Texture Indexing by a Hierarchical Representation

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Abstract. In this paper, a Hierarchical Entropy based Representation for texture indexing *HERTI* is presented. The hypothesis is that any texture can be efficaciously represented by means of a 1-D signal obtained by a *characteristic curve* covering a square (uniform under a given criterion and a given segmentation) region. Starting from such a signal, *HER* can be then efficaciously applied, taking into account of its generality, for image retrieval by content. Moreover, a Spatial Access Method (SAM), i.e. k-d-Tree, has been utilized in order to improve the search performances. The results obtained on some databases show that *HERTI* achieves very good performances with few false alarms and dismissals.

Keywords: Content Based Retrieval, Entropy, Textures, k-d-Tree.

1 Introduction

In the last years, in a growing number of applications, images constitute the main kind of data to be acquired and processed. In medicine, for instance, the possibility of producing databases containing images relative to clinical cases is fundamental as support to make decisions [1]. In particular, a lot of attention has been devoted to efficacious representations to obtain an approximated retrieval by content[2,3]. So, many techniques are devoted to describe shapes and, more in general, objects contained in a pictorial scene as signals [6,11], while other techniques are oriented to analyze textures, color and other features of interest for a specific case [1].

In this paper we are interested in studying the second class, and in particular, to deal with images containing textures. It's well known, in fact, that there are many fields (medicine, cultural heritage and so on) where an efficient analysis of the textures is of great importance to characterize the knowledge

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contained in the images. On the other hand, *HER* (Hierarchical Entropy based Representation), which is a very useful representation for 1-D signals [4,5], has been successfully used for the features extraction, achieving very promising results. So, the aim of this paper is to combine these two aspects in order to attain an efficacious retrieval on texture-based images. This leads us to define a characteristic curve, as explained in detail in Section 2, which allows us to see an intrinsic 2-D problem — the texture characterization — by means of a 1-D representation able to be processed by *HER*. In the following we'll denote this technique by *HERTI* (*HER* for Textures Indexing). The results obtained, performing *HERTI* on many databases seems to be very promising, with a significant performance improvement over other techniques.

The rest of the paper is organized as follows. A short review about *HER*'s theoretical formulation is presented in the first part of Section 2, where it is outlined the link between a given 1-D signal and its *HER*. The problem of describing the micro structure of a given texture as 1-D problem constitutes the topic of the second part of Section 2. In Section 3, the experimental results are presented, providing to test *HERTI* performances in terms of the *Normalized Recall*, well-known in literature. Finally, Section 4 gives the conclusions.

2 A Hierarchical Representation

In this section we give some details about *HER* (Hierarchical Entropy based Representation) which is a useful representation to represent a given signal [4, 5]. The underlying idea of this representation is to obtain a subset of the 1-D signal samples (that is its local maxima), and the associated energy.

Looking at this representation, two interesting aspects go on:

- the first one is its generality, so that it can be used whereas a 1-D problem is required;
- the second one is its ability to efficaciously describe a signal using few coefficients. In other words, it is so strongly hierarchical since it provides to renstitute the energy distribution of the signal under study with respect to the maxima.

Such a representation has been utilized to describe textures in a very particular way, and this will be described in the next Section after a short review about some fundamentals theoretical concepts of *HER*.

2.1 A Review about *HER*

Starting from a mono dimensional, time-discrete and finite signal $x(n)$ (i.e. $x(n) \neq 0$ for $n \in [0, N-1]$), the absolute maximum can be define as follows:

$$max = \begin{cases} x(i) & \Delta_{i+1} - \Delta_i < 0 \\ x(i_{min} + \frac{i_{max}-i_{min}}{2}) & \Delta_i = 0 \quad i \in [i_{min}+1, i_{max}] \\ & i_{max} - i_{min} \quad even \\ x(i_{min} + \lfloor \frac{i_{max}-i_{min}}{2} \rfloor) & \Delta_i = 0 \quad i \in [i_{min}+1, i_{max}], \\ & i_{max} - i_{min} \quad odd \end{cases} \tag{1}$$

where the operator Δ_i is:

$$\Delta_i = x(i) - x(i-1). \tag{2}$$

Now, we can consider the gaussian function having x_i as maximum and standard deviation $\sigma(x(i))$:

$$\sigma(x(i)) = \frac{1}{\sqrt{2\pi[E_r(x(i))]^{1/2}}}. \tag{3}$$

where:

$$E_r(x(i)) = (\frac{E(x(i))}{E - E(x(i))})E(x(i)) \tag{4}$$

is the relative energy, i.e. weighted by the total energy of the signal:

$$E = \sum_{i=0}^{N-1} |x(i)|^2. \tag{5}$$

The introduction of the foregoing gaussian function allows us to define the entropy associated to x_i:

$$S(x(i)) = \sum_{j=i+\sigma(x(i))}^{i-\sigma(x(i))} |x(j)|. \tag{6}$$

which can be interpreted as a sort of energy of the signal x in the range $R = [i - \sigma(x(i)), i + \sigma(x(i))]$ (see Fig. 1).

