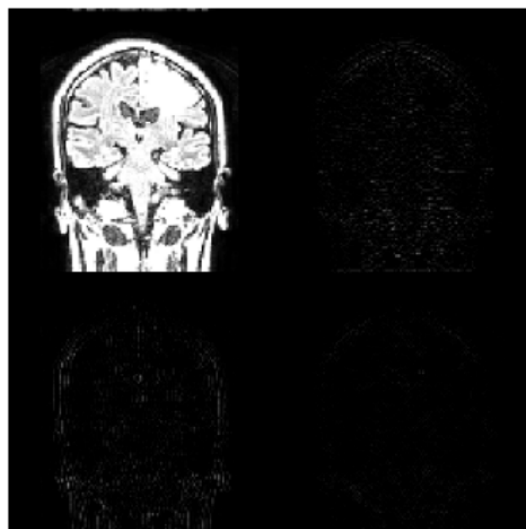
### 2.3.2 Definition

The CT is a directional transform, capable of capturing contours and fine details in images. The Figure 2.5 illustrates the CT, in which the input image consists of frequency components like Low Low (LL), Low High (LH), High Low (HL) and High High (HH).



**Figure 2.5:** Flowchart of Contourlet Transform

The LP at each level generates a Low pass output (LL) and a Band pass output (LH, HL, and HH). The Band pass output is then passed into DFB, which results in contourlet coefficients. The Low pass output is again passed through the LP to obtain more coefficients and this is done till the fine details of the image are obtained. Figure 2.6 shows the decomposition of brain MR Image.



**Figure 2.6:** Contourlet decomposition of brain MR Image

## 2.4 PET IMAGE DENOISING

### 2.4.1 Image Denoising

Image noise is a random variation of brightness and visible as grains. It may arise by the sensor and circuitry of a digital camera during the time of capturing or image transmission that adds spurious and extraneous information [11]. Noise in image is defined as pixels showing false or different intensity values instead of true or expected values. Natural image denoising is a process of reducing or removing noise from an image. In other words, it is defined as a process of guesstimating an original clean version of noise corrupted image [12].

The common types of noise that arises in a image are impulse noise (salt-and-pepper noise), amplifier noise (Gaussian noise), shot noise, quantization noise (uniform noise), film grain, on-isotropic noise, multiplicative noise (speckle noise) and periodic noise. Depending on owning different characteristics, which makes them distinguishable, each type of noise is able to afflict image in different context. As a result, noise reduction filters are developed to minimize the effects of noise in order to ameliorate image processing.

In paper [13], the developed framework was firstly evaluated for PET denoising. In this work the multiobservation aspect of the proposed HMT was exploited in order to associate both Wavelets and Contourlets coefficients to each voxel. An approach combining both Contourlet Denoising (CD) and Wavelet Denoising (WD), namely Wavelet-Contourlet Denoising (WCD), was proposed in order to obtain the optimal performance.

### 2.4.2 PET Image

PET is a nuclear medicine, functional imaging technique that is used to observe metabolic processes in the body. The system detects pairs of gamma rays emitted indirectly by a positron-emitting radionuclide (tracer), which is introduced into the body on a biologically active molecule.

Three-dimensional images of tracer concentration within the body are then constructed by computer analysis. In modern PET-CT scanners, three dimensional imaging is often accomplished with the aid of a CT X-ray scan performed on the patient during the same session, in the same machine.

