CHAPTER 5

Neural Network Based Computation for Image Segmentation
### CHAPTER 5

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5.1 INTRODUCTION

The morality of cancer in lungs is leading cause in men and women. This staging defines the lesion in cancerous treatment. It requires the proper treatment to lesion obtained in the treatment of lung cancer. It basically involves a primary tumor with the presence of lymph node metastases. The study of lung cancer is a challenge to the radiologist however the classification used in detection of tumors is based on the Thresholding methods used for detection. In the present work the OTSU’s Thresholding is used for CT and PET images.

The major steps involves in evaluating cancerous lesion by Gaussian pulse smoothening with in class variance. CT scan is used as an input for detecting lung cancer and finding abnormal areas in the scanned images. This area determines the cancerous lesion to the radiologist in a concise manner. For evaluating the performance measures neural network based computation is used as a therapy and guided treatment to the work proposed.

Fig. 5.1: shows cancerous lesion in lung cancer
5.2 Related Works

Machine Learning Algorithms in image segmentation and detection have been used in often in Image processing. Chumming Li et al. [39] proposed a method with level based segmentation method for intensity inhomogeneity.

**Observation:** The segmentation used in this approach reveals the problems in degradation of edge boundaries and intensity variations and the algorithm used is well known in image processing.

Martin dolejsi et al. [40] proposed a method to reduce the false positive responses to detect pulmonary nodules.

**Observation:** The pulmonary nodules classifier significantly reduce the number of false positive responses.

Micheal et al. [41] presented a method to improve the detection quality in lung cancer.

**Observation:** CAD method presented to automatically detect pulmonary nodule in lung cancer and hence the improved detection quality can be observed.

M H Hassoun et al. [40] proposed a method that uses back propagation algorithm in a feed forward network which is the part of neural network.

**Observation:** The method gives an idea to determine the image quality with well-known methods. From the above methods it is clear automatic extraction and detection of cancerous lesion is a challenging task and a optimized solution is needed to detect the pulmonary nodules of lung cancer lesions. The image processing is
finding problems with imaging devices which provides bad illumination and imperfection in intensity. The image segmentation finds difficulty to detect intensity inhomogeneity as it overlaps with various regions. This problem is slowly becoming a challenging task in image segmentation. As many algorithms rely on intensity in homogeneities in image segmentation. For tracking shapes and interfaces level set method is used which represents contours and surfaces.

Level set methods are further classified as edge based models and region based models. The major difficulty is defining a region description with intensity in homogeneities. Many methods have proposed by piecewise smoothing model but still it generates more computations and defining a boundary or anatomical region is serious problem in above said methods.

To overcome this problem novel region based method is given from image segmentation by using Otsu’s Thresholding and deriving a criterion function for region based boundaries. Further the image is fused together and enhanced to avoid unwanted noise and blur. Experimental results are evaluated by objective based criteria to give more meaning to the work carried further the input details are given to neural networks to compute the performance of image.

5.3 Exploration of Technologies used
5.3.1 Preprocessing

Computer aided diagnosis systems provides second opinion to the doctor for proper therapeutic treatment. It consists of simple
stages such as extraction of feature, Image enhancement and classification. Image pre-processing is to enhance the quality, contrast, orientation to the applied input image in order to find the abnormalities in the CT Image. Medical images need improvement in image quality and segmentation to have results more accurate. The objective of this process is to improve image quality, contrast and remove noise and increase the intensity to find the relevant parts of an image with appropriate intensity. Various ALU operations are performed to manipulate the pixels values and intensity variations to enhance or degrade intensity based on pixel values by using simple image commands.

```
b=imadd(a,50);
c=imsubtract(a,50);
IM2 = imcomplement(IM) computes the complement of the image IM.
d=imcomplement(a);
```

### 5.3.2 Image Segmentation

Segmentation and feature extraction are basic steps in image processing to extract the attributes for obtained input images. Dividing the image in constituent regions or objects is segmentation. Image segmentation algorithms are based on the properties of intensity values such as similarities and discontinuities. In discontinuities category the image based on abrupt changes of intensity defines edges in an image. For similarities categories the image is divided in sub regions according to defined values which refers to Thresholding and region based properties which are splitting,
merging and growing. Edges are to detect meaningful discontinuities in gray level values by using derivations. Thresholding Extraction of the objectives from the point is carried in background point and objective pairs.