When the signal has k maxima, we can define the entropy of whole signal as:

$$S = \sum_{i=1}^{k} S(x(i)). \tag{7}$$

Starting from the array containing the x's (k) maxima:

$$\hat{x} \quad \equiv \quad \{x_1, .., x_k\} \quad : \quad x_1 \geq x_2 \geq ..... \geq x_k \tag{8}$$

the signal y is built as follows:

$$y = \bigcup_{i_j=i_1}^{i_k} \mathbf{T}(\overline{R_{i_j}})G_{i_j}(\overline{R_{i_j}}). \tag{9}$$

where

$$G_{i_j}(\overline{R_{i_j}}) = S_{i_j}\Big|_{\overline{R_{i_j}}} \tag{10}$$

$$\overline{R_{i_j}} = R_{i_j} - (R_{i_j} \cap \bigcup_{t<j} R_{i_t}) \tag{11}$$

$$\mathbf{T}(X) = \begin{cases} 1 & x \in X \\ 0 & \text{otherwise} \end{cases} \tag{12}$$

y is uniquely determined by the first $2k$ elements of the array $\hat{y}$:

$$\hat{y} = \underbrace{\overbrace{i_1, G_{i_1}(\overline{R_{i_1}}), \cdots, i_k, G_{i_k}(\overline{R_{i_k}})}^{2k}, 0, \cdots, 0}_{N}. \tag{13}$$

and this latter represents the *HER* (Hierarchical Entropy Representation) of the signal x.

In order to compare two given signals x_1, x_2, we can utilize the Euclidean distance between the corresponding signals y_1, y_2, or, equivalently between the arrays $\hat{y_1}$ e $\hat{y_2}$, computed as follows:

$$D(\hat{y_1}, \hat{y_2}) = \sum_{i=0}^{N_1} |\hat{y}_1^{(i)} - \hat{y}_2^{(i)}|, \tag{14}$$

where N_1 is the maximum between the numbers of the representative coefficients of two arrays $\hat{y_1}, \hat{y_2}$. In practice, in all problems we applied *HER*, N_1 was very low.

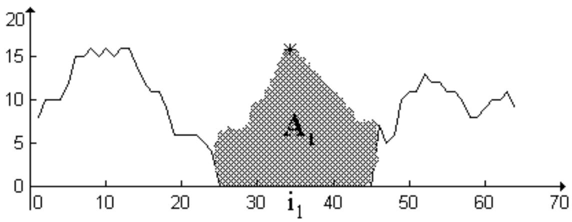

Fig. 1. For a given signal, the location of the (absolute) maximum and the relative area constitute the first two coefficients for *HER*.

Two immediate properties are:

- The distance D between a given signal and itself is obviously equal to zero.
- Any phase change for a signal does not change its *HER* (invariance to a signal phase change).

Finally, it is to be outlined that *HER* doesn't tend to the input signal, in the sense that we selected only the maxima of the signal, and then even if $\sigma = 0$ we should have the input signal sampled by its maxima. On the contrary, selecting all the points of the signal and defining the instantaneous energy density as follows:

$$\rho_{E(n)} = \frac{\sum_{n=n-\Delta}^{n+\Delta} s(n)}{2\Delta} \tag{15}$$

we have that:

$$lim_{\Delta/2 \to 1/2} \quad \rho_{E(n)} \to^{l_2} s(n). \tag{16}$$

Nonetheless, the maxima choice gives a good representation of the energy distribution.

HER has been utilized for many applications where the underlying problems required a 1-D representation. Now the problem is how to utilize this representation to describe a texture. In other words, how to obtain a 1-D representation from an intrinsic 2-D problem like the texture analysis. This will be the topic of the next Section.

3 Our Proposal

Starting from the foregoing representation, we can see now how to apply it to the textures.

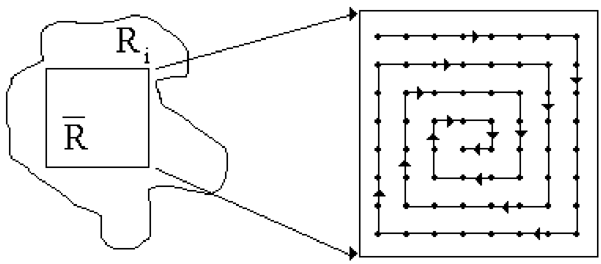

Fig. 2. The spiral covering a squared region.

