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## Bone segmentation in computed tomography images using a Hermite-based approach

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Abstract. Computed tomography images of the human bone system are essential for evaluation of abnormalities and disease detection. Structural and anatomical information can be assessed with computer tomography with the aim of performing diagnosis, planning and treatment evolution. Automatic segmentation can provide a fast, objective evaluation and quantification of the bone conditions. In this work, we propose a segmentation technique consisting of a region growing method implemented in the Hermite transform domain. The Hermite transform provides a powerful mathematical tool which is useful for extraction of the image features. These are obtained through a set of Hermite coefficients. A seed or a pre-segmentation is used to initialize the region growing approach and coefficients of the Hermite transform are posteriorly employed to grow the initial shape. We have used Hermite coefficients up to second order. Edge, gray level and zero crossing information obtained with the Hermite transform are configured for the growing criterion. Several computer tomography images were used for evaluation. Different metrics were employed for performance assessment and we have compared results of the proposed method against the manual segmentation. The obtained results demonstrate that the HT substantially improves the texture classification which is directly reflected into a better segmentation of the bone tissues. The region growing algorithm presents a better performance if it is applied to Hermite coefficients compared to the original method which is performed on the original image space.

#### 1. Introduction

In the last years, medical images have been essential in the evaluation and clinical diagnosis of many diseases [1,2]. Anatomical studies are commonly employed for operation planning, visualization of different data from the body, and also for therapy [3]. These anatomical structures can be visualized using imaging technique such as computed tomography (CT) which is a technique frequently used in the assess of bones. This application has taken great importance to characterize lesions and diagnosis of some illness such as bone metastases. A computer-aided diagnosis system might allow the analysis of bone features and detection of some anomalies [4]. Robust segmentation techniques are commonly used as a first step in the diagnosis task. However, the challenge here is to obtain a correct segmentation which in some way might improve the diagnosis and give significantly information of the bones condition. In the literature, different approaches have been reported for bone segmentation [5-9]. Many of them are based on finite element analysis [5], statistical shape models, non-rigid registration, and others [6-9].

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In this work, we present a semiautomatic segmentation model applied to the analysis of the column and bone structures obtained from CT data. The approach uses the Hermite transform and a region growing technique which is applied in the HT transform domain.

#### 2. Methodology

The general scheme of the proposed method is shown in Figure 1. This technique combines a Hermite transform for coding different texture in the CT image and a region growing method for bone segmentation.

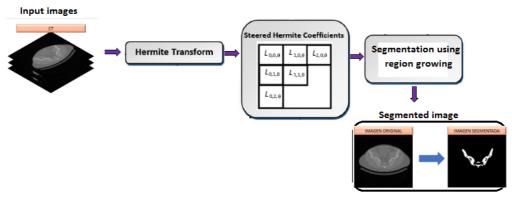


Figure 1. General diagram of the proposed method.

Details and descriptions of the propose approach, including the mathematical background and requirements, are exposed in the following sections. As mentioned, the segmentation process consists of a decomposition-based method using the Hermite transform combined with a region growing scheme. Firstly, an initial point or seed is needed. Here, the rest of pixels are classified using information from the neighborhood of that point which is evaluated on each Hermite coefficient. The approach works iteratively until reaching a stable condition which results in the segmented structure. Basically, the method consists of two parts: 1) The Hermite transform is computed from CT images, 2) The growing region technique is applied to each Hermite coefficient.

#### 2.1. The Hermite transform

The Hermite transform is a mathematical tool which has been used for coding image textures in medical applications. The coefficients of the HT can provide information regarding to intensity values, edges and zero-crossing. The HT allows to obtain the decomposition of a function l(x, y) as shown Equation (1).

$$L_{m,n-m}(p,q) = \iint_{-\infty}^{\infty} l(x,y) P_{m,n-m}(x-p,y-q) V^{2}(x-p,y-q) dxdy,$$
(1)

where  $V(x, y) = \frac{1}{(\sigma\sqrt{\pi})^2} e^{-(x^2+y^2)/\sigma^2}$  is the Gaussian function and  $P_n(x, y) = \frac{1}{\sqrt{2^n n!}} H_m(x/\sigma) H_{n-m}(y/\sigma)$  are the normalized polynomials [10-12]. These filters can also be described using Gaussian derivative operators which are expressed in Equation (2).

$$O_{m,n-m}(x,y) = \frac{1}{\sqrt{2^n(n-m)m!}} \left[ \frac{d^m}{d\left(\frac{x}{\sigma}\right)^m} \frac{d^{n-m}}{d\left(\frac{y}{\sigma}\right)^{n-m}} V^2(x,y) \right].$$
(2)

Figure 2 presents the HT coefficients up to order 2 applied to CT image. We employed the Hermite coefficients until second order  $(L_{00}, L_{10}, L_{20})$ . Each coefficient is able to extract a different image

point until segmenting the bone structure.

