

Image Processing Facilities for Echographic Measurements

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Abstract – The aim of the paper is to present a flexible dedicated application, HealthImag, able to integrate different medical facilities. Representative quantitative parameters are used for echographic measurements. Important facilities concerning the preprocessing, specific quantitative parameter measurements, data visualization are considered for medical investigations.

Keywords: HealthImag, echographic, fractal, texture.

I. INTRODUCTION

The HealthImag application was developed as a dedicated medical image processing application based on previous medical applications [1], based on VC++ 6.0 platform. The aim was to offer more flexibility and facilities to the HealthImag application and to use new technologies offered by Microsoft .NET Platform and C# language.

The processing of medical images can be divided in two categories [2]: pre-processing facilities for corrections and enhancements (because of contrast problems or imperfections in the image acquisition system) and image analysis facilities for determining some parameters, descriptors or statistical results. The application takes into account both categories presented above by implementing general functions like rotations, contrast adjustments, histogram adjustments, RGB adjustments, HSL adjustments, some kinds of spatial filters and implementing some analysis like automatic or semi-automatic objects detections (resulting some parameters), determining textural descriptors or implementing some specific analysis used for echographic images assisted diagnosis.

HealthImag is a modular application, composed by DLLs (Dynamic Link Libraries) modules. In this way, new functionality can be added very easily by creating new DLLs.

II. HEALTHIMAG MAIN FACILITIES

HealthImag offer some general facilities like:

- Opening an image from the disk or clipboard.
- Saving an image under different formats (jpeg, bmp, png, gif, tiff).

- Computing the image histogram (grayscale histogram or color histograms).

- Geometric operations: resize, zoom, flip, mirror, rotate, crop or clone an image.

- *Color* filters: grayscale filter, RGB adjustment, HSL adjustment, invert filter, filters for extracting components colors, contrast adjustment, gamma adjustment, image binarization.

- Spatial filters: Smooth filter, Sharpen filter, Mean filter, Blur filter or Custom filter (the spatial matrix can be defined by the user).

- Gradient edge detection filters: Sobel and Prewitt filters.

- Two source filters: adding two images, removing an image from another image, the mean of two images.

In Fig. 1 it can be viewed an example for using the image binarization operation. The threshold for binarization is automatically computed but the user can modify it.

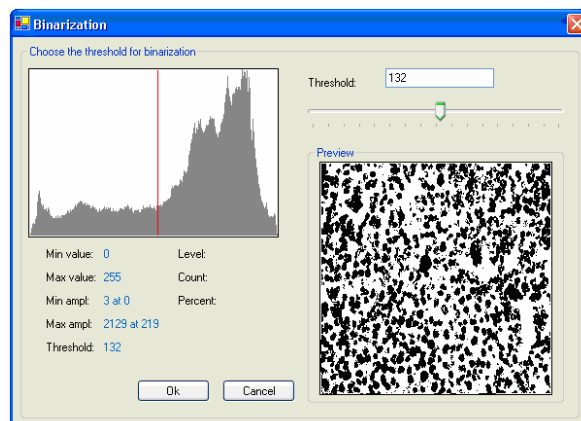


Fig. 1. Image binarization

III. HEALTHIMAG DEDICATED MEASUREMENTS

In this section are described some dedicated measurements offered by HealthImag like objects detection, fractal dimension computing, or Haralick descriptors computing.

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A. Objects detection

Objects detection operation can be used for discovering objects in an image. Considering an input image this operation can discover objects according to a threshold. This threshold can be automatically computed or it can be selected by the user. Along with this threshold an Otsu algorithm is used for detecting objects in the image.

For every object discovered the following parameters are computed [4]:

- **Feret X Diameter** – defined by the X dimension of the rectangle containing the object.
- **Feret Y Diameter** – defined by the Y dimension of the rectangle containing the object.
- **Form Factor (ff)** – is defined by the following relation:

$$ff = \frac{P^2}{2\pi A} \quad (1)$$

,where P is the perimeter of the object and A is the area of the object.

