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# Wavelet Based Decomposition and Approximation for Bone Cancer Image

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**ABSTRACT**

Wavelet algorithms are useful tool for signal processing such as image compression, decomposition, approximation and denoising. Wavelets prove an efficient representation of images. It decomposes an image into subbands, approximation, horizontal, vertical and diagonal. This paper proposes the wavelet based image decomposition and approximation for bone images for detecting cancer. A single level decomposition puts a signal through two complementary low-pass and high-pass filters. The output of the low-pass filter gives the approximation coefficients, while the high pass filter gives the detail coefficients. In this system, Haar functions are act as a wavelet input. These are the simplest wavelets; these forms are used in many methods of discrete image transforms and processing. The important research challenge of this paper is to improve the visual quality of bone image through image processing in order to detect bone cancer at an early stage.



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## INTRODUCTION

Image processing techniques have been widely used in the last decade in medical imaging and the microscopic field received a consistent effort from researchers. Considering the importance of the pathological results for human health and the applications difficulties, many computer aided image analysis systems have been proposed (Al Bovik, 2009). The image processing techniques are of special interest because they allow large scale statistical evaluation in addition to classical eye screening evaluation and are used in both sections of the pathology: cytology (the study of cells) and histology (anatomical study of the microscopic structure of tissues).

The human body is divided into four types of tissue: connective tissue, nervous tissue, epithelial tissue and muscle tissue. Connective tissues of the adult body are divided into proper connective tissues and specialized connective tissues. Bone tissue is a specialized connective tissue characterized by vascularization and hard consistency. It is the main tissue of mature bones. The hardness of bone tissue is due to the large amount of mineral salts and collagen fibers in extracellular matrix. This tissue is composed by three types of cell: osteoblasts, osteoclasts and osteocytes. Our skeleton is made up of two hundred and six bones, divided in two types: cortical (compact) and trabecular (spongy). Approximately 80% of all bone mass in skeleton is composed by cortical bone and 20% of trabecular bone.

A bone tumor, (also spelled as bone tumour), is a neoplastic growth of tissue in bone. Abnormal growths found in the bone can be either benign (noncancerous) or malignant (cancerous). Bone tumors may be classified as "primary tumors", which originate in bone or from bone-derived cells and tissues, and "secondary tumors" which originate in other sites and spread (metastasize) to the skeleton. Carcinomas of the prostate, breasts, lungs, thyroid & kidneys are the primary carcinomas that most commonly metastasize to the bone. Secondary malignant bone tumors are estimated to be 50 to 100 times as common as primary bone cancers. Primary tumors of bone can be divided into benign tumors and cancers. Common benign bone tumors may be neoplastic, developmental, traumatic, infectious, or inflammatory in etiology. Some benign tumors are not true neoplasms, but rather, represent hamartomas, namely the osteochondroma. The most common locations for many primary tumors, both benign and malignant include the distal femur and proximal tibia. Since, by definition, benign bone tumors do not metastasize, all secondary bone tumors are metastatic lesions which have spread from other organs, most commonly carcinomas of the breast, lung, and

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prostate. Reliable and valid statistics on the incidence, prevalence, and mortality of malignant bone tumors are difficult to come by, particularly in the oldest (those over 75 years of age), because carcinomas that are widely metastatic to bone are rarely ever curable, biopsies to determine the origin of the tumor in cases like this are rarely done.

The survival of bone cancer patients is related to the extent of their disease at the time of diagnosis. In the absence of distant metastases, the spread of tumors to the mediastinal lymph nodes is a major determinant of both the prognosis and the therapeutic approach. Proper staging is important for selecting patients who may benefit from surgical resection and for defining the treatment modalities of patients who will undergo radiotherapy.

The remaining of this paper is organized as follows. Section 2 gives a related study on different applications of wavelet. Section 3 describes 2D discrete wavelet transform; Section 4 discusses the proposed system architecture. Experimental results are introduced in section 4, while section 5 contains the conclusion and future enhancements of this work.

