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Original Research Article

Daubechies wavelets based Texture Analysis of HCC using Computed Tomography Images

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Abstract: The aim of this work to classification of regions in CT Abdomen where we define the hepatocellular carcinoma, liver, spine and ribs, the features of the classified regions of the whole images (as raw data) were classified furthers using linear discriminate analysis. The result of the classification showed that the HCC areas were classified well from the rest of the tissues although it has characteristics mostly similar to surrounding tissue. Several texture features are introduced using Daubechies wavelet, The Daubechies wavelet measures the gray level variations in a CT images, and it complements the coefficient of Daubechies wavelet Features extracted from the coefficient can be used to estimate the size distribution of the sub patterns. The Daubechies wavelet and its features seem very useful in texture classification. The classification accuracy of hepatocellular carcinoma 97.1 %, liver accuracy 91.7 %, While the spine and ribs showed a classification accuracy of 97.1, 91.2 % respectively.
Keywords: Daubechies wavelets, HCC, Computed Tomography, Wavelet Transform.

INTRODUCTION:

The most familiar medical imaging studies for early identification of liver diseases comprise ultrasonography (US), computed tomography (CT), magnetic resonance imaging (MRI). CT is often the preferred method for diagnosing many different cancers than ultrasonography, since the image allows a physician to confirm the presence of a tumor and to measure its size, precise location and the extent of the tumor's involvement with other nearby tissue. Despite the excellence of CT images has been appreciably improved during the last years, it is hard in some cases, even for experienced doctors, to make a 100% precise diagnosis. In radiology computer-aided diagnosis (CAD) are procedures in medicine that help doctors in the analysis of medical images.

In clinical practice, when dynamic CT of the liver is performed, three image series are usually acquired: the first one – before the contrast agent injection, the next two ones – after its injection, at arterial and at portal phase of its propagation [1]. The two post-injection acquisition moments correspond, respectively, to the maximal concentration of contrast agent that reaches the liver first via the hepatic artery, next – via the portal vein. The arterial phase starts after about 25-35 seconds after the intravenous injection of contrast agent, the portal one – after about 60-70 seconds. In some cases, a fourth – delayed hepatic phase is considered [2]. It takes place after about 5 -10 minutes succeeding the injection. Each of the three (or even four) images enhances a different tissue property that could reveal a development of pathology. In the case of the liver CT – it can be excessive or insufficient growth of the arterial or of the portal vascular tree. After injection of the contrast agent, the high vascularization regions are more enhanced than those with normal vasculature, and less vascularized regions appear darker. The presence of contrast agent in hepatic vessels results also in changes of texture properties, imperceptible to the naked eye.

Hepatocellular Carcinoma (HCC), the most common primary liver tumor, accounts for 85-90% of primary liver cancer. It is the third most common cause of cancer death and the fifth most common cancer worldwide.

The traditional methods to differentiate normal liver tissues from abnormal ones are largely depending on the radiologist experience. Thus Computer-Aided Diagnosis (CAD) systems based on image processing and artificial intelligence techniques have aroused a lot of interest, since they can provide constructive diagnosis suggestions to clinicians for decision-making [3].

Only seldom physicians use 3 phasic CT images for detecting HCC tumor in the liver. The first series of CT scanning is performed during the arterial phase, which takes place 20 to 30 seconds after the injection of the contrast agent. This is the time period when the majority of the contrast agent is flowing through the hepatic artery. The second series of CT scanning is taken from 60 to 70 seconds after the initiation of the infusion, when the majority of the contrast agent is flowing through the hepatic portal vein. This set of CT is defined as the portal-venous phase (PVP). A third scanning is often performed during the equilibrium phase (10– 20 minutes after the infusion) when the contrast agent is equally concentrated in the hepatic artery and portal vein.

In general, HCC diagnosis is based on noninvasive imaging tests [4,5]. In patients with cirrhosis and a focal hepatic lesion = 2 cm, the diagnosis may be confidently established on the basis of typical imaging features showing areas of arterial enhancement and regions promptly “washed out” (fainter than the liver tissue) in the venous or delayed phase of four-phase multidetector computed tomography (CT) exam (where the four phases are unenhanced, arterial, venous, and delayed) [4, 6].