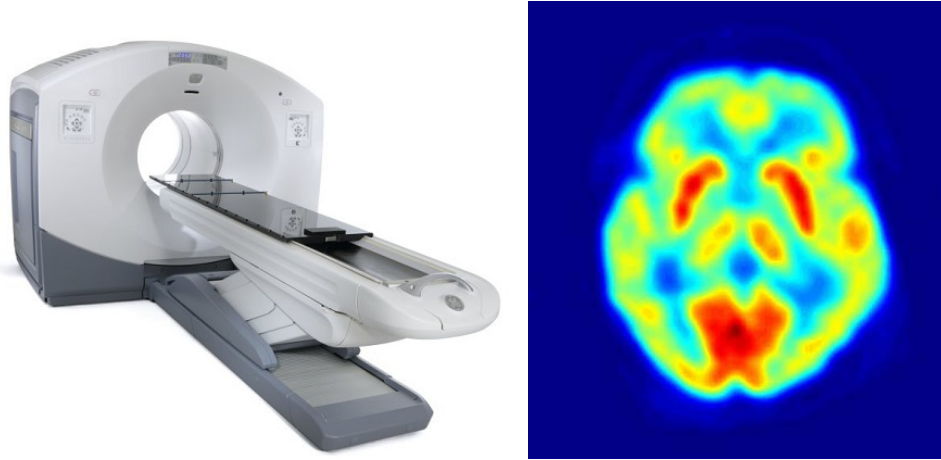
The examples of PET system and PET brain image can be seen in Figure 2.7.

### 2.4.3 Wavelet PET Denoising

#### 2.4.3.1 Concept of denoising

A more precise explanation of the wavelet denoising procedure can be given as follows. Assume that the observed data is [14]:

$$X(t) = S(t) + N(t) \quad (2.5)$$



**Figure 2.7:** PET system and PET brain image

where  $S(t)$  is the uncorrupted signal with additive noise  $N(t)$ .

Let  $W(\cdot)$  and  $W^{-1}(\cdot)$  denote the forward and inverse wavelet transform operators. Let  $D(\cdot, \lambda)$  denote the denoising operator with threshold  $\lambda$ .

We intend to denoise  $X(t)$  to recover  $\hat{S}(t)$  as an estimate of  $S(t)$ . The procedure can be summarized in three steps:

$$Y = W(X) \quad (2.6a)$$

$$Z = D(Y, \lambda) \quad (2.6b)$$

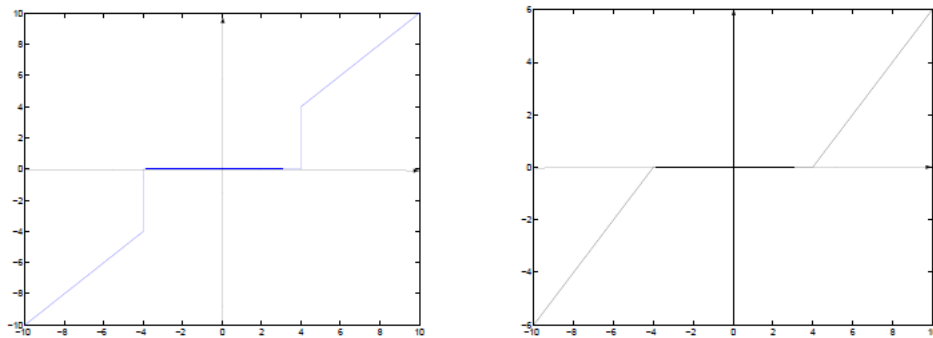
$$\hat{S} = W^{-1}(Z) \quad (2.6c)$$

while  $D(\cdot, \lambda)$  being the thresholding operator and  $\lambda$  being the threshold.

#### 2.4.3.2 Thresholding

In fact, small coefficients are dominated by noise, while coefficients with a large absolute value carry more signal information than noise. Replacing noisy coefficients (small coefficients below a certain threshold value) by zero and an inverse wavelet transform may lead to a reconstruction that has lesser noise [14].