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feature. The goal is to use the texture features obtained from the Hermite coefficients to grow the seed

Figure 2. Hermite coefficients up to second order applied to a CT image.

#### 2.2. Region growing

The classification criterion is based on the pixel homogeneity using the coefficients of the HT. The evaluated pixels are classified depending on the degree of similarity or homogeneity of a region on each coefficient. For this purpose, we used the criteria given by Equation (3).

$$C(p,q,r) = L_{m,n-m}(p,q) - L_{m,n-m}(p^{r},q^{r}),$$
(3)

where  $L_{m,n-m}(p,q)$  represents the Hermite coefficient value at point (p,q), and  $L_{m,n-m}(p^r,q^r)$  corresponds to the average value computed from the neighborhood of that point. The method is iterated until the growing process is stopped.

#### 3. Results

The obtained result using an image example obtained from our database can be observed in Figure 3. Here, we illustrate the result obtained with the classical region growing method implemented in the original image space, and the result with the proposed approach using the HT combine with region growing. The performance using the classical region growing presents an adequate convergence in the bone edge due to the contrast in this part. However, the performance reached inside the bone region is poor and limited. The result with the proposed method illustrates that much of the mentioned

(a)

deficiencies are corrected. It is consequence of using several texture features, provided by the HT, to in the growing criteria.

Figure 3. Segmentation results. (a) Original image, (b) result obtained using the classical region growing method implemented in the original image space, (c) result using k-means, (d) result obtained with the proposed method.

Figure 4 shows other image result of the segmentation obtained with the proposed method. It can be noted how the bone structure has been efficiently extracted.

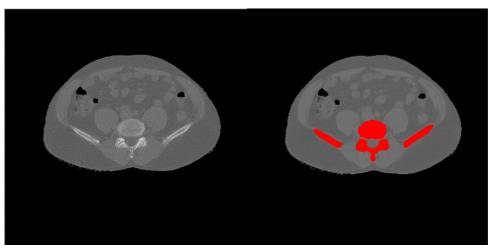


Figure 4. Segmentation result using HT and region growing.

For the quantitative evaluation, we calculated the point to curve distance between the expert segmentation and the segmentation with the proposed method. We compared the classical region growing algorithm with the proposed approach. Table 1 presents the obtained results for two patients. We computed the results for all images of the complete CT study and average (avg) the results for each patient. The standard deviation (std) is also reported for each case.

Patients	Number of	Classical region growing	k-means clustering technique	The HT with region growing
	images	$(avg \pm std)$	$(avg \pm std)$	$(avg \pm std)$
1	15	$9.28\pm4.10$	$11.15 \pm 5.06$	$2.60 \pm 1.43$
2	20	$6.05\pm3.22$	$8.64\pm3.91$	$2.18\pm2.12$

Table 1. Average point to curve distance (pixels) of the CT database

#### 4. Discussion

Segmentation of bone tissues in CT images is not an easy task. Some image features of the bone region are very similar to other regions of the image representing other type of tissues. Processing the image by using the original image space might result inconvenient since all texture information is not explicit. Point to curve distance, measured in pixels, has been used as evaluation metric. As reference for comparison, the expert segmentation has been considered. From the results reported in Table 1, we can see how the segmentation process is substantially improves when using coefficients obtained with the HT, obviously compared to the original region growing method. The ability of this transformation to decode different image texture helps the method to find more similar pattern inside the bone structure. The average and the standard deviation findings reveal the good performance obtained with the proposed framework.

Qualitative evaluation can be also analyzed from the results in Figure 3. It can be seen that the bone tissues are better extracted using the Hermite-based region growing method. A high number of pixels inside the bone region are missing during classification with the original method. The reason is that using the intensity feature as the only growing criteria fails in classifying the complete region. The same reasoning can be extended to the results obtained with the k-means method. Our main finding here is that the HT results advantageous to improve the segmentation performance since different image features are taken into account for pixels classification.

#### 5. Conclusions

In this work, we have designed a segmentation method based on the Hermite transform and a region growing approach for shape segmentation of bone structures in CT images. The implementation of the region growing scheme in the domain of the HT become advantages since several image features can be analyzed which improves the segmentation process. The obtained results demonstrate that the HT can improve the texture classification of the bone tissues which is directly reflected in a better segmentation. Moreover, images are better characterized if we project the data in the space provided by the Hermite transform. Although the method has been tested using CT bone images, as future work, it can be extended to other applications.

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