This system use frequency domain as convolution for segmentation and feature extraction. Image processing tools describes spatial and frequency domain to transfer the image properties. These are of wide varieties in the image to extract the region of interest by using Fourier transform with same size. The equation of DFT describes image interpretation with convolution domain.

The DFT is the sampled as Fourier Transform. The number of frequencies corresponds to the number of pixels in the spatial domain image, the two-dimensional DFT is given by:

$$F(k, l) = \frac{1}{N^2} \sum_{i=0}^{N-1} \sum_{j=0}^{N-1} f(i,j) e^{-2\pi \frac{ki + lj}{N}}$$  \hspace{1cm} (5.1)

F(i,j) is the image in the spatial domain and the exponential term is the basis function corresponding to each point F(k,l) in the Fourier space. The equation can be interpreted as: the value of each point F(k,l) is obtained by multiplying the spatial image with the corresponding base function and summing the result. In a similar way, the Fourier image can be re-transformed to the spatial domain. The inverse Fourier transform is given by:

$$f(i,j) = \frac{1}{N^2} \sum_{k=0}^{N-1} \sum_{l=0}^{N-1} F(k,l) e^{2\pi \frac{ki + lj}{N}}$$  \hspace{1cm} (5.2)

To obtain the result for the previous equations, a double sum has to be calculated for each image point. However, because the Fourier
Transform is separable, it can be written as

\[ F(k, l) = \frac{1}{N} \sum_{j=0}^{N-1} P(k, j) e^{-2\pi \left(\frac{l}{N}\right)} \] (5.3)

Where

\[ P(k, j) = \frac{1}{N} \sum_{i=0}^{N-1} f(i, j) e^{-2\pi \left(\frac{k}{N}\right)} \] (5.4)

Using those last two formulas, the spatial domain image is first transformed into an intermediate image using N one-dimensional Fourier Transforms. This intermediate image is then transformed into the final image, again using N one-dimensional Fourier Transforms.

5.3.3. Neural Networks

A neural network is a massively parallel distributed processor that has a natural propensity for storing experiential knowledge and making it available for use. It resembles the brain in two respects:

1. Knowledge is acquired by the network through a learning process.
2. Interneuron connection strengths known as synaptic weights are used to store the knowledge.

The Artificial Neural Network follows

1. Information-processing system.
2. Neurons process the information.
3. The signals are transmitted by means of connection links.
4. The links possess an associated weight.
5. The output signal is obtained by applying activations to the net input.

The processing of Neural Network follows with the neuron is the basic information processing unit of a NN. It basically consists of
1. A set of links, describing the neuron inputs, with weights $W_1, W_2, ..., W_m$

2. An adder function (linear combiner) for computing the inputs.

$$u = \sum_{j=1}^{m} W_j X_j$$

3. Activation function: for limiting the amplitude of the neuron output.

$$y = \varphi(u + b)$$

The Multi-layer neural network use the following to construct a network.

Input: records without class attribute with normalized attributes values.

Input Vector: $X = \{ x_1, x_2, ..., x_n \}$

where $n$ is the number of (non class) attributes.

Input Layer – there are as many nodes as non-class attributes i.e. as the length of the input vector.

Hidden Layer – the number of nodes in the hidden layer and the number of hidden layers depends on implementation.

The operation neural network operation is described as

![Fig. 5.2: Neural Network operation](image)
5.4 Image Smoothening using Gaussian Pulse

Denoising is the method by low pulse filtering to reduce noise and reduces the blurs in edges. These filters smoothen the image by stopping the detail information. The noise obtained images is random which may be in brightness variation or change in color information. Gaussian noise is a type of noise that occurs only during image acquisition as poor illumination or high temperature or signal intensity.

Gaussian distribution showing in one dimension as

\[ G(x) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{x^2}{2\sigma^2}} \]  

Whereas \(\sigma\) is standard deviation that has mean as zero in distribution.

Where as in circularly asymmetric form of two dimensional

\[ G(x,y) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}} \]  

The above pixel matrix shows the total sum of pixel values as 1/245 and defines Gaussian smoothening

This can be achieved b point spread function with discrete pixels which can perform convolution with non-zero value. The mask used in the Gaussian can be pixel is not accurate but varies non linearly across the pixel.