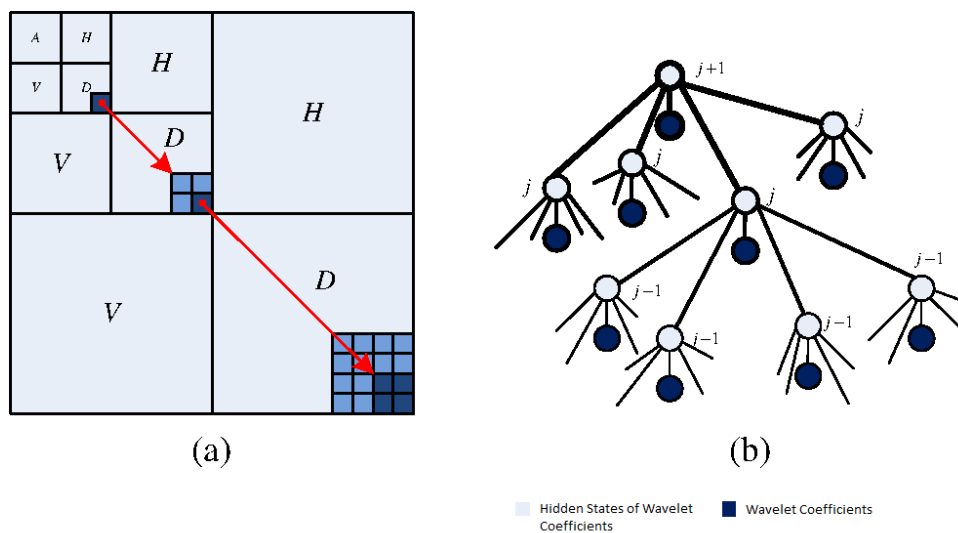
Hard threshold is a "keep or kill" procedure and is more intuitively appealing. The alternative, soft thresholding (whose transfer function is shown in Fig 4), shrinks coefficients above the threshold in absolute value.



**Figure 2.8:** Hard and Soft Thresholding

#### 2.4.4 Contourlet PET Denoising

#### 2.4.5 Wavelet-Contourlet PET Denoising



**Figure 2.9:** Discrete Wavelet Transform and Hidden Markov Tree models

## 2.5 PET/CT IMAGE SEGMENTATION

### 2.5.1 Introduction

Segmentation is the process of splitting an observed image into its homogeneous or constituent regions. Segmentation may also be thought of as labeling process, where each pixel in a given image is assigned a designating the region or class to which it belongs. If the observed image  $y$  is defined on a rectangular  $M \times N$  lattice  $\Omega$ , indexed by a pair  $(i, j)$  so that  $\Omega = (i, j); 1 \leq i \leq M \text{ and } 1 \leq j \leq N$  and the label  $x$  will be defined on the same label. Thus for each pixel site  $s = (s_i, s_j)$  there is a label  $x_s$  which specifies to which region the pixel  $y_s$  belongs. The relationship between gray scale values and levels is represented by Bayesian Likelihood function. It is modeled by probability distribution of the pixel values, model parameter and the prior distribution of models. Then segmentation is an optimization problem of the labels on entire image[15].

Graph partitioning methods are an effective tools for image segmentation since they model the impact of pixel neighborhoods on a given cluster of pixels or pixel, under the assumption of homogeneity in images. In these methods, the image is modeled as a weighted, undirected graph. Usually a pixel or a group of pixels are associated with nodes and edge weights define the (dis)similarity between the neighborhood pixels. The graph (image) is then partitioned according to a criterion designed to model "good" clusters. Each partition of the nodes (pixels) output from these algorithms are considered an object segment in the image.

MRFs are completely characterized by their prior probability distributions, marginal probability distributions, cliques, smoothing constraint as well as criterion for updating values. The criterion for image segmentation using MRFs is restated as finding the labeling scheme which has maximum probability for a given set of features.

