# Wavelet Features Extraction for Medical Image Classification

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**Abstratct:** *In this paper, we present a method for classification of medical images. Wavelet features of different modalities of medical images are extracted. Then mean and standard deviation of extracted wavelet features are computed. We utilize K-Nearest Neighbor classifier to classify medical imaging modalities as X-ray, MRI and CT. Experiments are conducted on medical database containing 4,500 images. We achieve 99.96% classification accuracy which presents the efficiency of our proposed approach.*

**Keywords:** *Wavelet, Central Moments, K-Nearest Neighbor, Medical Image Classification*

## 1. Introduction

Automatic medical image classification is a technique for assigning a medical image to a class among a number of images categorizes. Due to computational complexity its important task in the content-based image retrieval. Various medical image retrieval systems are available today that classify image according to image modalities, orientations, body part or disease. The need for systems that can store, represent and provide efficient retrieval facilities of images CBIR for medical image database dose not aim to replace the physician by predicting the disease of a particular case but to assist the doctor [1,10].

However, generating huge amounts of medical images is useless without organizing and searching capability. Handling various types of medical images, such as Standard Radiography (X-ray), Computed Tomography (CT), Magnetic Resonance Imaging (MRI) and etc., in the Health Database System require different methods and techniques [8, 4]. In every medical image modality, physicians must combine the information from different images to fully visualize the imaged anatomical structure. Therefore, it is needed to archive all kinds of medical imaging modalities with their imaged orientations and anatomical structure information [2, 7, 11].

Several imaging categorization systems are proposed to automatically classify images and their related information in large medical datasets. IBM has introduced ILive (Interactive Life sciences imaging visualization & exploration) system [9]. ILive is developed for the automatic categorization of medical images according to their modalities. Imaging modalities include: X-rays, MRI, Histological staining, Micrographs, Photographs of internal organs and Photographs of internal tissues. The system is based on semantical set of visual features and their relevance. Hence, its organization depends on capturing the semantics of different imaging modalities.

Modality categorization by textual annotation interpretation in medical imaging was proposed in [3]. A rule-based medical image modality categorization approach was presented. In order to determine the medical image modality, the textual annotation was interpreted using a set of 96 production rules defined by expert radiologist. Malik and Zremic [2] categorized imaging modalities using image size, number of bits per pixel, number of rows, number of columns, dimensionality and the color information of the input images. The derived information was compared with the data given in the lookup table. Further, to classify images to a narrower group of imaging modalities, the low level global and local features were extracted. It is well known that imaging modalities like X-Ray, US and MRI have substantial difference in their grayscale contrast. Similarly, boundary information of Ultrasound images are different from other imaging modalities. Therefore, grayscale contrast information, boundaries, color composition of regions and frequency information were considered as low level features. In [2], Florea et al. focused on content-based automatic medical image categorization methods, in the on-line context of the CISMeF health-catalogue. The categorization of medical images according to their modality, anatomic region and view angle was based on texture and statistical features. Images were divided into a number of predefined blocks. Texture and statistical features of each block were extracted. To describe image texture, they used the Haralick's co-efficient extracted from the gray-level co-occurrence matrix and Gabor wavelet. Statistical features also derived from gray-level statistical measures. For dimensionality reduction, they proposed and evaluated a symbolic image representation approach. They exploited K-Nearest Neighbor to classify the medical image modalities. Han and Chen [5] proposed an approach for the automatic modality classification of medical images. In their approach, visual feature and textual feature were extracted for modality classification. They also suggested fusion of different extracted visual and textual features. Visual feature was extracted based on global and local features. Histogram descriptor of edge, gray or color intensity and block-based variation were considered as global features. For a local feature, they used SIFT histogram. The binary histogram of some predefined vocabulary words for image caption was utilized for textual feature. They fused different features using normalized kernel functions for SVM classification.