***Related Study:***

Wavelet provides a very sparse and efficient representation for images. In recent years, several schemes for bone tumor analysis using wavelet were introduced. In this chapter, we explained the different applications of image processing using wavelet. Wavelet provides a very sparse and efficient representation for images. In recent years, several schemes for mammogram analysis using wavelet were introduced. Liu *et al*. (2001) proved that the use of multi-resolution analysis of mammograms improve the effectiveness of any diagnosis system based on wavelets coefficients. In their mammogram analysis study, they used a set of statistical features with binary tree classifier in their diagnosis system. Ferreira and Borges (2006) indicated that, the biggest wavelet coefficients in the low frequency (approximation) of wavelets transform could be used as a signature vector for the corresponding mammogram. Essam *et al*. used a multi-resolution mammogram analysis in multilevel decomposition to extract a ratio of the biggest coefficients of the approximation. Nisthula et.al employs an easy, fast and reliable technique to detect cancerous tissue in bone by using different image processing techniques such as contrast enhancement, edge detection and image fusion.

Approximation by wavelet is a new tool in mathematics, physics, and engineering. Morlet *et al*. first introduced the idea of wavelets as a family of functions constructed from translation and dilations of a signal function called mother wavelet.

***2D Discrete Wavelet Transform:***

2D Discrete Wavelet Transform (2D DWT) (Al Bovik, 2009; Liu Sheng *et al*., 2001) is used in image processing as a powerful tool solving to image analysis, denoising, image segmentation and other. 2D DWT can be applied as a convolution of a selected wavelet function with an original image or it can be seen as a set of two matrices of filters, row and column one. Using a separability property of DWT, the first part of decomposition consists of an application of row filters to the original image. The column filters are used for further processing of image resulting from the first step. This image decomposition (Liu Sheng *et al*., 2001) can by mathematically described by the following Equation,

$$Z = X * I * Y$$

where Z is the final matrix of wavelet coefficients, I represents an original image, X is a matrix of row filters and Y is a matrix of column filters.

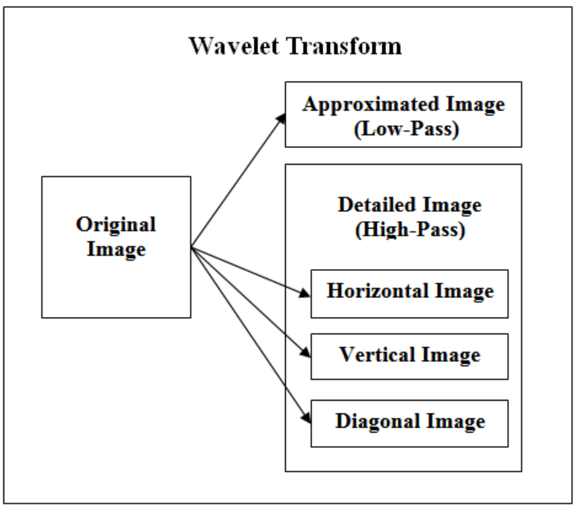


**Fig. 1:** Process of Decomposition

In the first level of decomposition of 2D DWT, the image is separated into four parts. Each of them has a quarter size of the original image (Liu Sheng *et al*., 2001). They are called approximation coefficients (Low-Low or LL), horizontal (Low-High or LH), vertical (High-low or HL) and detail coefficients (High-High or HH) (ucia Dettori, Lindsay Semler, 2007; Majdi Al-Qdaha, *et al*., 2005), see Figure 2. Approximation coefficients obtained in the first level can be used for the next decomposition level.

The motivation for using the discrete wavelet transform is to obtain information that is more discriminating by providing a different resolution at different parts of the time–frequency plane. The wavelet transforms allow the partitioning of the time-frequency domain into nonuniform tiles in connection with the time–spectral contents of the signal. The wavelet methods are strongly connected with classical basis of the Haar functions; scaling and dilation of a basic wavelet can generate the basis Haar functions.