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The corner values should be ‘1’. Gaussian uses convolution methods. The equation is multiplied for 2D in to two separable x and y components to produce kernel value. Using standard deviation as large and it can convolve several times with very small value of Gaussian which can be computed easily.

Filter = f special (Gaussian [2 2], 0.5);

H size [2, 2] is Size of filter and sigma (0.2) is a 2x2 matrix of Gaussian function

Filtered image = imfilter (unfiltered image, my filter, replicate);

It can be produced by the sensor and circuitry of a scanner or digital camera. Image noise can also originate in film grain and in the unavoidable shot noise of an ideal photon detector. Image noise is an undesirable by-product of image capture that adds spurious and extraneous information. Fusion Combinational or integration of acquired images.

5.5 Proposed Image segmentation method

![Diagram](image_url)

**Fig. 5.3:** Block diagram for cancer lesion detection from the given CT/PET image
Each block in fig is defined in different steps to describe Visual quality of CT images.

1) Input image: The Input image is carried with the CT image or PET image to provide motion of the patient. For identifying the Region of Interest in CT motion images. The given input image is automatically subjected in generation of the sinograms to get rough data and estimation about the image. In the simplest form of CT imaging only the desired cross sectional plane of the body is irradiated using a finely collimated ray of X-ray photons. Ray integrals are measured at many positions and angles around the body scanning the body in the process. The principle of image reconstruction from projections is then used to compute an image of a section of the body hence the name computed tomography.

2) Preprocessing: In the above block diagram this step is carried out with CT images to avoid noise corruptions and make the data more accurate and provide better illusion with appropriate amount of Intensity in the next step rough data is generated.[18]

3) Image Smoothening: Gaussian noise impulse is used to smoothen the region of interest in the center part of the image.

4) Image Enhancement: The principle objective of enhancement techniques is to process an image, so that the result is more suitable than the original image for a specific application. The approaches are divided into two types is Spatial domain method and Frequency domain method. The spatial domain refers to the image plane itself and approaches in this category are based on direct manipulation of
pixels in an image. The frequency domain processing techniques are based on modifying the Fourier transformation of an image. For the given results shown frequency domain processing techniques are used.

5) Blurring Initial Check Point: To identify the artifacts and to detect the anomalies in the image blurring from initial point with spatial mask is used.

6) Smoothening: To smoothen the image in center part to signify the difference from edge boundaries and the resulted is extremely accurate solution with more efficient optimization techniques

7) Iteration count: To identify the Region of Interest (ROI) from initial point 50 iterations are performed.

8) Region of Interest: This region gives the detected anomalies of lung cancer detected with specific measures.

9) Classification Methods

Selected Features are applied on the classifier the recognition ability of the classifiers depends on the choice of the used diagnostic features as well as the available training data.

- Feed forward Back Propagation Neural Network

5.6 OTSU Thresholding

To segment an image is done by simplest known approach Thresholding. The threshold techniques are based on pixel values such as gray level, colour which belong to the class. This depends on the gray level values and it shares an overlap between gray level objects.
If \( f(x, y) > T \) then \( f(x, y) = 0 \) else \( f(x, y) = 255 \).

Otsu’s Thresholding is based on conversion of gray scale in monochrome image. It briefly depends on binarization methods. The region homogeneity measured is variance. It selects the two groups of pixels as within class variance. It defines distribution of bimodal gray level values and it fits the image approximately.

It performs automatic clustering which assumes two classes of pixels which are foreground and background and it computes the thresholds optimum value. It provides minimization between within class variance and class variance. It defines histogram with adaptive value for providing illuminate equally with respect to brightness as bimodal value.

\[
\sigma_w^2(t) = q_1(t)\sigma_1^2(t) + q_2(t)\sigma_2^2(t)
\]

(5.8)

Where the class probabilities are estimated as

\[
q_1(t) = \sum_{i=1}^{1} p(i) \quad q_2(t) = \sum_{i=1}^{1} p(i)
\]

(5.9)

And the class means are given by

\[
\mu_1 = \frac{\sum_{i=1}^{1} ip(i)}{q_1(t)} \quad \mu_2 = \frac{\sum_{i=1}^{1} ip(i)}{q_2(t)}
\]

(5.10)

When full range of gray scale values run \([1, 256]\) if exploits the relation between within class variance and class variance. The quantities can be computed by changing the threshold values. It involves the iteration by measuring the spread of pixel values to both sides.
5.6.1. A Faster Approach

To find the threshold class variance between minimum and maximum is computed Within Class Variance $\sigma^2_W = W_b \sigma^2_b + W_f \sigma^2_f$ (as seen above). The threshold which forms within class variance with the weighted sum of variances of each class.

