# Characterization of Normal Tissues in Computed Tomography using Textural Information

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## ABSTRACT
This paper discusses the process of developing an automated imaging system for classification of tissues in medical images obtained from typical Digital Imaging and Communication in Medicine (DICOM) format of a Computed Tomography (CT) scans. It focuses on using wavelet based multi-resolution texture analysis. The approach consist of two steps: automatic extraction of most discriminative texture features of regions of interest in CT medical images and segmentation is performed that automatically identifies the various tissues. A wavelet-based texture descriptors coupled with the implementation of a minimum distance classifier approach is carried out.Preliminary results for a 3D data set from abdomen CT scans are presented.

## Keywords
Texture analysis, DICOM (Digital imaging and communication in medicine), multi-resolution analysis, Wavelet transform, Computed Tomography

## 1. Introduction
The research presented in this article is part of an ongoing project [1]-[4], aimed at developing an automated imaging system for classification of tissues in medical images obtained by Computed Tomography (CT) scans. Automated imaging system for segmentation of tissues in medical images modalities obtained from typical DICOM format of a computed tomography scans is in high demand in order to increase the productivity of radiologists when interpreting and diagnosing hundreds of images every day. Classification of human organs in CT scans using shape or gray level information is particularly challenging due to changing shape of organs in a stack of slices in medical images and gray level intensity overlap in soft tissues. On the other hand, healthy organs are expected to have consistent and homogeneous textures within tissues across multiple slices. Therefore, this work focuses on using texture analysis for the classification of tissues from abdomen CT scans. The approach consists of two steps: automatic extraction of the most discriminative texture features of regions of interest in the CT medical images and creation of a classifier that will automatically identify the various tissues. This paper focuses on a comparison of wavelet-based texture descriptors, coupled with the implementation of a minimum distance classifier approach. Texture is a commonly used feature in the analysis and interpretation of images. Texture can be characterized by a set of local statistical properties of the pixel gray level intensity. It measures the variations in a surface, looking at properties like smoothness, coarseness and regularity. The discrete wavelet transform maps the image onto a low-resolution image and a series of detail images, providing a multi-scale representation of the image. The low-resolution image carries little energy and was not included in the texture analysis. First and second order statistics of the wavelet detail coefficients provide texture descriptors that can discriminate contrasting intensity properties spatially distributed throughout the image, according to various levels of resolution (see [5], [6] for a similar approach).

## 2. Methodology
### 2.1. Wavelets
A wavelet is a mathematical function that can decompose a signal or an image with a series of averaging and differencing calculations. Wavelets are typically used in image decomposition and compression. The Daubechies D4 transform has four wavelet and scaling coefficients. The sum of the scaling function coefficients are also one, thus the calculation is averaging over four adjacent pixels. Since the size of the filter is greater than the incoming image, both a mirroring and a periodic extension of the filter were tested. The mirror extension, which involves mirroring the last two pixels of the image, generally proved to be the optimal choice.Wavelets are typically used in image decomposition and compression (both lossless and lossy), since the image can be decomposed and then reconstructed by simply reversing the decomposition process. Wavelets calculate average intensity properties as well as several detailed contrast levels distributed throughout the image. Wavelets can be calculated according to various levels of resolution (or blurring) depending on how many levels of averages are calculated. They are sensitive to the spatial distribution of grey level pixels, but also are able to differentiate and preserve details at various scales or resolutions. This multi-resolution quality allows for the analysis of gray level pixels regardless of the size of the neighbourhood. These properties lead to the idea that wavelets could guide researchers to better texture classification of human organs in CT scans. Daubechies wavelet is used in this article. Daubechies is conceptually more complex, and generally has a higher computational overhead. The Daubechies wavelet uses overlapping windows, so the results reflect all changes between pixel intensities.

### 2.2. The data set
The results were obtained from abdomen CT scan 2D DICOM (Digital Imaging and Communications in Medicine) images. The data consists of 250 2D DICOM consecutive slices, each slice being of size 512 by 512 and having 12-bit gray level resolution, which is to be segmented into various tissues i.e. liver, bladder, and kidney. The segmentation process generated 60 liver slices, 40 bladder slices, 54 kidney slices.

Wavelet are extremely sensitive to contrast in the gray level intensity, therefore, in order to use wavelet based texture description it was necessary to eliminate all background pixels to avoid mistaking the edge between the artificial background and the organ as a texture feature. Each slice was therefore further cropped, and only square sub images fully contained in the interior of the segmented area were generated, resulting in 300 slices of pure single organ tissue( 150 liver, 105 bladder,45 kidney) .The data set was then divided into a training and a testing set.