Categorization of medical images means selecting the appropriate class for a given image out-of a set of pre-defined categories. This is an important step for data mining and content based image retrieval. Classification accuracy of medical imaging modalities depends on the extracted features of images and also the type of a utilized classifier. Classification accuracy can be increased using appropriate combination of the features with a particular classifier. Thus, to have an automatic medical image categorization, classification system has to be more robust, efficient and accurate.

In this direction, the approach proposed in this paper discuss about apply the DWT and DCT for extracted the feature as well using mean and standard deviation. Medical images are classified into 3 different categories: 1- X-ray, 2- MRI and 3- CT.

The rest of the paper is organized as follows. Our proposed model to categorize medical imaging modality is presented in section 2. Section 3 gives the details of the experiments followed by the results. Finally, conclusions are given in section 4.

## 2. Proposed model

In this paper, we apply Discrete Wavelet Transform and Discrete Cosine Transform techniques for extract the features of an image. Wavelet transform computes the approximation coefficients matrix and details coefficient matrices. DCT returns the two-dimensional discrete cosine transform coefficient of an image. Moreover, the mean and standard deviation are computed from the coefficient matrices and consider as feature set. K-Nearest Neighbor classifier is employed to classify medical imaging modalities. Fig. 1 shows the stages of the proposed model.

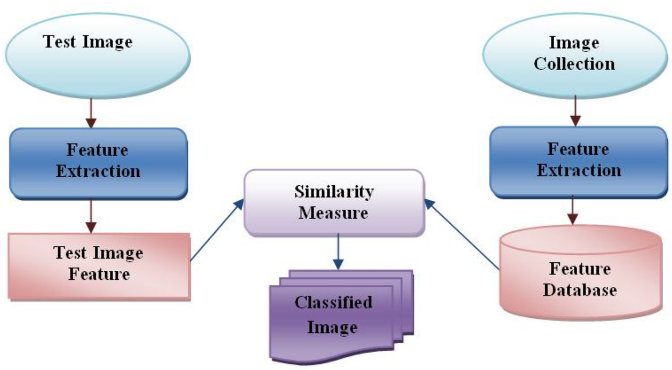



*Fig 1. Block-diagram of the proposed model*

### 2.1 Feature Extraction

In this stage, features are extracted from the whole image. We apply two techniques on the given image. In the first technique, Wavelet Discrete Transform is applied. The coefficient matrices were generated for the approximation, horizontal, vertical and diagonal details. Discrete Cosine Transform is the second method. The DCT decomposes the signal into underlying spatial frequencies, which then allow further processing techniques to reduce the precision of the DCT coefficients. The DCT coefficients of an image can be used as feature, which has the ability to represent the regularity, complexity and some texture features of an image. We exploit mean and standard deviation of the obtained coefficient matrices. For example, in the first level of DWT we generate three matrices in horizontal, vertical and diagonal direction. Instead of using all elements of each matrix, we compute the mean and standard deviation of each matrix and store in the feature vector. In this direction, mean and standard deviation are calculated using Equation 1-2. Let {F1, F2, F3, …, FN} be frequencies of the gray levels 1, 2, …, N, then:

$$\mu = \frac{\sum_{i=1}^{N} F_i}{N} \qquad (1)$$

$$\sigma = \sqrt{\frac{\sum_{i=1}^{N} \left(F_i - \mu\right)^2}{N}} \qquad (2)$$

### 2.2 Classification

To automatically classify the medical imaging modalities into 3 different categories, K-Nearest Neighbor (KNN) classifier is applied. KNN is one of the most popular machines learning technique for classification. Compared to most of the complex classifiers, KNN is fast and accurate. In this paper, the dissimilarity distance between training and testing samples are measured using Euclidean distance as well Chebyshev distance. Let $\{T_{r1}, T_{r2}, ..., T_{rf}\}$ and $\{T_{e1}, T_{e2}, ..., T_{ef}\}$ be f features of training and testing data. Then, the Euclidean distance and Chebyshev distance are computed using Equation 3and 4 below.

$$\text{Euclidean Distance} = \sqrt{\sum_{k=1}^{f} \left(T_{rk} - T_{ek}\right)^2} \qquad (3)$$

$$\text{Chebyshev Distance} = Max\left(\left|T_r - T_e\right|\right) \qquad (4)$$

The KNN is iterated under varying K values and also the number of training and testing samples.