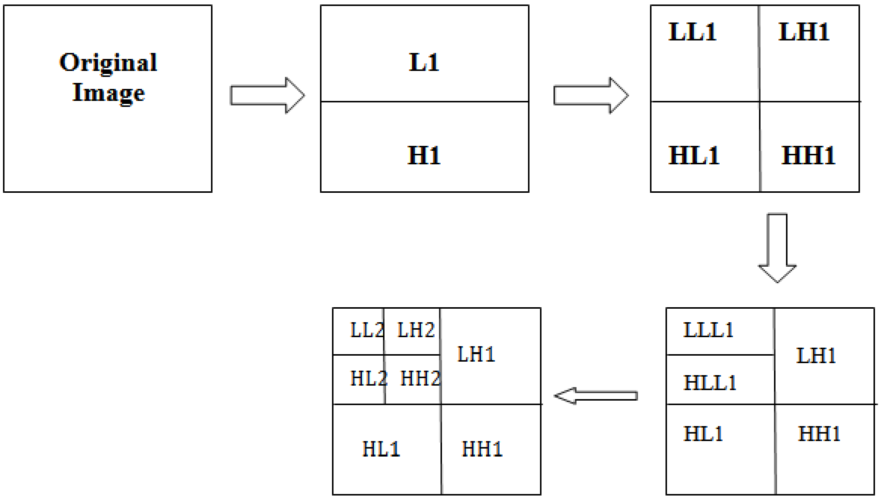


**Fig. 2:** Scheme of decomposition up to the second level

Due to its low computing requirements, the Haar transform has been mainly used for image processing and pattern recognition. From this reason two dimensional signal processing is an area of efficient applications of Haar transforms due to their wavelet–like structure.

***Proposed System Architecture:***

The following diagram explains the architectural structure of our proposed system. The input is taken as a bone image and it is converted into approximation coefficient (i.e. low-pass filter) and detail coefficient (i.e. high-pass filter) using 5-level wavelet decomposition. Then, we can set approximation coefficient into zero; the main purpose is it removes low frequencies from the image. The image is reconstructed using only the remaining wavelet coefficients and we get new approximation coefficient. Then new approximation coefficients ANDed with detail coefficient get new coefficient. This new coefficient can be converted into preprocessed image using wavelet reconstruction.

***Experimental Results:***

We have implemented and tested our approach on the MRI scan bone image. Wavelets are used as a multiscale level decomposition to represent MRI scan image. In each approximation level, the biggest 50 coefficients of approximation, horizontal, vertical, and diagonal is used to be the feature vector of the corresponding mammogram. We consider the image size is 576 × 576 (i.e. 331776 coefficients).

The following diagram shows the Horizontal, Vertical and Diagonal Details of the Input Image.

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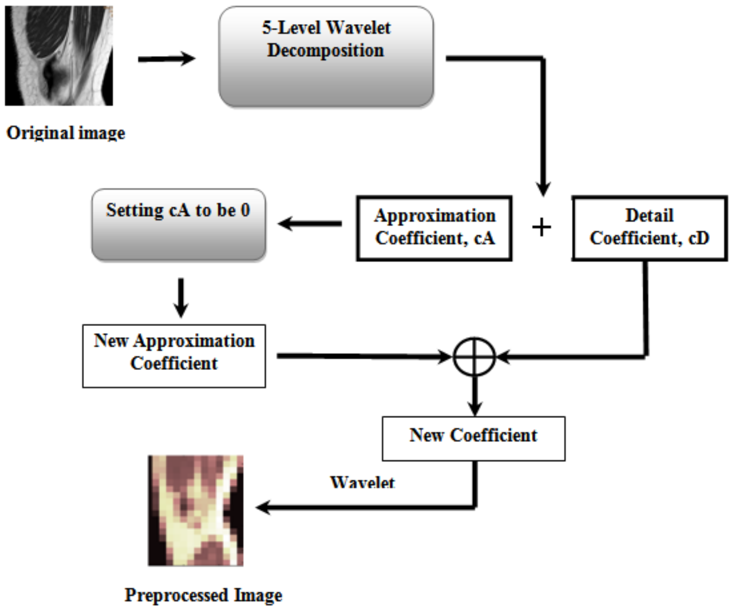


