Feature Classification in Ultrasound Textures for Image Quality Assessment:a Preliminary Study on the Characterization and Selection of Haralick Parameters by Means of Correlation Matrices

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***Abstract* – This paper describes a preliminary study on feature selection from the gray level co-occurrence matrix (GLCM) among the 14 features proposed by R.M. Haralick (1979) with the aim to apply them to ultrasound image classification and Quality Assessment. In particular4 main-classes of images with different patterns (Lines, Chess, alternates Row and Circles)have been implemented and different levels ofspeckle noisehave been added to simulate ultrasound images with different textures.With the aim to characterize therelationship betweenHaralickfeatures and the pattern type, size, contrastand noise, someCorrelation Matrices have been implemented. Preliminary results are explained and discussed.**

***Keywords* – diagnostic ultrasound, Haralick textural features, uniformity, B-mode, quality assessment**

I. INTRODUCTION

The use of ultrasounds (US), indiagnostic medical imaging has expanded enormously over the last two decades (according to [1-3] the global diagnostic ultrasound market ranges between \$4 and \$7 billion in 2016), largely due to the fact that allows real-time visualization of moving structures,it issuitable for many clinical applications and it is safer than other diagnostic technologies (e.g. high and low voltage radiography, X-ray Computed Tomography CT, Positron Emission Tomography PET, etc.). As in other diagnostic systems [4-11], medical ultrasound images contain several structural and texture details that can be related to evaluate the health status of the patient[12, 13]. On the other hand, US image analysis from specific test objects (e.g. ultrasound phantoms) can be used by technicians for quality assessment of the diagnostic equipment [14-27]: in particular 2D image uniformity is one of the most important parameters that can be related to ultrasound system performances [28, 29] nevertheless its objective measurement is a research challenge. To this aim recent studies [30-32] proposed a method based on pattern recognition and image segmentationby means of gray-level co-occurrence matrices (GLCM) [33]applied to a Region of Interest (ROI) of the ultrasound image.In [34] Haralick proposed a set of 14 features$\{f_1, f_2,\ldots,f_{14}\}$ calculated from a GLCM, whose elements areestimates of the probability of transitions from one gray level to another in a given direction at a given inter-pixel distance. Even if the technique has been applied in several papers dealing with biomedical image processing (as a single example refer to [35]) the high number of features make the GLCM application difficult, therefore a selection of the more significant of them is required. In the present work a criterion for Haralick featuresselectionby means of a preliminary study of their correlation properties is proposed.

II. DESCRIPTION OF THE METHOD

The proposed study is subdividedintothreemainparts: (a) Imagetest set definition (b) Criterion fordirection and inter-pixel distance (IPD) determination in GLCM calculus and finally (c)Haralick feature extraction andcharacterization by means of Correlation Matrices.

A. Image test set definition:4 main-classes

In order to investigate the Haralick features interdependence and behaviour depending on some pattern characteristics related to Field of View (FOV), contrast and noise of two-dimensional ultrasound images,4 main image classes with different texture have been implemented (fig. 1).In particular, the image characteristics in each class are set in order to consider the following issues:

1. The variabilityof the imageproprieties related

with the presence of different pattern size and contrast level.

2. Thevariability of the image proprieties related with the presence of different levels of speckle noise.

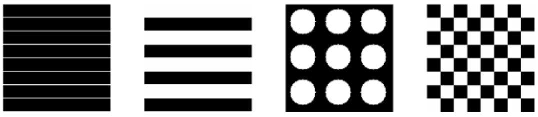
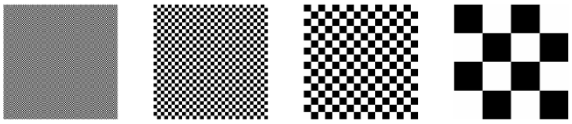


Fig. 1. Patterns of the 4 main-classes:Lines,Alternates Row, Circle and Chessboard.

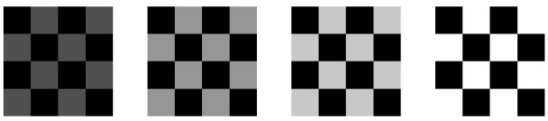
From the above considerations,in our study 6 increasing sizes have been selected for each pattern class (Fig.2). This is related to both the clinical practice and quality assessment procedures where the FOV of the ultrasound system may be changeddepending on theenvironmental context and task demands [36].