## 3. Experiments, Result and Analysis

### 3.1 Image Data Set

In this paper, the medical images are collected from the Emdadi Hospital, Mashhad, Iran. Experiments are conducted on 4,500 medical images having different sizes. Images include various anatomical structures and image orientation. The database contains 3 different models of images that are X-ray, Magnetic Resonance Imaging (MRI) and Computer Tomography (CT). Each category includes 1,500 images. The X-ray images are of PNG format. MRI and CT images are in DICOM format. The images which are of DICOM type are converted to JPEG format.

### 3.2 Experimental Set up

In the proposed approach, we perform 2- level wavelet to decomposition. Hence the coefficient matrices for all levels were generated. The coefficient matrices were generated for the approximation, horizontal, vertical and diagonal details. We apply Haar wavelet to decompose images. To compare the efficiency of our proposed approach, we consider the Discrete Cosine Transform. The discrete cosine transform (DCT) is often used in signal and image processing, especially for loss data compression. In DWT and DCT techniques the coefficient matrices are extracted. Therefore, in DWT we have 3 matrices in horizontal, vertical and diagonal direction. One coefficient matrix obtains form DCT method. Mean and standard deviation of each matrix are computed and consider as feature vector. Then, the images are classified using KNN classifier. The classifier is trained by 40%, 50% and 60% random samples of different medical images. The sample images include various anatomical structure and image orientation. The similarity measure is calculated based on Euclidean and Chebyshev distance and compare it. The classification accuracy is calculated using Equation 5 and results are tabulated in Table 1, Table 2and Table 3.

$$\text{Accuracy Rate} = \frac{\text{Number of Correctly Classified Testing Samples}}{\text{Total Number of Testing Samples}} \times 100 \quad (5)$$

From the experimentation, it can be observed that the classification rate carried on DWT approach is given higher than the classification accuracy of DCT. By analyzing the results, we observed that, highest classification accuracy has been achieved by Discrete Wavelet transform through Euclidean similarity measure. Therefore, we achieve 99.96% accuracy for K=3 using DWT method along with Euclidean distance. Fig. 2 shows the classification accuracy rate of DWT and DCT using Euclidean measure for K=1, 3, 5, 7 and 9.

| 40% | Discrete Cosine Transform | | Discrete Wavelet Transform | |
|---|---|---|---|---|
| | Chebyshev Distance | Euclidean Distance | Chebyshev Distance | Euclidean Distance |
| **K=1** | 82.55 | 82.66 | 99.92 | 99.92 |
| **K=3** | 81.84 | 82.4 | 99.84 | **99.96** |
| **K=5** | 81.03 | 81.55 | 99.73 | 99.95 |
| **K=7** | 79.66 | 80.59 | 99.73 | 99.84 |
| **K=9** | 77.03 | 78.99 | 99.66 | 99.66 |

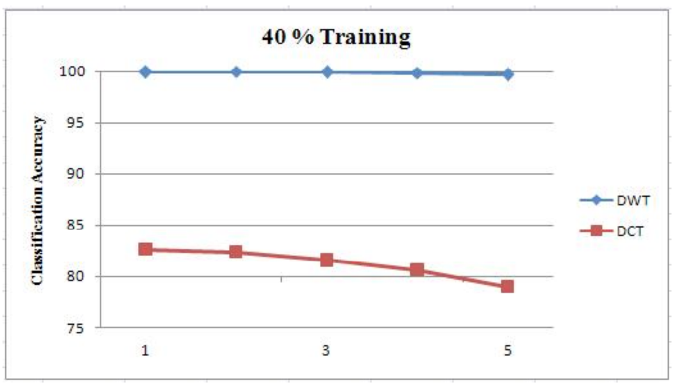
*Table1. Classification accuracy in % with 40% for training*