In terms of image segmentation, the function that MRFs seek to maximize is the probability of identifying a labeling scheme given a particular set of features are detected in the image

where  $V_c(x)$  is the clique potential and  $C$  is the set of all possible cliques. In the image domain, we assume that one pixel has at most 4 neighbors: the pixels in its 4-neighborhood. Then the clique potential is defined on pairs of neighboring pixels

The HMRF-EM framework was first proposed for segmentation of brain MR images [9]. Given an image  $Y = (y_1, y_2, \dots, y_N)$  where each  $y_i$  is the intensity of a pixel, we want to infer a configuration of labels  $X = (x_1, x_2, \dots, x_N)$  where  $x_i \in L$  and  $L$  is the set of all possible labels which means the hidden process is a finite valued one (REFERENCE: IMAGE AND SIGNAL RESTORATION USING PAIRWISE MARKOV TREES) In a binary segmentation problem,  $L = \{0, 1\}$ . According to the MAP criterion, we seek the labeling  $x^*$  which satisfies:

$$X^* = \underset{x}{\operatorname{argmax}} \{ \Pr(Y | X, \Theta) P(X) \} \quad (2.7)$$

The prior probability  $P(X)$  is a Gibbs distribution, and the joint likelihood probability is given by:

$$\begin{aligned}
\Pr(Y | X, \Theta) &= \prod_i \Pr(y_i | X, \Theta) \\
&= \prod_i \Pr(y_i | X_i, \theta_{x_i})
\end{aligned} \tag{2.8}$$

where

$$\Pr(y_i | X_i, \theta_{x_i})$$

is a Gaussian distribution with parameters  $\theta_{x_i} = (\mu_{x_i}, \sigma_{x_i})$  and  $\Theta = \{\theta_l | l \in L\}$  is the parameter set, which is obtained by the EM algorithm.

### 2.5.2 EM Algorithm

We use the EM algorithm to estimate the parameter set  $\Theta = \{\theta_l | l \in L\}$ . We describe the EM algorithm by the following [16]:

1. Start: Assume we have an initial parameter set  $\Theta^{(0)}$
2. E-step: At the  $t^{th}$  iteration, we have  $\Theta^{(t)}$  and we calculate the conditional expectation:

$$Q(\Theta | \Theta^{(t)}) = \sum_x \Pr(x | Y, \Theta^{(t)}) \ln(\Pr(x, Y | \Theta)) \tag{2.9}$$

where  $x \in X$ , set of all possible configurations of labels.

3. M-step: Now maximize  $\Pr(\Theta | \Theta^{(t)})$  to obtain the next estimate:

$$\Theta^{(t+1)} = \underset{\Theta}{\operatorname{argmax}} \{\Pr(\Theta | \Theta^{(t)})\} \tag{2.10}$$

Then let  $\Theta^{(t+1)}$  to  $\Theta^{(t)}$  and repeat from the E-step.

The above equations are in general are computationally difficult and here we have assumed the parameters are random processes to simplify our implementation[? ]. Let  $G(z; \theta_l)$  denote a Gaussian distribution function with parameters  $\theta_l = (\mu_l, \sigma_l)$ :

$$G(z; \theta_l) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{(z - \mu_l)^2}{2\sigma^2}\right) \tag{2.11}$$

We assume that the prior probability can be written as:

$$P(X) = \frac{1}{Z} \exp(-U(X)) \tag{2.12}$$

where  $U(X)$  is the prior energy function. We also assume that

$$\begin{aligned}
\Pr(Y | X, \Theta) &= \prod_{i=1} \Pr(y_i | x_i, \Theta_{x_i}) \\
&= \prod_i G(y_i; \theta_{x_i}) \\
&= \frac{1}{Z'} \exp(-U(Y | X))
\end{aligned} \tag{2.13}$$

With these assumptions, the HMRF-EM algorithm is given below:

1. Start with initial parameter set  $\Theta^{(0)}$ .
2. Calculate the likelihood distribution  $P^{(t)}(y_i | x_i, \theta_{x_i})$ .
3. Using current parameter set  $\Theta^{(t)}$  to estimate the labels by MAP estimation:

$$\begin{aligned}
X^{(t)} &= \underset{x \in X}{\operatorname{argmax}} \{ \Pr(Y | X, \Theta^{(t)}) P(X) \} \\
&= \underset{x \in X}{\operatorname{argmin}} \{ U(Y | X, \Theta^{(t)}) + U(X) \}
\end{aligned} \tag{2.14}$$

The algorithm for the MAP estimation is discussed below.