Suppose that we have an image Ω with its segmentation obtained at a given scale level. Of course, we'll have a given number of subregions R_i such that:

$$\bigcup_i R_i \equiv \Omega \quad and \quad R_i \cap R_j = 0. \tag{17}$$

It's obvious that, starting from this segmentation, it is possible to study the micro structure of any R_i looking at its information. So, for a given region (of interest) $\hat{R}_i$ we can always determine a subdomain having any shape. In this paper we selected a squared region $\overline{R}$:

$$\overline{R} \quad : \quad l \cdot l = |\overline{R}| \tag{18}$$

where l is the size of $\overline{R}$, such that

$$\overline{R} \subseteq R_i. \tag{19}$$

Starting from $\overline{R}$, we now look for a curve γ representative of it, so that *HER* can be applied. Our proposal consists in a *spiral* covering the whole region, as shown in Fig. 2. In other words we have obtained in this way a 1-D signal too, to be utilized using the results of the previous Section.

4 Experimental Results

HERTI's performances have been tested implementing it on a PC 233 MHz using MATLAB under WINDOWS 98 operating system. In this case, even if the 1-D signal obtained using the technique explained in the foregoing Section is quite complicate, we have fixed the number of the maxima for *HER* at 4. As in many other applications, a fixed number of maxima allows us to utilize *k-d-Tree* as spatial access structures. In fact, as well-known in literature, it performs better than the sequential search leading to a very low computational time [7,8,9,10, 12,13].

In order to give objective measures of the obtained results, we utilize the following valuation criteria usually used for testing a retrieval system:

The *Recall*: the system ability in retrieving all relevant time-series;

The *Precision*: the system ability in retrieving only relevant time-series.

In literature we can find also the *Normalized Recall* (*NR*), see [3], which can be defined as follows. Starting from a set of time-series, where the number of the relevant ones is REL. Now, if *Ideal Rank* and *Average Rank* are defined as follows:

$$IR = \frac{\sum_{r=1}^{REL} r}{REL}, \tag{20}$$

$$AR = \frac{\sum_{r=1}^{REL} RANK_r}{REL} \tag{21}$$

the difference AR-IR, gives a measure of the effectiveness of the system, and it can be normalized, in order to range between 0 and 1, in this way:

$$NR = 1 - \frac{AR - IR}{TOT - REL}. \tag{22}$$

The images composing our database are $50 \times 50 \times 8$ bits and relative to single cells of liver (sound and cyrrotic), extracted from images acquired by an

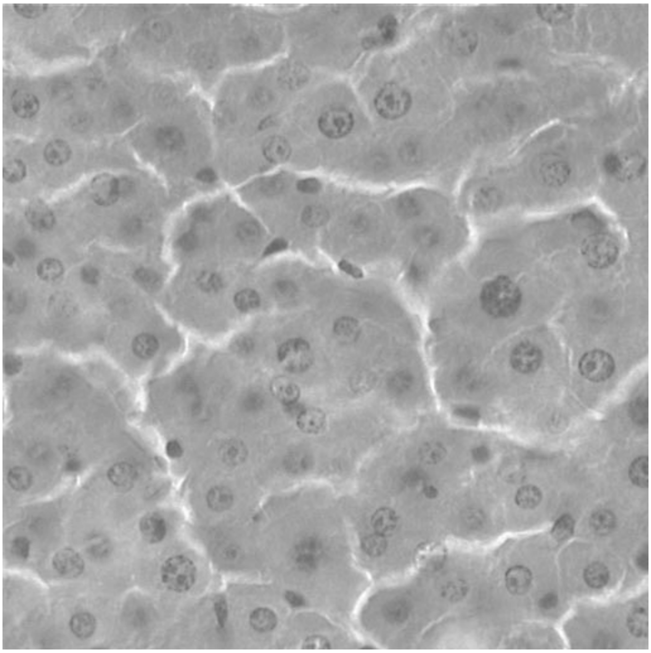

Fig. 3. 512 × 512 × 8 bits: An example of normal liver.