**Fig. 3:** Proposed System Architecture

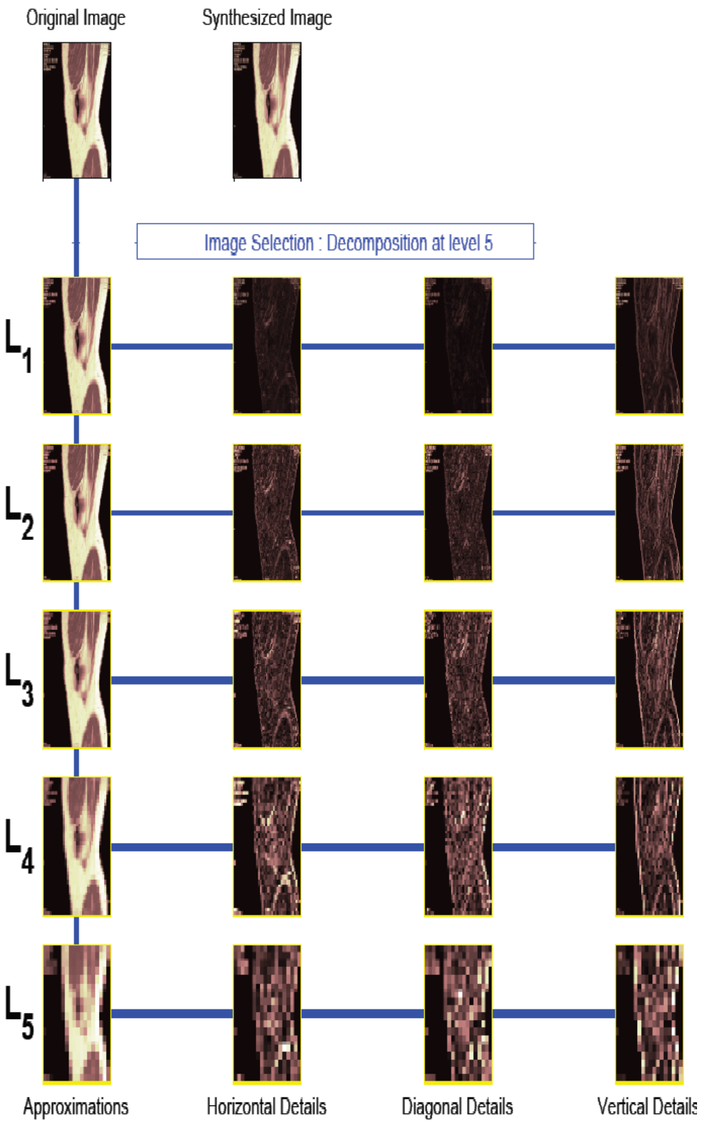


**Fig. 4:** Horizontal, Vertical and Diagonal Details of the Input Image

The following snapshot shows the modified decomposition at level 5,

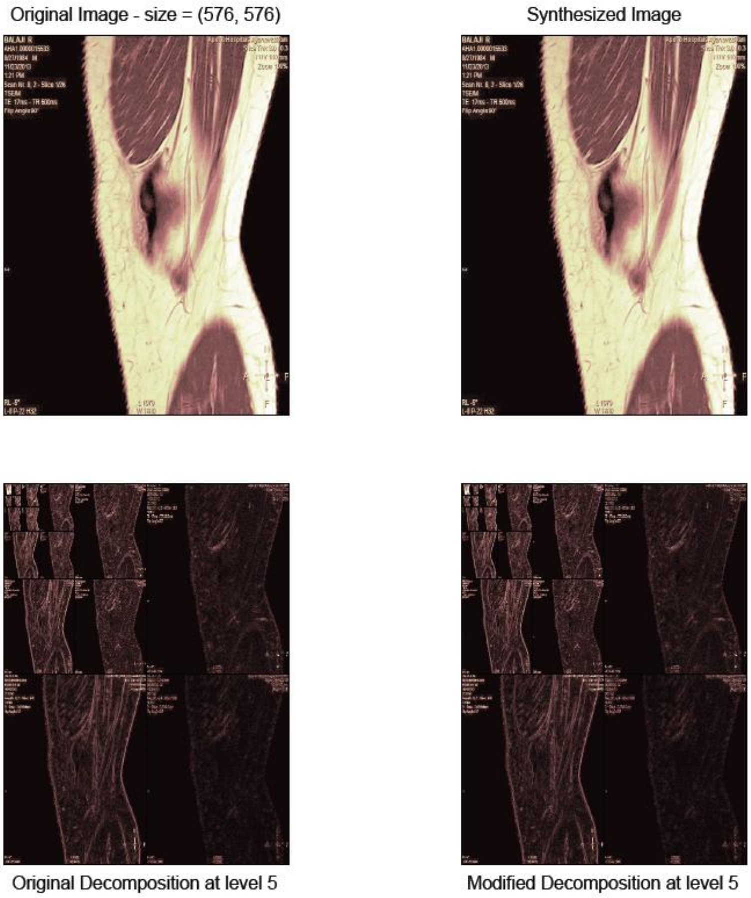


**Fig. 5:** Modified Decomposition of Original Image at level 5

histogram and cumulative histogram of it. In this paper, approximation coefficient has tested from level 1 to level 5. It is described in the figure 7.