- **Mass Center** coordinates:

$$xc = \frac{\sum_k x(k)}{P}, yc = \frac{\sum_k y(k)}{P} \quad (2)$$

,where (x(k), y(k)) k=0,...,P are points from the object contour and P is the number of points considered.

- **Regularity (reg)** – defined by the following relation:

$$reg = \frac{d_{med}}{var} \quad (3)$$

,where d_{med} is the mean distance from the object contour to the object mass center and var is the variance of these distances.

- **Ondulation factor (fond)** – obtained considering the relation:

$$fond = \frac{2P}{\pi(\max d^2 + \min d^2)} \quad (4)$$

,where P is the perimeter of the object and d is the distance from the object mass center to the object contour.

- **Excentricity (exc)** – obtained considering relation :

$$exc = \frac{\max d}{\min d} \quad (5)$$

,where $\min d$ is the minim distance from the object mass center to the object contour and $\max d$ is the maxim distance from the object mass center to the object contour.

In Fig. 2 it can be seen an image with some objects in it. By pointing with the mouse an object, it's becoming highlighted and the result can be seen in the object properties window. In this window are listed the number of objects, the current object number and all parameters described above.

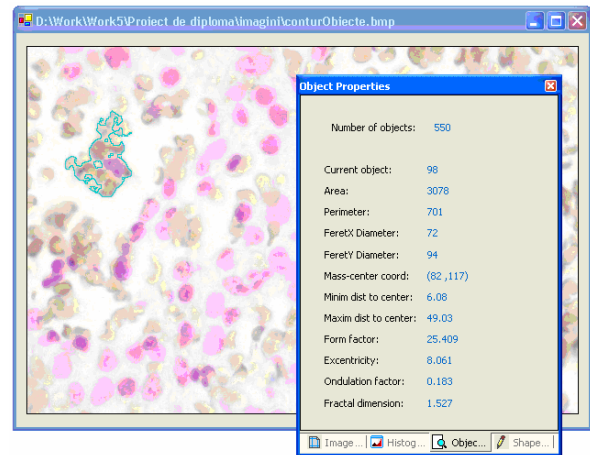


Fig. 2. Object detection results

Also, the fractal dimension of the object is computed. Fractal dimension is a statistical quantity used to measure the roughness of an object and can be used for comparing objects or for statistical measurements. Fractal dimension computing will be presented in the next section.

There is the possibility to save the results in a text file.

B. Fractal dimension computing

Fractal dimension is related to the objects detection operation presented in the previous section. For every object the fractal distance can be computed and listed in the Object Properties Window. Fractal dimension (also called fractal distance) is a property of a fractal object.

Fractals can be considered as self-similar patterns that repeat themselves. Smaller part of the fractal can be reflected in the entire fractal (this property is called self-similarity). Fractals can be very useful tools because the fractal geometry is the real geometry of the nature (like Mandelbrot said) . Most objects in nature aren't formed of squares or triangles, but of more complicated geometric figures. Objects like ferns or coastlines are shaped like fractals. Their

appearance led to the development of concepts like fractal dimensions [5].

Fractals proved to be very useful tools in many science domains. Fractal geometry achieved popularity through the efforts of B. Mandelbrot with his book *The Fractal Geometry of Nature*.

Self-similarity is a very important property of a fractal.

A shape S is called *exactly (linearly) self-similar* [6] if the whole S can be splitted into parts $S_i : S = S_1 \cup S_2 \cup \dots \cup S_n$ and the parts satisfy two restrictions. First restriction is that each part S_i is a copy of the whole S scaled by a linear contraction factor r_i , and the second restriction is that there is no intersections between parts in the sense of dimension.