Wavelet and Wavelet Transform:

The main idea of this approach consists in the observation that pixels belonging to one element of the object can possess similar properties for example, the gray value. Further, wavelet transforms surface rapidly in various regions, such as telecommunications, radar target recognition, and texture image classification [7]. The main advantage of wavelets is that they have a varied window size, which can be wide for slow frequencies and narrow for the fast ones, thus resulting in optimal time-frequency resolution in all frequency ranges [8]. Discrete wavelet packet analysis is an extension of the discrete wavelet trans forms, and discrete wavelet packet transform (DWPT) al lows both detailed and approximate results to be decom posed further.

A wavelet transform is the representation of a function by wavelets, and it is a generalization of the classical wavelet tree decomposition, providing an effective representation of the time frequency properties [9].

Recently, wavelet transforms rapidly emerged in such various fields as telecommunications, radar target recognition, and texture image classification [10]. The main advantage of wavelets is that they have a varied window size, which can be wide for slow frequencies and narrow for the fast ones, thus resulting in optimal time-frequency resolution in all frequency ranges [11]. Furthermore, owing to the fact that windows are adapted to the transients of each scale, wavelets lack the requirement of stationary [10].

Traditionally, discrete wavelet transform only recursively decomposes the low frequency band, but some high-frequencies are worth it to decompose for getting more information. Discrete wavelet packet analysis is an extension of the discrete wavelet transforms, and discrete wavelet packet transform (DWPT) allows both detailed and approximate results to be decomposed further, which can use a low-pass filters collection and high-pass filters collection to decompose the coefficient of detailed results.

Thus, the detailed sub-bands can be further decomposed. The advantage of wavelet packet analysis is that it can possibly combine the different levels of decomposition in order to achieve the optimum time-frequency representation of the original [11].

In less than 20 years, wavelets have risen from a research curiosity to a standard signal processing tool in engineering and applied mathematics. While the mathematical foundations of wavelets and multiresolution analysis were laid down by Mallat and Meyer [12], [13], Daubechies had a lasting impact on the field with her construction of the first family of compactly supported, orthogonal wavelet bases of L2 (R) [14]. Owing to their remarkable properties and ease of implementation, the Daubechies wavelets became popular right away and led to a multitude of successful signal processing applications, such as compression, denoising, classification, or fusion, especially during the wavelet rush that took place in the 1990s.

A good part of the success of wavelets is due to their fundamental vanishing moment property or, equivalently, the ability of the scaling functions to reproduce polynomials. Indeed, the special way in which the basic functions interact with polynomials is the crucial ingredient that endows wavelets with their good approximation properties for signals in Sobolev and/orBesov spaces; in particular, it explains why piecewise smooth signals tend to have sparse wavelet expansions. This observation applies particularly well to the field of image processing, where wavelets have had (and are still having) a profound impact. In this paper, we construct generalized wavelet bases that can be tuned to wider classes of signals, e.g., with multiple narrow bands or exponential trends. Still, we will retain the user-friendly properties of Daubechies wavelets; namely, compact support and othonormality (or biorthogonality if one also wants to include symmetry). Our starting point is the constraint that the scaling functions should reproduce a predefined set of exponential polynomials that is, functions of the form P (t) $e^{\alpha t}$ where a polynomial is and is a complex parameter. For the aforementioned signal types, exponential polynomials ensure approximation properties that are comparable to those provided by standard polynomials for slowly varying signals.

Illustration

Our derivations have concrete implications for discrete signal processing, as illustrated in Fig. 1. We compare discrete orthonormal wavelet transforms of a signal made of two distinct frequency components. Classical 8-tap Daubechies filters were used in Fig. 1(a). We observe that a significant part of the energy is contained in the wavelet sub bands, because the scaling filters are not suitable for the representation of pure sinusoids.