The following snapshot (i.e. figure 6) shows the bone image is analyzed at level 1 with approximation coefficients. And also describes corresponding

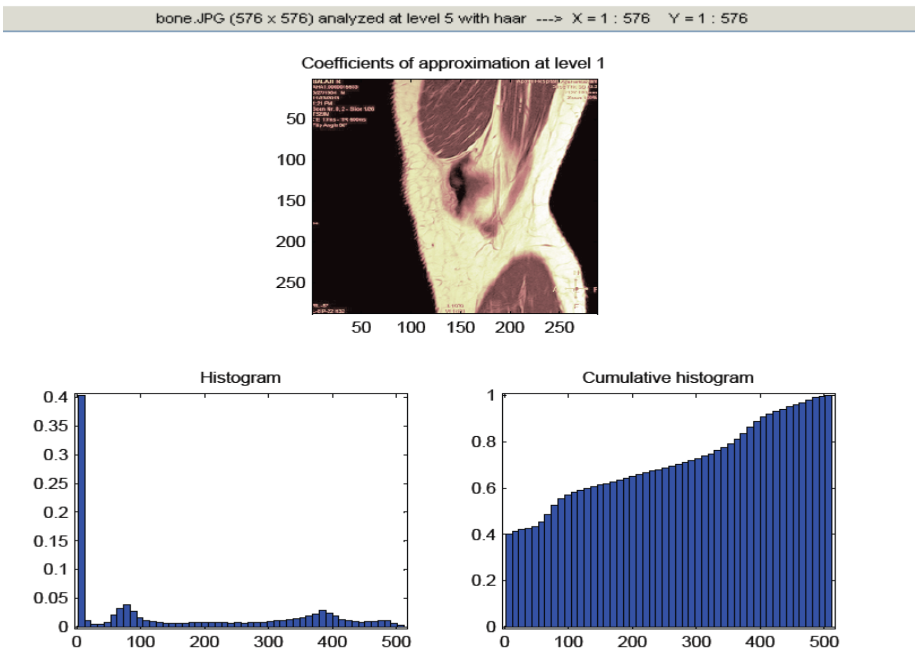


**Fig. 6:** Approximation Coefficient and its Cumulative Histogram

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The following figure shows the approximation coefficient of bone image with level 2 – level 5.