The fractal dimension can be defined in many ways. We will consider here two important dimensions [6]:

1. Similarity Dimension

The definition of similarity dimension is related to the fact that the cube unit in D -dimensional Euclidean space is self-similar. This means that for any positive integer b the cube can be decomposed into $N = \text{pow}(b, D)$ number of cubes, each cube scaled by the similarity ratio $r = 1/b$, and overlapping (at most) along $(D-1)$ - dimensional cubes.

The *similarity dimension* d_{sim} is defined by the following relation:

$$d_{sim} = \frac{\log(N)}{\log\left(\frac{1}{d}\right)} \quad (6)$$

2. Box Dimension

The similarity dimension can be used only for exactly self-similar shapes. For more general sets, the similarity dimension is replaced by the box dimension. For an set A in Euclidean space of dimension E , and for any $\delta > 0$, a δ -cover of A is a collection of sets of diameter δ whose union contains A . $N_\delta(A)$ is defined as the smallest number of sets in a δ -cover of A . Then the *box dimension* d_{box} of A can be computed using the relation:

$$d_{box} = \lim_{\delta \rightarrow \infty} \frac{\log(N_\delta(A))}{\log\left(\frac{1}{\delta}\right)} \quad (7)$$

When the limit does not exist, the above relation can be modified by replacing the *lim* with *lim sup* and *lim inf*, defining in this way the *upper* and *lower box dimensions*:

$$\overline{d}_{box} = \limsup_{\delta \rightarrow \infty} \frac{\log(N_\delta(A))}{\log\left(\frac{1}{\delta}\right)} \quad (8)$$

$$\overline{d}_{box} = \liminf_{\delta \rightarrow \infty} \frac{\log(N_\delta(A))}{\log\left(\frac{1}{\delta}\right)} \quad (9)$$

Besides these two dimensions it also can be considered other types of dimensions like: mass dimension, Minkowski–Bouligand dimension or Hausdorff–Besicovitch dimension.

The algorithm used for computing the fractal distance in HealthImag is the Box-counting algorithm. The Box-counting dimension is much more used than the self-similarity dimension because the box-counting dimension can be used on images that are not exactly self-similar (most real-life images are not self-similar).

Considering [7] a well known fractal (Sierpinsky gasket), the image can be covered with a grid of square cells with cell size r (Fig. 3). For digital images the cell size can be considered as the number of pixels. In this example the number of grids containing a part of the structure is $N = 51$ out of 90 boxes.

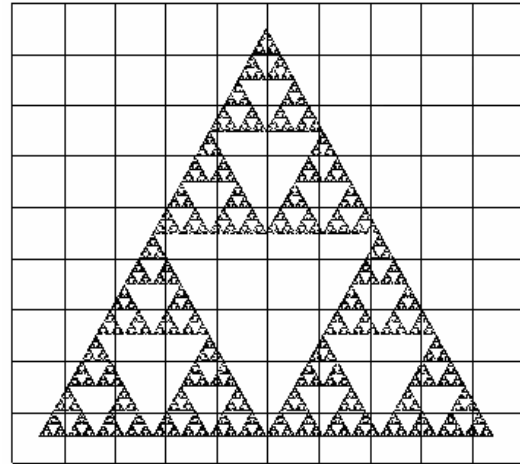


Fig. 3. Image overlaid with a grid of squares in order to compute the fractal distance [7]

The plot (called Richardson-Mandelbrot) containing different box sizes r can be viewed in the Fig. 4.

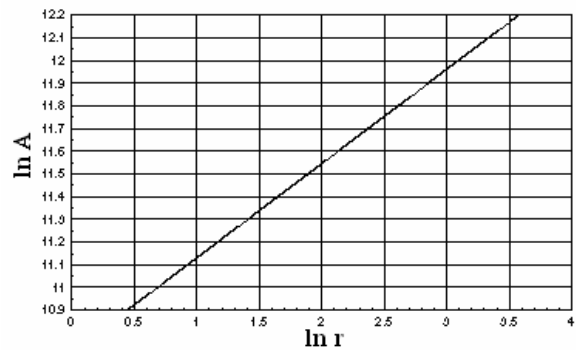


Fig. 4. Richardson-Mandelbrot plot for different box sizes in pixels [7]

For this example the slope of the resulting line is 0.414 and the fractal dimension is computed using the relation:

$$d_f = 2 - s = 2.0 - 0.414 = 1.586 \quad (10)$$

This is a simple example and the plot is a straight line but for real-life images the fractal dimension computing is not as simple as in this case. Note that the box counting procedure can be extended to three dimensions if cubes are used instead of squares. HealthMag allows choosing the box dimensions for computing the fractal distance (Fig. 5).