Between Class Variance $\sigma^2_B = \sigma^2 - \sigma^2_W$ \hfill (5.11)  
\[= W_b(\mu_b - \mu)^2 + W_f(\mu_f - \mu)^2 \quad \text{where} \quad \mu = W_b \mu_b + W_f \mu_f \] \hfill (5.12)  
\[= W_b W_f (\mu_b - \mu_f)^2 \] \hfill (5.13)

5.6.2 Clustering (The Otsu Method)

It can define the within-class variance as the weighted sum of the variances of each cluster:

$$\sigma^2_{Within}(T) = n_b(T) \sigma^2_B(T) + n_o(T) \sigma^2_O(T)$$ \hfill (5.14)

Where

$$n_b(T) = \Sigma_{i=0}^{T-1} p(i)$$ \hfill (5.15)

$$n_o(T) = \Sigma_{i=T}^{N-1} p(i)$$ \hfill (5.16)

$$\sigma^2_B(T) = \text{the variance of pixels in the background (below threshold)}$$

$$\sigma^2_O(T) = \text{the variance of the pixels in the Foreground (above threshold)}$$

And $[0,N-1]$ is the range of intensity levels.

By subtracting within the class variance as total variance the distribution can be obtained

$$\sigma^2_{Between}(T) = \sigma^2 - \sigma^2_{Within}(T)$$ \hfill (5.16)

$$= n_b(T)[\mu_b(T) - \mu]^2 + n_o(T)[\mu_o(T) - \mu]^2$$ \hfill (5.17)

Where $\sigma^2$ is the combined variance and $\mu$ is the combined mean.
Notice that the between-class variance is simply the weighted variance of the cluster means themselves around the overall mean.

Substituting \( \mu = n_B(T)\mu_B(T) + n_O(T)\mu_O(T) \) and simplifying, we get

\[
\sigma_{\text{between}}^2(T) = n_B(T)n_O(T)[\mu_B(T) - \mu_O(T)]^2
\]  

(5.18)

The threshold can be obtained in the following steps:

1. Divide pixels into different clusters
2. Calculate the cluster mean value
3. Square the difference mean value
4. The pixel value of one cluster multiply with the other

The individual intensity and cluster are calculated between two clusters. The relationship of recurrence or between variance classes to update one cluster with the other.

Using simple recurrence relations we can update the between-class variance as we successively test each threshold.

\[
n_B(T + 1) = n_B(T) + n_T
\]  

(5.19)

\[
n_O(T + 1) = n_O(T) - n_T
\]  

(5.20)

\[
\mu_B(T + 1) = \frac{\mu_B(T)n_B(T) + n_TT}{n_B(T + 1)}
\]  

(5.21)

\[
\mu_O(T + 1) = \frac{\mu_O(T)n_O(T) - n_TT}{n_O(T + 1)}
\]  

(5.22)

This method is sometimes called the \textit{Otsu} method.

5.7 Neural Network based Computation

5.7.1 Problem Solving

Select a suitable NN model based on the nature of the problem. Construct a NN according to the characteristics of the application domain. Train the neural network with the learning procedure of the
selected model. Use the trained network for making inference or solving problems.

5.7.2 Neural Network Toolbox

Neural Network learns by adjusting the weights so as to be able to correctly classify the training data and hence, after testing phase, to classify unknown data.

1. Neural Network needs long time for training.
2. Neural Network has a high tolerance to noisy and incomplete data.
3. The Matlab neural network toolbox provides a complete set of functions and a graphical user interface for the design, implementation, visualization, and simulation of neural networks.

5.7.3 General Creation of Network

It supports the most commonly used supervised and unsupervised network architectures and a comprehensive set of training and learning functions.

```
net = network
net = network (num Inputs, num Layers, bias Connect, input Connect, layer Connect, output Connect, target Connect).
```

5.7.4 Description

NETWORK creates new custom networks. It is used to create networks that are then customized by functions such as NEWP, NEWLIN, NEWFF, etc.

The Training and adaptation

1. Incremental training: updating the weights after the presentation of each single training sample.
2. Batch training: updating the weights after each presenting the complete data set.