For Fig. 1(b), the filters (of the same length) were adapted to the input signal, so that it gets transferred entirely in the scaling function sub bands. From a practical standpoint, the only difference between (a) and (b) is that the latter uses scale-dependent filters. This shows that tuning our generalized wavelet bases to the class of signals to be decomposed can yield sparser representations than classical wavelets, at strictly the same computational cost.

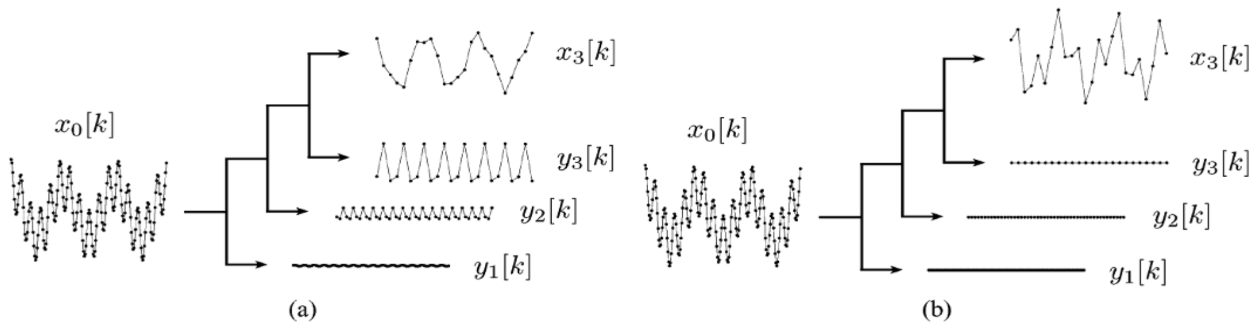


Fig. 1. Three-level discrete orthonormal wavelet transforms of a signal with two harmonic components ($x_0[k] = \cos(k\pi/32) + \cos(k\pi/6)$). The wavelet coefficients are $y_1[k]$, $y_2[k]$, and $y_3[k]$; $x_3[k]$ contains the scaling function coefficients at the coarsest level. (a) Using 8-tap Daubechies filters (corresponding to $\vec{\alpha} = [0\ 0\ 0\ 0]$ in Section IV-B). (b) Using scale-dependent 8-tap generalized Daubechies filters (corresponding to $\vec{\alpha} = [i\pi/32\quad i\pi/32\ i\pi/6\quad i\pi/6]$).

RESULTS AND DISCUSSION:

In this paper there were features extracted from Hepatocellular Carcinoma (HCC) CT images using Daubechies wavelets based on Texture Analysis. And this features showed significant correlation with the predefined classes (HCC, Liver, Spine and Ribs).

