

MODIFIED FOURIER TRANSFORM RECOGNITION OF ECHOGRAPHIC IMAGES

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ABSTRACT

The recognition of echotexture in echographic images may fail due to the distortions introduced by the scan system. We have implemented a rotation and scale invariant recognition method of echographic textures. The significant features assumed to characterise the images are vectors whose components are the values of a modified Fourier transform (MFT) of the images. Our method assures a good reliability and allows a short computation time, also when implemented on small computers. The method has till now been proved over breast and thyroid images, exhibiting a very good discrimination capability.

1 RECOGNITION OF ECHOTEXTURES BASING ON MFT VECTORS

1.1 Introduction

Echographic images may be affected by geometrical, rotation or scale, distortion, due to the scan system. A recognition method of echographic textures must therefore be rotation and scale invariant; moreover the features assumed to characterise the images would have to assure a good reliability and to allow a short computation time, also when the recognition method is implemented on small computers. A new method answering to the above requirements is now presented and applied to categories of echographic images. In the past an optical recognition method for echotextures was presented [5], which operated by comparing the unknown image with different reference samples. The method now presented, completely different in its digital approach, shift, rotation and scale invariant, still analyses unknown images by comparing them with selected reference samples.

1.2 The recognition method

The distortion invariant method we have implemented uses as significant feature a vector whose components are the values of a modified Fourier transform (MFT) of the images [1]. These MFT vectors are calculated for each sample image belonging to a group which represents a specific pathology. Samples are taken small enough that each of them may be considered typical of a defined status of the tissue and large enough that texture is predominant. MFT vectors generated by each group are assumed to represent one possible status of the

tissue. Images to be analysed are then scanned by a window of the same size of the sample, for each scansion step the MFT vectors are calculated and the Euclidean distance between these and that of the sample is patterned on a similarity map. If the reference group consists of more than one sample image, the Euclidean distance is calculated as the arithmetic mean of the Euclidean distances from each sample.

1.3 The modified Fourier Transform

The expression of the analogic MFT [1] is shown in (1).

$$F(\omega) = \iint_{\Omega} f_1(x) h[\omega, f_2(x)] dx \quad (1)$$

where $x = (y, z)$ is a bidimensional vector and ω is a monodimensional variable;

$$f_1 \equiv f_1[f(x)], \quad f_2 \equiv f_2[f(x)],$$

$$h \equiv h[\omega, f_2(x)],$$

are three arbitrary Invariant Functions (IF) and $f(x)$ represent the light intensity of the image.

Rotation translation and scaling can be joined in the following transformation:

$$x' = \beta (x_o + T \cdot x) \quad (2)$$

where β is a constant representing scaling, x_o is a bidimensional translation vector and T is a rotation matrix.

The application of (2) modifies the MFT giving:

$$F(\omega) = \frac{1}{\beta} \iint_{\Omega} f_1(x) h[\omega, f_2(x)] dx \quad (3)$$

In order to obtain the scale invariance a normalisation of the values obtained from (3) is carried out.

The IF we have chosen are:

$$f_1(x) = f_2(x) = f(x)$$

$$h[\omega, f(x)] = K^{\omega f(x)} \quad (4)$$

where K is a scalar, because the relative variation of an exponential function is able to discriminate small variations of image brightness.

Replacing the integral with a sum, equation (1), according to (4), becomes:

$$F(\omega) = \sum_{z=0}^N \sum_{y=0}^N f(y, z) K^{\omega f(y, z)} \quad (5)$$

giving the discrete expression of the MFT we have employed.

The choice of the base k of the exponential function h in (4) is a compromise solution giving a good discrimination between dissimilar images and a low sensitivity to the noise. Exponential functions with a base very greater than 1 produce, for great values of ω , too sharp variations for small changes of the brightness $f(x)$; on the contrary exponential functions with a base less than 1 may produce an inadequate discrimination, especially when the images are textures. The choice of K can be made each time as occasion may require. The valuation by means of the similarity map of a set of unknown images may be expressed in quantitative form by a table reporting the maximum values of the Euclidean distance between the images and the sample, for example the healthy sample. This may lead to identify a threshold value between "sick" and "healthy". The choice of the relevant function and parameters (f_1, f_2, h, K) has been the result of an optimisation procedure carried out using two sets of breast and thyroid echo-images.

In expression (5), once fixed the parameter ω , the different terms depend only on the value of the brightness of each pixel. If the images that are compared are binary, that is their pixels are of intensity unitary or null, the discrimination relies on the probability that different images have a different number of white and black pixels, but this can be not true, and is certainly not true if the scale invariance normalisation has been made. Giving up the normalisation, the method maintains only shift and rotation invariance. On the contrary the method is at the most effective to analyse multi-gray-levels structured images, as the echographic texture; its intrinsic shift-invariance is a precious quality when window scanning an image, unlike for instance Fourier-Mellin descriptors [2-4], in which a slight variation of a centroid produces very great errors .