## 2.3. Texture Features extraction

The discrete wavelet transform were used for feature extraction of texture information.Daubechies wavelet filters were applied to each of the 300 cropped images, using three different levels of resolution. At each resolution level three detail coefficient matrices were calculated resulting in three matrices representing the vertical, horizontal and diagonal structures of the image. Several texture statistics features were obtained. The most common statistics calculated are mean and standard deviation. The wavelets were then preprocessed, by taking the absolute value of each coefficient and binning each detail into sixteen bins. Once the preprocessing was completed, the histogram of each of the details coefficient matrix was calculated. First, a histogram was calculated from each wavelet detail. The histogram calculated on wavelet coefficients measures the frequency distribution of contrast levels. Mean and Standard Deviation texture descriptors were then extracted from the histogram of each coefficient matrix. Fig1 and Fig2 shows the flow of work carried in extracting texture features and segmentation of region of interest of human organ tissues from CT scan images of abdomen in DICOM format.

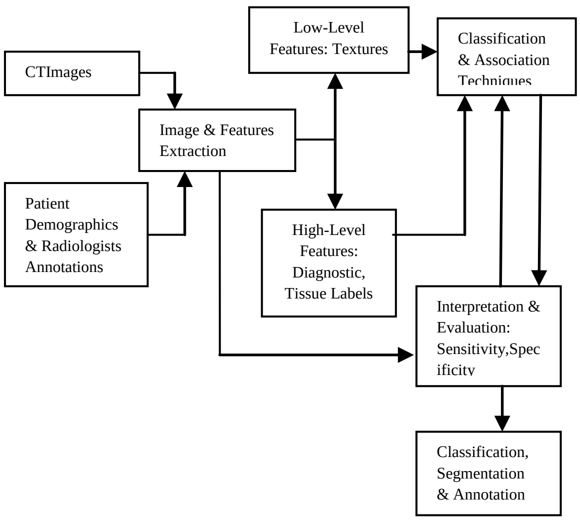


**Figure1: Steps performed to obtain results**

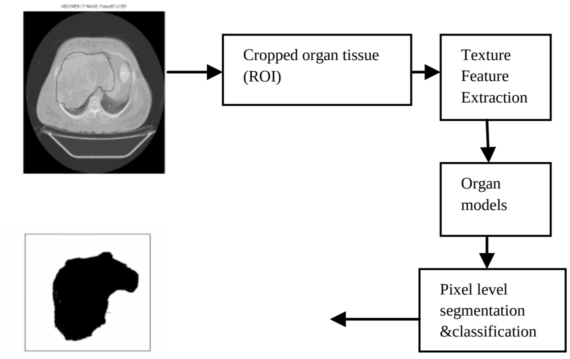


**Figure2: stages in organ segmentation**

## 2.4. Classification

The classification step was carried out using a minimum distance classifier uses the Euclidean distance. Out of 250 cropped medical slices, approximately 67% of the data were then used for training and 33% were used for testing. By using this principle the distance between feature vector of the test images and feature vector of training images are calculated. A misclassification matrix is a table that lists each organ and its true positives, true negatives, false positives and false negatives (Table 1). The number of true positives is the number of organs that are correctly classified as that organ. The number of false positives is the number of organs that are incorrectly classified as that organ. The number of true negatives is the number of other organs that are incorrectly classified as the organ. The number of false negatives is the number of other organs that are correctly classified as other organs. From the misclassification matrix specificity, sensitivity, precision, and accuracy statistics were computed. Specificity measures the accuracy among positive instances, and is calculated by dividing the true negatives by the number of all other organ slices. Sensitivity measures the accuracy among negative instances, and is calculated by dividing the number of true positives by the total number of that specific organ slices. Precision measures how consistent the results can be reproduced. Accuracy reflects the overall correctness of the classifier, and is calculated by adding the true positives and negatives together and dividing by the entire number of organ slices.

**Table 1: Measures of classification performance**

| Measure | Definition |
|---|---|
| Sensitivity | True Positives / Total Positives |
| Specificity | True Negatives / Total Negatives |
| Precision | True Positives / (True Positives + False Positives) |
| Accuracy | ( True Positives + True Negatives) / Total Samples |

## 3. Results and future work

Results are compared on two families of wavelets: Biortogonal and Daubechies(D4).While there has been considerable work done for characterization of normal tissues within different organs. The tools used in this project may also be used to assist segmentation, annotation and automatic selection of context sensitive tools for various tissue. Results were tested over ten patients data. The results lead us to conclusion that the incorporation of other texture model such as Gray level co-occurrence model (GLCM) and Ridglet transform into current approach will increase the performance of the classifier, and will also extend the classification functionality to other organs.

## 4. References

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