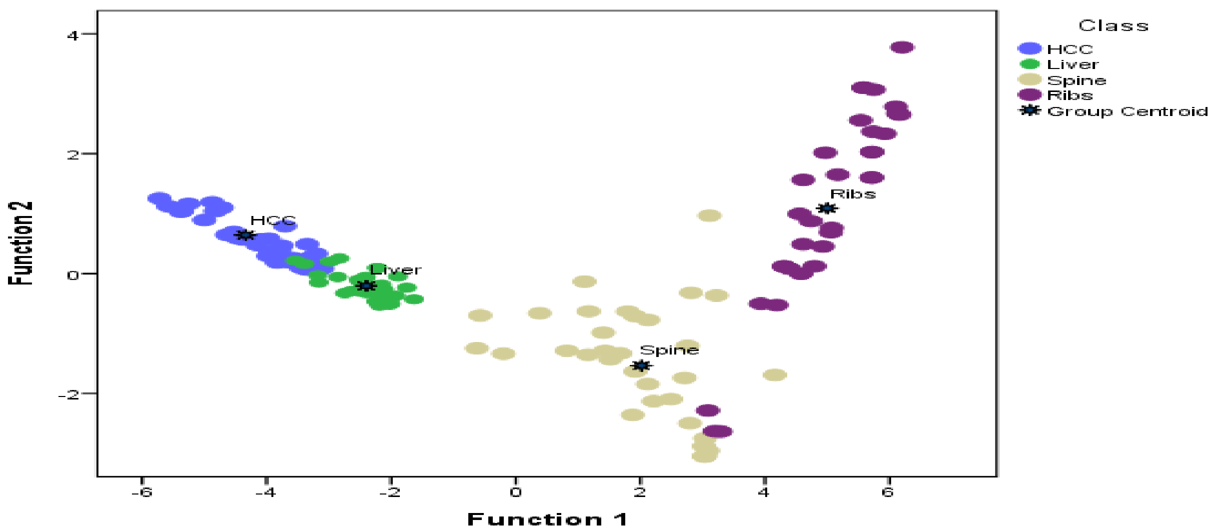
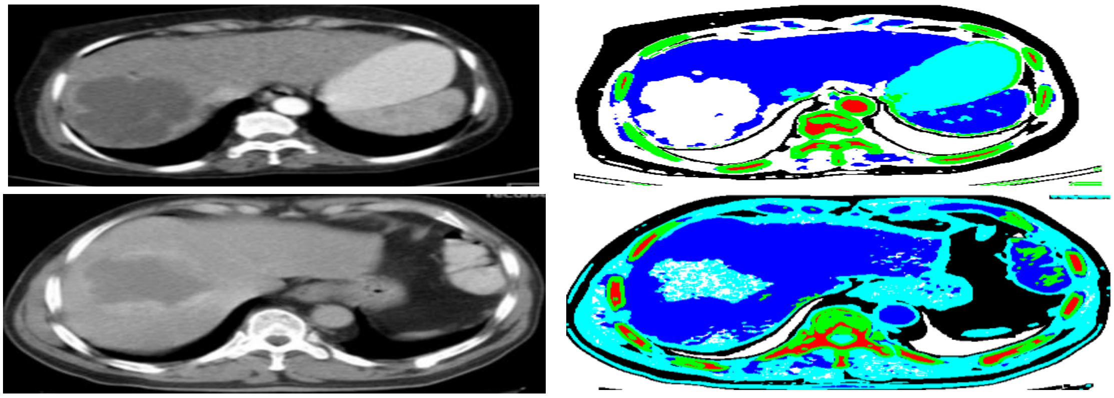


Fig 2: show Scatter plot generated using discriminante analysis function for four classes represents: HCC, Liver, Spine and Ribs.

To classify the hepatocellular carcinoma, liver, spine and ribs the features of the classified regions of the whole images (as raw data) were classified furthers using linear discriminate analysis. The result of the classification showed that the HCC areas were classified well from the rest of the tissues although it has characteristics mostly similar to surrounding tissue.



(A) **(B)**

Fig (3) CT images image (A) and classification map (B), the original image (A) classified to (B) color map demonstrate the liver lesion.

Table 1: Showed the classification accuracy of the HCC using linear discriminant analysis:

Classes		**Predicted Group Membership**				**Total**
		HCC	**Liver**	**Spine**	**Ribs**	
Original	HCC	**97.1**	2.9	.0	.0	100.0
	Liver	8.3	**91.7**	.0	.0	100.0
	Spine	2.9	.0	**97.1**	.0	100.0
	Ribs	.0	.0	8.8	**91.2**	100.0

94.2% of original grouped cases correctly classified

Table (1) show classification score matrix generated by linear discriminante analysis and classification accuracy of 94.2%. The classification accuracy of hepatocellular carcinoma 97.1 %, liver accuracy 91.7 %, While the spine and ribs showed a classification accuracy of 97.1, 91.2 % respectively.

CONCLUSION:

The classification of regions in CT Abdomen we define the hepatocellular carcinoma, liver, spine and ribs and the features of the classified regions of the whole images (as raw data) were classified furthers using linear discriminate analysis. The result of the classification showed that the HCC areas were classified well from the rest of the tissues although it has characteristics mostly similar to surrounding tissue.

Several texture features are introduced using Daubechies wavelet. The Daubechies wavelet measures the gray level variations in an image. It complements the coefficient of Daubechies wavelet Features extracted from the coefficient can be used to estimate the size distribution of the sub patterns. The Daubechies wavelet and its features seem very useful in texture classification.

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