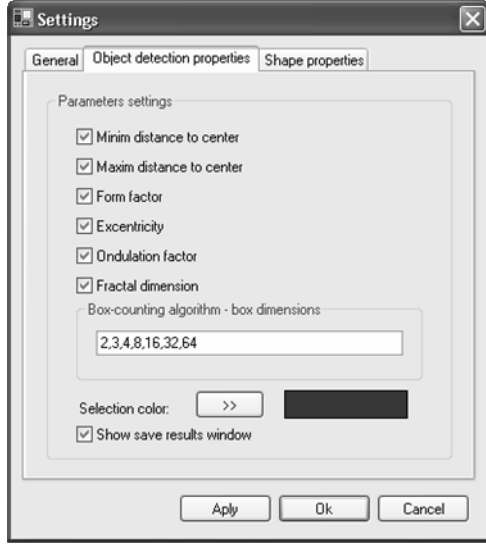


Fig. 5. The settings window in HealthMag

C. Textural Analysis

Generally, in some pictures, it can be easily to see the specific regions, having a similar grey or colour value, repeated over the image. This kind of pattern is called a texture.

While there isn't a universally accepted formal definition of a texture, a major characteristic is the *repetition of a pattern or patterns over a region*. The pattern may be repeated exactly or, usually, with small variations on the theme, possibly in function of the position. There are also random aspects related to the patterns repetition (that cannot be ignored) like: the size, shape, color and orientation of the elements of the patterns can vary over the region. It can be considered that the difference between two textures is contained in the degree of variation alone, or in the statistical distribution related to the patterns.

Haralick Descriptors

The Haralick descriptors are usually used for image classification. These descriptors contain information about the patterns that can be founded in textures. Statistical characteristics can be extracted from textural images as nine Haralick descriptors [8]. These

descriptors are computed using the *co-occurrence matrix*. The *co-occurrence matrix* is a matrix of relative frequencies C_{ij} with which **two** neighborhood pixels separated by distance vector d occur on the image, one with gray level i and the other with gray level j [9]. The *co-occurrence matrix* is computed using a $m \times n$ window. In order to compute the Haralick descriptors we need some initials parameters:

$$\mu_i = \sum_{i=1}^n \sum_{j=1}^m i C_{ij} \quad \mu_j = \sum_{i=1}^n \sum_{j=1}^m j C_{ij} \quad (11)$$

$$C_i = \sum_{j=1}^m C_{ij} \quad (12)$$

$$\text{var}(i) = \sum_{i=1}^n \sum_{j=1}^m (i - \mu_i)^2 C_{ij} \quad (13)$$

$$\text{var}(j) = \sum_{i=1}^n \sum_{j=1}^m (j - \mu_j)^2 C_{ij} \quad (14)$$

Because the *co-occurrence matrix* can be computed considering four directions we have four sets of Haralick descriptors.

Relations for Haralick descriptors are given below, where C is the co-occurrence matrix and C_{ij} is the element contained at the row i and at the column j in the *co-occurrence matrix* C [8].