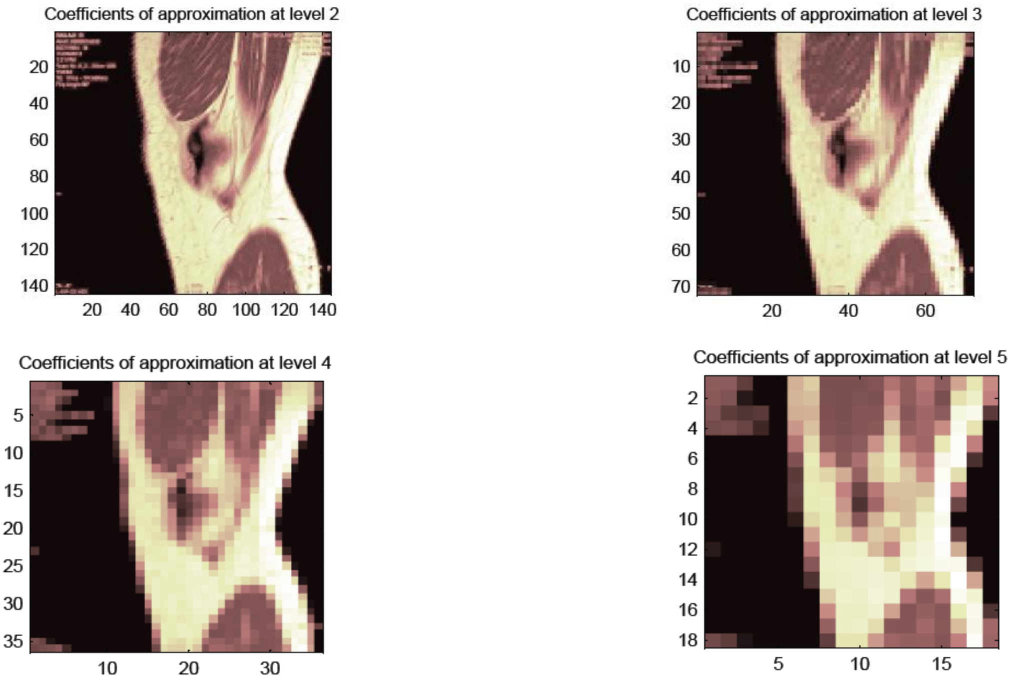


**Fig. 7:** Approximation Coefficient of bone image at Level 2-5.

The following snapshot (i.e. figure 8) shows the approximation reconstructed of bone image with level 1, level 4 and level 5.

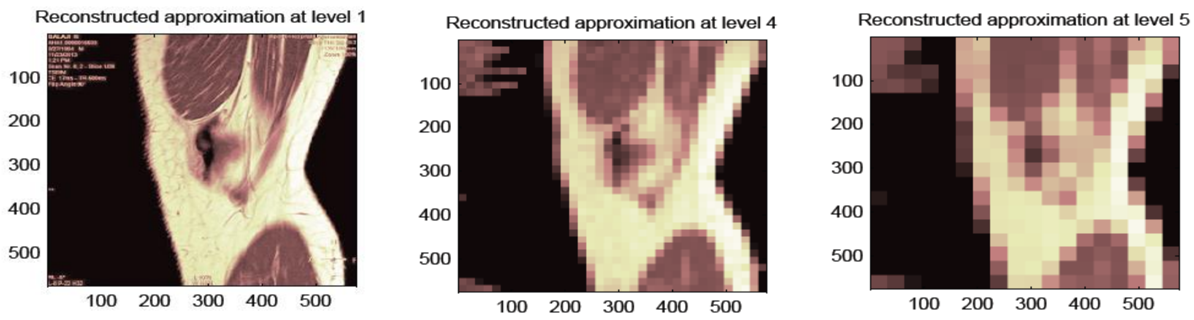


**Fig. 8:** Approximation Reconstructed of bone image at Level 1, 4, 5.

***Conclusion And Future Enhancements:***

Wavelets provide stable and efficient representation of images. In this study, a MRI scan bone image is used. Firstly, bone image is decomposed using wavelet functions, and then a set of coefficients is extracted from each decomposition level. The experimental results show that, the extracted features based on approximation (low frequency) give a better performance than details (high frequency). In this paper, the differences between wavelet subbands (approximation and details) are studied but only approximation is practically implemented. The detail and de-noised (i.e. hard and soft and also unscaled and white noise) will be studied in future.

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