4. Calculate the posterior distribution for all  $l \in L$  and all pixels  $y_i$ :

$$\Pr^{(t)}(l | y_i) = \frac{G(y_i; \theta_i) \Pr(l | x_{N_i}^{(t)})}{P^{(t)}(y_i)} \tag{2.15}$$

where  $x_{N_i}^{(t)}$  is the neighborhood configuration of  $x_i^{(t)}$  and

$$P^{(t)}(y_i) = \sum_{l \in L} G(y_i; \theta_i) \Pr(l | x_{N_i}^{(t)}) \tag{2.16}$$

Note here we have

$$\Pr(l | x_{N_i}^{(t)}) = \frac{1}{Z} \exp(-\sum_{j \in N_i} V_c(l, x_j^t)) \tag{2.17}$$

5. Use  $P^{(t)}(l | y_i)$  to update the parameters:

$$\begin{aligned}
\mu_l^{(t+1)} &= \frac{\sum_i P^{(t)}(l | y_i) y_i}{\sum_i P^{(t)}(l | y_i)} \\
(\sigma_l^{(t+1)})^2 &= \frac{\sum_i P^{(t)}(l | y_i) (y_i - \mu_l^{t+1})^2}{\sum_i P^{(t)}(l | y_i)}
\end{aligned} \tag{2.18}$$



### 2.5.3 MAP Estimation

In the EM algorithm, we need to solve for  $x$  that minimizes the total posterior energy

$$X^* = \underset{x \in X}{\operatorname{argmin}} \{U(Y | X, \Theta) + U(X)\} \quad (2.19)$$

with given  $Y$  and  $\Theta$ , where the likelihood energy is

$$\begin{aligned} U(Y | X, \Theta) &= \sum_i U(Y_i | X_i, \Theta) \\ &= \sum_i \left( -\frac{(y_i - \mu_{x_i})^2}{2\sigma_{x_i}^2} + \ln(\sigma_{x_i}) \right) \end{aligned} \quad (2.20)$$

The prior energy function  $U(x)$  has the form

$$U(X) = \sum_{c \in C} V_c(X) \quad (2.21)$$

where  $V_c(X)$  is the clique potential and  $C$  is the set of all possible cliques.

In the image domain, we assume that one pixel has at most 4 neighbors: the pixels in its 4-neighborhood. Then the clique potential is defined on pairs of neighboring pixels:

$$V_c(x_i, x_j) = \frac{1}{2} (1 - I_{x_i, x_j}) \quad (2.22)$$

Where

$$I_{x_i, x_j} = \begin{cases} 0 & \text{if } x_i \neq x_j \\ 1 & \text{if } x_i = x_j \end{cases} \quad (2.23)$$

We have developed an iterative algorithm to solve (2.19):

1. To start with, we have an initial estimate  $X^{(0)}$ , which is from the previous loop of the EM algorithm.
2. Provided  $X^{(k)}$ , for all  $1 \leq i \leq N$ , we find

$$X_i^{(k+1)} = \underset{l \in L}{\operatorname{argmin}} \{U(y_i | l) + \sum_{j \in N_i} V_c(l, x_j^k)\} \quad (2.24)$$

1. Repeat step 2 until  $U(Y | X, \Theta) + U(X)$  converges or a maximum  $k$  is achieved.

## **Chapter 3**

# **Implementation**

## **Chapter 4**

# **Result and Discussion**

### **4.1 CHALLENGES**

In unsupervised image segmentation is the process of identifying and detecting the constituent regions of an image, while having no prior knowledge of the number of regions in the image. This problem can be formulated in Bayesian framework, but it needs a lot of optimization.

## **Chapter 5**

## **Conclusion**

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