2 EXPERIMENTAL BACKGROUND

This method was first applied to a set of 256x256 breast echographic images that were compared with four different 16 x 16 samples. Subsequently we have analysed a set of 512x512 thyroid images. The scanning step is 4 pixels. The comparison is visible as a 256x256 or 512x512 image which is darker in the zones more similar to the sample. We have used a common PC with a Pentium 90 Mhz processor. Programming language is C++ in Window environment. To speed up the process it

could be suggested to create a matrix containing the values of all possible terms of (5). Assuming $f(x, y) \in [0, 255]$ and $\omega \in [0, 10]$, the dimensions of this matrix are 255x10. We have applied directly expression (5), because the computation time of every single addend of (5) resulted less than the access time to the matrix. A considerable increase in speed has been obtained minimising the number of accesses to the storing file of the image on the hard disk. The ideal solution would be to load the image once for all in the memory as a 256x256 or 512x512 matrix, but this is not possible utilising small computers and we think it convenient to preserve the possibility that the program can run on small PC. This could permit the most ample and general use of the program, seeing that the intrinsic simplicity of the method allows it.

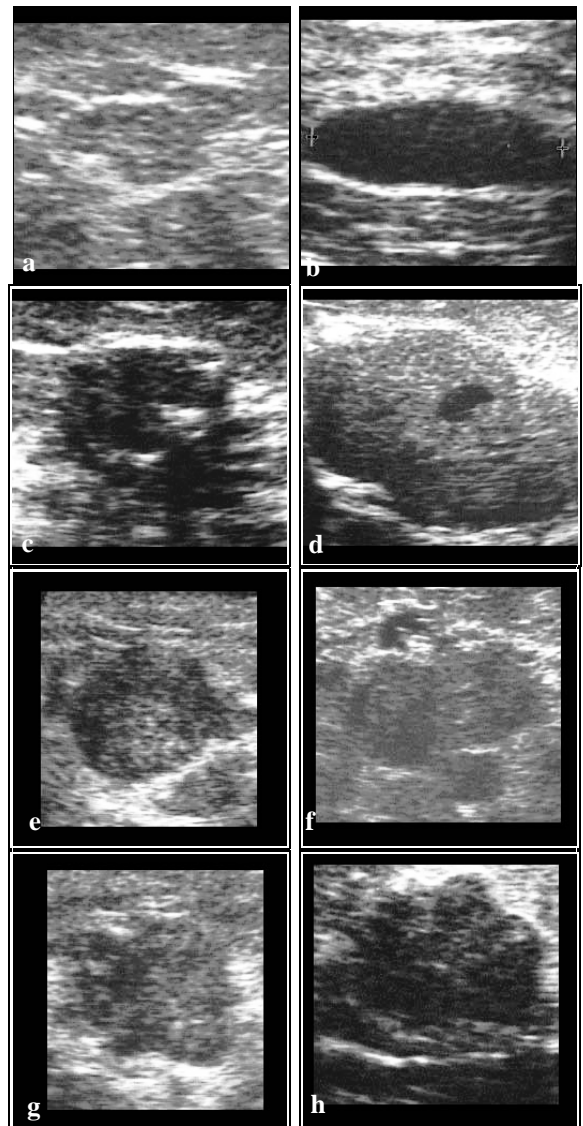


Fig. 1: Breast echographic images to be compared with four samples (fig. 2).

In conclusion, to speed up the program, we adopted the following technique: the MFT of all 4x4 echography portions, whose dimensions are equal to those chosen

for the scansion step of the analysis window, are stored in a 3D matrix, named M/4, of real numbers (64x64x10 or 128x128x10). The MFT of each 16x16 ecography portion, to be compared to the samples, is computed by adding, for each step, the 16 values of the corresponding 4x4 sub-matrix of M/4. This is a consequence of the fact that, as it results in (5), the MFT does not depend on the spatial position of each pixel, but only on its light intensity, weighed by a suitable function in order to increase the sensitivity to brightness variations. The above exposed technique minimises the disk access time and avoids redundant calculations, since each MFT of the 4x4 image portion is utilised 16 times for the 16x16 windows.

3 RESULTS

3.1 Breast echo-images

Eight breast echographic images, to be considered significant from a clinical point of view, are reported in fig.1. From them the four samples of fig.2 have been chosen.



Fig. 2: Four samples of breast echotexture

Fig.3 shows, very enlarged, the first sample of fig.2, in such a way as to emphasize the 16x16 pixel structure.

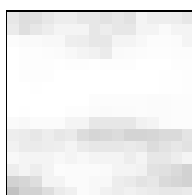


Fig.3: sample of fig.2a very enlarged.

Table 1 shows the minimum distances obtained from the comparison of the eight images and the four samples.