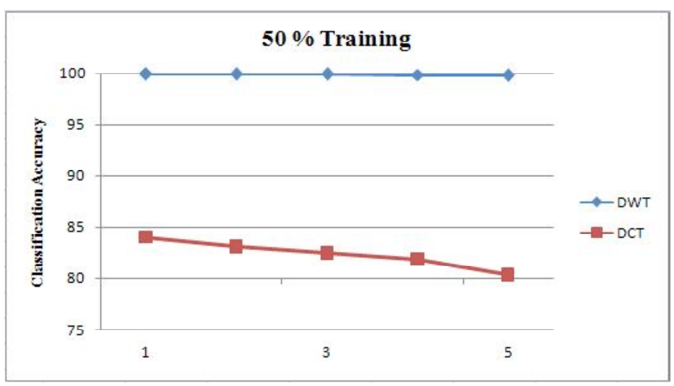
| 50% | Discrete Cosine Transform | | Discrete Wavelet Transform | |
|---|---|---|---|---|
| | Chebyshev Distance | Euclidean Distance | Chebyshev Distance | Euclidean Distance |
| **K=1** | 83.91 | 84.04 | 99.95 | 99.95 |
| **K=3** | 82.79 | 83.06 | 99.86 | 99.91 |
| **K=5** | 81.86 | 82.44 | 99.73 | 99.91 |
| **K=7** | 83.08 | 81.9 | 99.68 | 99.86 |
| **K=9** | 80.13 | 80.3 | 99.59 | 99.82 |

*Table2. Classification accuracy in % with 50% for training*

| 60% | Discrete Cosine Transform | | Discrete Wavelet Transform | |
|---|---|---|---|---|
| | Chebyshev Distance | Euclidean Distance | Chebyshev Distance | Euclidean Distance |
| **K=1** | 85.22 | 83.88 | 99.94 | 99.94 |
| **K=3** | 82.44 | 88 | 99.83 | 99.88 |
| **K=5** | 81.72 | 82.05 | 99.7 | 99.88 |
| **K=7** | 81.55 | 81.77 | 99.61 | 99.88 |
| **K=9** | 79.94 | 80.48 | 99.49 | 99.77 |

*Table3. Classification accuracy in % with 60% for training*



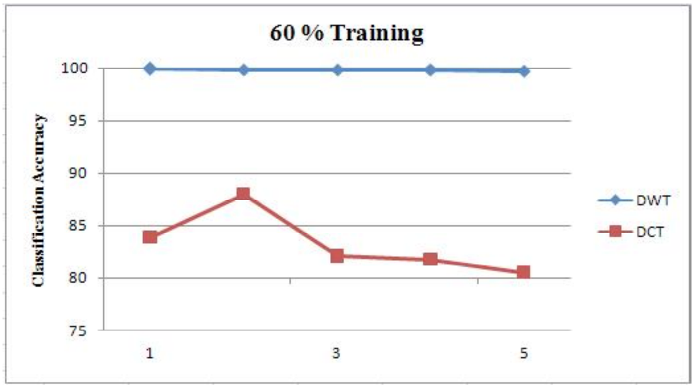



***Fig2.** Classification accuracy of medical imaging modalities using our proposed approach*

## 4. Conclusion

In this paper, Discrete Wavelet transform technique is applied to decompose of an image. We extract three coefficient matrices of DWT as well one coefficient matrix of DCT and compute the mean and standard deviation of each matrix. The extracted features are fed to the K Nearest Neighbor classifier to categorize medical image modality. Unlike considering the DCT for feature extraction, DWT approach is more accurate and efficient for classification. Reducing the number of features to decrease the time complexity and increasing the number of medical image categorization shall be our future work. Further, we have a plan of applying our proposed approach on other large dataset.

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