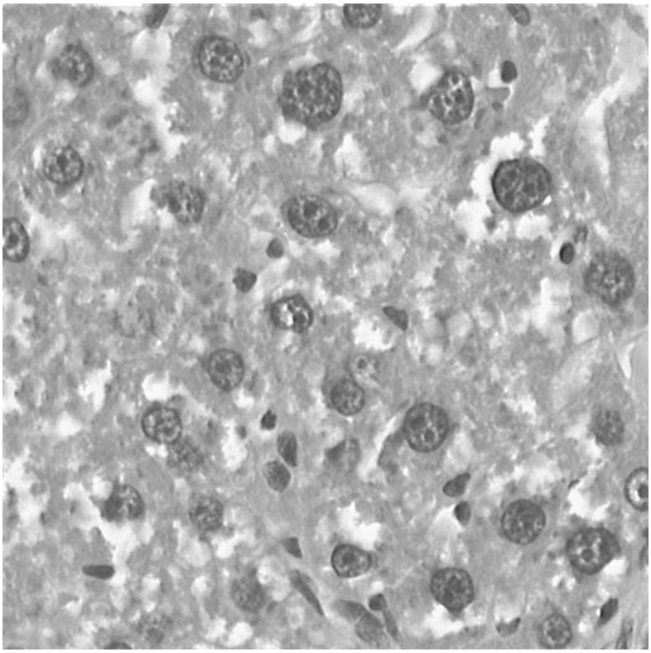

Fig. 4. 512 × 512 × 8 bits: An example of cirrotic liver.

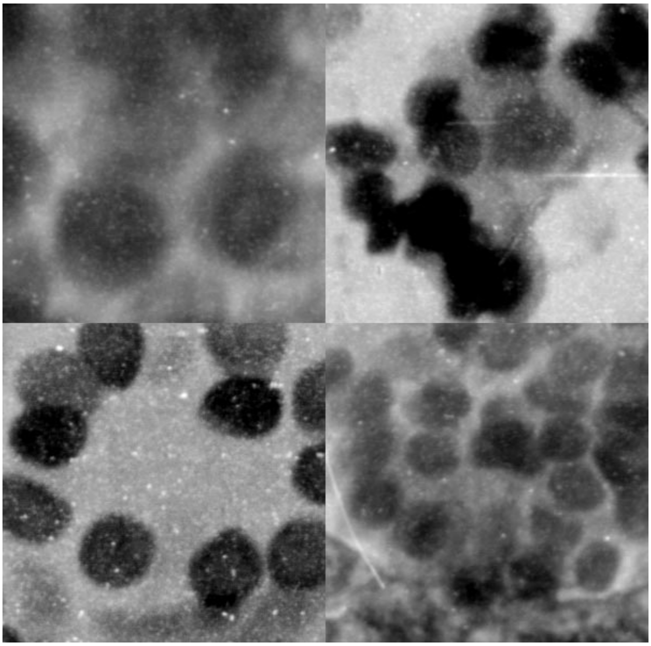

Fig. 5. 600 × 600 × 8 bits thyroid image acquired by an electroni microscope at 250x: healthy along with three different pathologies.

Table 1. *Normalized Recall* relative to *HERTI* on our liver's database.

Measure	*Value*
Size of idb	1960
Number of queries	15
Normalized Recall	.987

Table 2. *Normalized Recall* relative to the *Euclidean Distance* on the same database.

Measure	*Value*
Size of idb	1960
Number of queries	15
Normalized Recall	.972

Table 3. *Normalized Recall* relative to *HERTI* on our thyroid's database.

Measure	*Value*
Size of idb	2000
Number of queries	20
Normalized Recall	.981

Table 4. *Normalized Recall* relative to the *Euclidean Distance* on the same database.

Measure	*Value*
Size of idb	2000
Number of queries	20
Normalized Recall	.975

electronic microscope at 40x. Examples of these latter, i.e. respectively normal and cirrotic liver, are shown in Figg. 3 and 4. The evaluation of our technique performances has been made in this way. After selecting in our database, composed by 1960 cells images, 15 heterogeneous ones as queries, for each of them, we manually selected the 20 most similar ones and then we computed the *NR*.

The results showed that *HERTI* achieves very good results and is very efficacious in retrieving the same clinical case. Moreover, it's very interesting to outline that the results, contained in Table 1, are very promising (very close to 1) and look to be better than the ones obtained with databases containing (originally without any transform) 1-D signals (see for instance [5]). This demonstrates that also our solution of seeing a bidimensional signal as mono dimensional one has been efficacious.

Performing for the same queries, the Euclidean Distance (*ED*), which is a useful comparison representing an indicative test for many indexing techniques, we can see that, as shown in Table 2, *HERTI* performs better than *ED*, also considering that the former utilizes only 8 coefficients — the maxima and their associated energy.

Another example is shown in Fig. 5 where *HERTI* has been performed on a database containing images relative to thyroid along with three different pathologies. In this case *HERTI* performs better than *ED* too. In Table 3 and 4, there are the results in terms of Normalized Recall of, respectively, *HERTI* and *ED*.

5 Conclusions

In this paper, *HERTI*, a novel technique for a content based retrieval on images databases, has been presented. In particular *HERTI* is based on *HER*, utilized yet on time-series databases with good results, considering an intrinsic 2-D problem like the texture analysis as 1-D problem by means of the concept of characteristic curve covering all textel. So, the combination of this concept along the generality of *HER*, allowed us to obtain very promising results, revealing a good ability in retrieving images by content.

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