- **Texture cluster tendency**

$$H_1 = \sum_{ij} (i - \mu_i + j - \mu_j)^2 C_{ij} \quad (15)$$

- **Texture entropy**

$$H_2 = - \sum_{ij} C_{ij} \log C_{ij} \quad (16)$$

- **Texture contrast**

$$H_3 = \sum_{ij} |i - j| C_{ij} \quad (17)$$

- **Texture correlation**

$$H_4 = \frac{\sum_{ij} (i - \mu_i)(j - \mu_j) C_{ij}}{\sqrt{\text{var}(i) \text{var}(j)}} \quad (18)$$

- **Texture homogeneity**

$$H_5 = \sum_{ij} \frac{C_{ij}}{1 + |i - j|} \quad (19)$$

- **Texture inverse difference moment**

$$H_6 = \sum_{ij, i \neq j} \frac{C_{ij}}{|i-j|} \quad (20)$$

- **Maximum texture probability**

$$H_7 = \max_{ij} C_{ij} \quad (21)$$

- **Texture probability of run length of 2**

$$H_8 = \sum_i \frac{(C_i - C_{ii})^2 C_{ii}}{C_i^2} \quad (22)$$

- **Uniformity of texture energy**

$$H_9 = \sum_{ij} C_{ij}^2 \quad (23)$$

In the Fig. 6 it can be seen the result for computing Haralick descriptors. There is the possibility to choose the direction used for the *co-occurrence matrix* (horizontal direction, vertical direction, etc). Also, the results can be saved as text files on the disk.

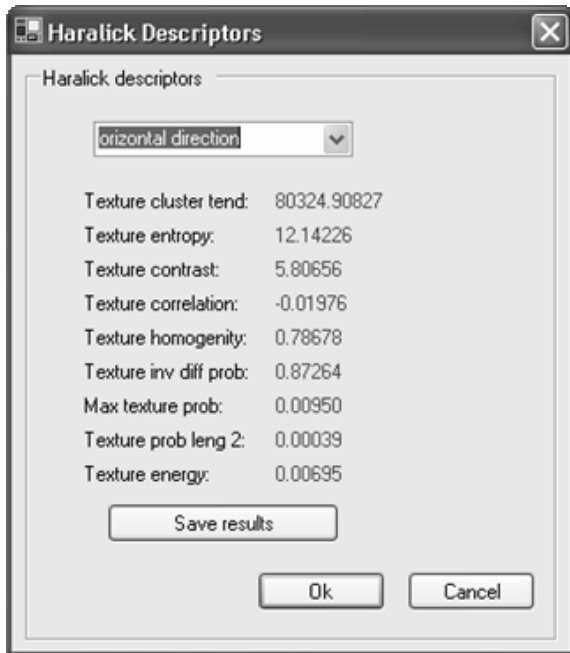


Fig. 6. Haralick descriptors values for a given image

IV. ECHOGRAPHIC MEASUREMENTS

These kinds of measurements can be used for echographic images analysis. If a simple inspection of an echographic image is not very relevant, by using some modern methods in image analysis the precision of the diagnostic can be drastically improved.

In the analysis of an echographic image the following steps are required:

- setting the initial state of the image acquisition system.
- obtaining the image using the image acquisition camera.
- applying the considered echographic measurement.
- showing the results like numerical data or using some graphical plots.

The results for different images can be compared (of course, by using the same settings for the image acquisition camera).

By using enough images a domain of values can be defined and used for comparing affections or severity degrees for the same affection.

Healthmag offer the possibility to make an image correction by extracting from an image another image considered a reference image. In this way, existing defects in the acquisition system can be eliminated.

A. Pixel neighborhood analysis

This analysis is used for obtaining information from the pixels neighborhood. Using the mouse cursor, the user can see the information related to the greyscale levels for pixels contained in the proximity of the pixel pointed. For this kind of analysis a 3 x 3 or 5 x 5 matrix can be considered. Along with the greyscale values also the mean and the medial values are computed.

For a given image, the results are showed in the pixel neighborhood information window (Fig. 7).