When using adapt, both incremental and batch training can be used. When using train on the other hand, only batch training will be used, regardless of the format of the data. The big plus of train is that it gives you a lot more choice in training functions (gradient descent, gradient descent w/momentum, Levenberg-Marquardt, etc.) which are implemented very efficiently.

There are several types of training functions:

1. Supported training functions
2. Supported learning functions
3. Transfer functions
4. Transfer derivative functions
5. Weight and bias initialize functions
6. Weight derivative functions

5.7.5 Neural Network Toolbox GUI

1. The graphical user interface (GUI) is designed to be simple and user friendly. This tool lets you import potentially large and complex data sets.

2. The GUI also enables you to create, initialize, train, simulate, and manage the networks. It has the GUI Network/Data Manager window.

3. The window has its own work area, separate from the more familiar command line workspace. Thus, when using the GUI, one might "export" the GUI results to the (command line)
workspace. Similarly to "import" results from the command line workspace to the GUI.

4. Once the Network/Data Manager is up and running, create a network, view it, train it, simulate it and export the final results to the workspace. Similarly, import data from the workspace for use in the GUI.

**5.7.6. Feed Forward Back Propagation Neural Network**

Neural Network is a set of connected input/output units where each connection has weight associated with it the number of units in the hidden layer and the number of hidden layers depends on implementation. The output layer has as many units as the number of classes. The network is feed forward in that none of the weights cycles back to an input unit or to an output unit of a previous layer.

Back propagation learns by iteratively processing a set of training data[19]. It is a case of supervised Classification learning, neural network learns by adjusting the weights so as to be able to correctly classify the training data and hence after testing phase to classify unknown data.

**5.8 Region Props**

The regions of image properties is measured by using this method in matlab.

\[
\text{STATS} = \text{region properties} (\text{BW}, \text{properties})
\]

\[
\text{STATS} = \text{region properties} (\text{CC}, \text{properties})
\]

\[
\text{STATS} = \text{region properties} (\text{L}, \text{properties})
\]

First property defines the properties of the connected objects in an
image. Second property indicates the connected components in a structure. Third property indicates the labeled region in the matrix. Properties of regions are used in shape measurements with respect to gray scale value. The region properties define centroid, area bounding box.

The measurements with pixel values are also carried into pixel value, maximum intervals. The regions are used filled area on the pixels of image maximum intensity and minimum intensity specifies the region with low and high intensity.

### 5.8.1 Shape Measurements

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### 5.8.2 Pixel Value Measurements

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<td>'MeanIntensity'</td>
<td>'PixelValue'</td>
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Fig. 5.4: Shows the centroid and bounding box

This figure illustrates the centroid and bounding box with centroid as red dot and white and green box as bounding box.

Fig 5.5: Shows the different regions of extrema at left and right
This figure illustrates the regions of extrema at left and right of the boundaries.

Fig. 5.6: Shows the original with a single region and the returned image
5.9 Experimental Results

Fig. 5.7: Shows GUI Model showing input images of CT and PET

Fig. 5.8: Shows original CT Image given as Input
Fig. 5.9: Shows original PET Image as Input

Fig. 5.10: Shows Guassian Smoothed CT Image

Fig. 5.11: Shows the CT image after Enhancement
Fig. 5.12: Shows CT Image after segmentation

Fig. 5.13: Shows Guassian smoothed PET Image

Fig. 5.14: Shows PET Image after enhancement
Fig. 5.15: Shows PET Image segmentation

Fig. 5.16: Shows Integration of both PET and CT Images

Fig. 5.17: Shows PET Image after Segmentation
5.9.1 Cancer Lesion Detection

Fig. 5.18: Shows PET image Lesion Detection

Fig. 5.19: Shows the difference of bone and lesion detection

5.9.2 Performance Measures

Fig. 5.20: Shows the details of cancer lesion detection in comparison with Neural networks and segmented image
Test and Results

Fig. 5.21: Shows the Neural network layer with feed forward propagation

Fig. 5.22: Performance measures for the training state

Fig. 5.23: Shows a regression state for given training state
5.10 Discussion

From the above discussion it is clear that neural network based computation is the best for comparing the details of segmentation of cancerous lesion to the trained network. The performance measures gives the approach a strength that this work is justified to segmented part of the cancerous lesion.