Tab.1: minimum distances of the images of fig.1 from the samples of fig.2

| | fig.2-a | fig.2-b | fig.2-c | fig.2-d |
|---------|-----------|------------|-----------|-----------|
| fig.1-a | 9.286 e-6 | 1.345 e-1 | 4.121 e-7 | 2.237 e-2 |
| fig.1-b | 1.796 e-6 | 1.029 e-2 | 3.851 e-7 | 1.645 e-7 |
| fig.1-c | 3.553 e-6 | 1.214 e-12 | 1.031 e-6 | 2.303 e-6 |
| fig.1-d | 1.367 e-5 | 2.906 e-6 | 1.348 e-6 | 3.599 e-7 |
| fig.1-e | 1.413 e-6 | 2.393 e-2 | 2.946 e-7 | 3.737 e-6 |
| fig.1-f | 1.479 e-3 | 2.278 e-1 | 1.631 e-7 | 6.783 e-2 |
| fig.1-g | 1.381 e-5 | 7.519 e-2 | 2.720 e-7 | 3.231 e-3 |
| fig.1-h | 2.079 e-8 | 2.402 e-7 | 1.631 e-7 | 1.640 e-6 |

The choice of the reference samples to be considered representative of the type of tissue to be evidenced is determinant for the issue of recognition process. For example the analysis of table 1 shows very evidently how figure 1-a presents zones more similar to samples 2-a and 2-c.

Four similarity maps are reported in fig.4; they have been obtained comparing the image of fig. 1-d with the

four samples of fig. 2 and are composed of little monochromatic squares whose dimensions are equal to the scansion step. The reading rule of a similarity map is that each map appears darker just in the zone more similar to the sample taken for the test. In this way the most interesting clinical zones are shown up.

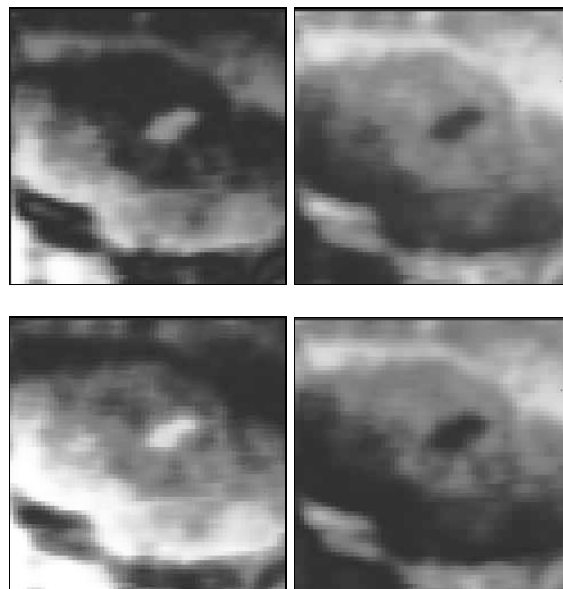


Fig.4: similarity maps a, b, c, d: comparison between echo image 1-d and samples a, b, c, d of fig.2.

The recognition is unaffected by geometrical distortion and rotation. We have produced a 20% distortion in horizontal direction and a rotation of 30 degrees in an echographic image. The similarity map follows the distortion (fig.5).

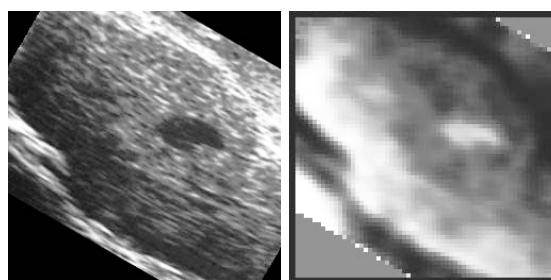


Fig.5: distorted image and similarity map.

3.2 Thyroid echo-images

The thyroid images we have analysed are not a homogeneous set as concerns the brightness, because they have been acquired, after tuning up brightness and contrast to give to the doctor an optimum representation. It is thus evident that in this situation a method based on a brightness comparison between an image and samples extracted from different images cannot be applied. Nevertheless we have observed that also an interior comparison, that is a comparison performed with a sample extracted from the same image, results of great

usefulness to emphasize the variations of the echotexture with respect to the selected sample. Fig. 6 shows a thyroid echo-image and three comparison maps with samples extracted from the zones marked with the white cross and superimposed (enlarged) on the low-left corner of each map. The effectiveness of the method in analysing the affinity between different zones inside a same image results evident.

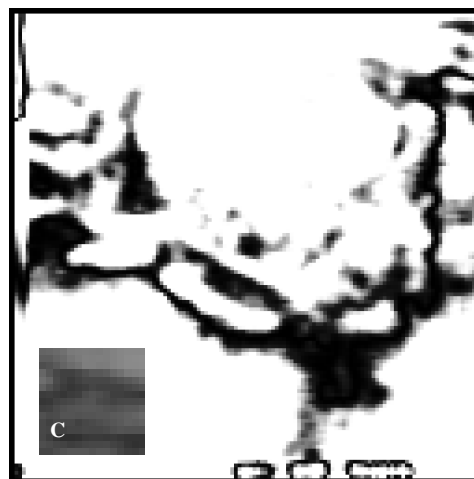


Fig.6: thyroid echo-image and comparison maps.

4 CONCLUSIONS

We believe, owing also to the short computation time, the method can now be ready for clinical application. Careful tests, including biopsy, could contribute to a better knowledge of the correspondence between echostructure and different types of tissue, since the discrimination capability of the method proved to be well over the one of an expert human eye.

The images of breast and thyroid we have analysed till now have been kindly placed at our disposal by General Hospital of Gorizia and via Internet by Cattinara Hospital of Trieste.

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