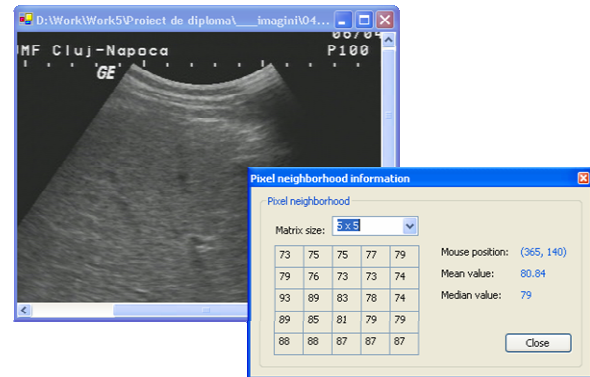


Fig. 7. Pixel neighborhood analysis

The same analysis can be used automatically (Fig. 8).

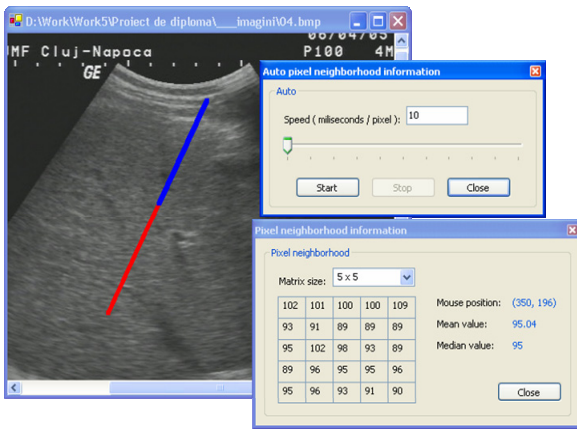


Fig. 8. Automatic pixel neighborhood analysis

The user select a straight line and using a timer (the timer frequency can be modified by the user) the pixels from the line are analyzed in the same way as the previous analysis.

For every point contained in the line greyscale levels, mean values and median values are listed. The process of scanning the considered line can be stopped or resumed by the user.

At the end, the results are plotted (Fig. 9). There are 3 plots: grayscale plot, mean plot and median plot.

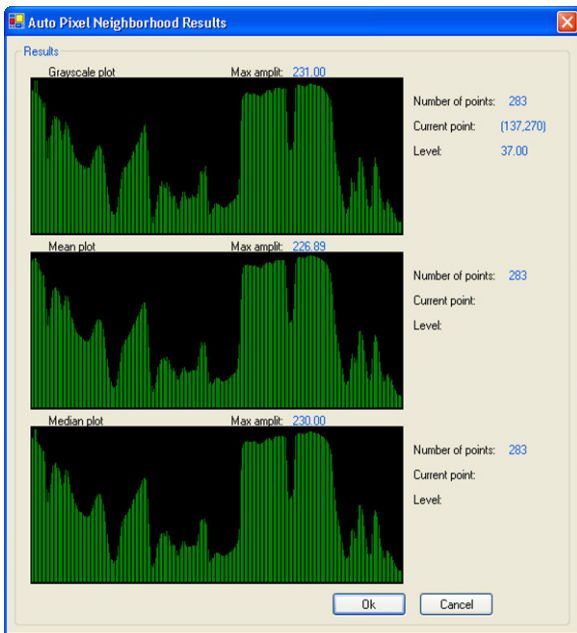


Fig. 9. Plotting the results of the *automatic pixel neighborhood* analysis

V. CONCLUSIONS

The HealthMag application is a powerful instrument that can be used for image corrections and enhancements or for dedicated medical analysis. HealthMag has an easy-to-use GUI (graphical user interface) and can be a good tool for a medical staff. Implementations for some analysis in an automatic

way can significantly reduce the time for analyzing medical images.

Implemented using some new technologies like .NET, HealthMag offer some modern possibilities to process images, to analyze images or to show results. Also, new functionality can be added very easily by implementing new DLLs modules containing the desired functionality.

The application is used in a radiology department at the University of Medicine "Iuliu Hatieganu" Cluj-Napoca. Relevant medical results are expected considering an assisted diagnosis process. Statistics facilities will be implemented to generate different medical reports.

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