(a) (b) (c) (d)

Fig. 2. Example ofdifferent texture(cell) sizes for a same main-class (Chessboard).(a) pattern cell size of 1pixel(i.e. 1 px white and 1 pxblack) (b) 2 pixelcell size(c) 8 pixel cell size (d) 32 pixel cell size.

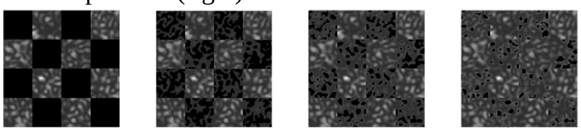
Moreover, in order to consider the effect of contrast-level each pattern above is proposed with 4 different contrast levels(Fig.3).



(a) (b) (c) (d)

Fig. 3. Example of test images with different contrast levels

Afterwards, asynthetic speckle noise [37]has been implemented and added with6 increasing levels, in order toenhance the presence of speckle in each main-class of different patterns (fig.4).



(a) (b) (c) (d)

Fig. 4. Example of test images withdifferent speckle noise level.

Therefore, the image test set is made of 4 different class of textures (fig.1) whosepatterns are processed in order to obtain test images with different pattern size, contrast and speckle noise: a total of 576 test images are produced (4 different patterns ×6 cell size ×4 contrast levels ×6 speckle noise levels).

B. Grey Level Co-occurrence Matrix calculus: direction and inter-pixel distance selection

The GLCM is a traditional mathematical tool for texture analysis, becauseit can be used to determine the spatial interrelationships of the gray levelsin an image [38]: eachelement p_{ij}in the GLCMis thefrequency atwhich two neighbouring pixels separated by a (inter-pixel) distance d(IDP) along a direction θ (e.g. 0°, 45°, 90°, 135°)occurin the image, where one of them has gray level i and the other j.In other terms $p_{ij}$is the number of occurrences of the pixel values *(i,j)* lying at distance d in the imageand the GLCM represents the frequency of all possible pairs of adjacent pixel values in the entire image (therefore the GLCM is a $N_g \times N_g$ matrix, where N_g is the highest gray level that can be found in the image). In this stepthe GLCMsfor all the image test set are calculated (i.e. for all the images of the main-classes above mentioned)taking into account different directions and IDPs.In particular,for each test image the GLCMs are evaluated for the two directions that are usually considered in Ultrasound Image Quality Tests, i.e. θ=0° and θ=90°.On the other hand, a Fast Fourier Transform (FFT) analysis on each test image has been implemented for both directions and the IDP value (IDP_{GLCM}) is determined from the frequency ν_{p_min} of the first peak detected in the corresponding FFT spectrumby means of an adaptive threshold algorithm: with the aim to reduce the computational complexity, only one IDP value is here selected for each direction in the test image.At the end of this step, two GLCMs for every test image have been provided, i.e. $GLCM_H(\theta=0°, IDP_{GLCM}=1/\nu_{p\_minH})$,$GLCM_V(\theta=90°, IDP_{GLCM}=1/\nu_{p\_minV})$.

In tables 1 and 2 are reported some examples of IDP_{GLCM} values obtained for different patterns of the chessboard main class: it can be noted that theydepend on both patterncell size and speckle noise level. In particular for higher speckle noise levels the patterns tend to disappear and the IDP_{GLCM}become similar each other. Anyway, at lower noise levels the outcomes of the adaptive threshold method are affected by a large dispersion, that is likely due to the variance of the speckle noise spectra.

Table1.Example of IPD valuesfrom the peak frequency adaptive threshold detection on the chessboard class at different cell size

Pattern cell size (px)	**IDP_{GLCM} (px)**
1	2
2	4
4	8
8	16
16	32
32	64

Table2.Example of IPD values fromthe peak frequency adaptive threshold detection on the chessboard classat differentcell size and speckle noise levels

Pattern cell size	IDP$_{GLCM}$lev.1(px)	IDP$_{GLCM}$ lev.2 (px)	IDP$_{GLCM}$ lev.3 (px)	IDP$_{GLCM}$ lev.4 (px)	IDP$_{GLCM}$ lev.5 (px)	IDP$_{GLCM}$lev.6 (px)
1	2	2	2	14	14	9
2	4	4	4	12	14	9
4	8	25	25	12	14	9
8	16	16	16	9	9	9
16	32	9	9	14	14	9
32	64	21	21	16	14	9

C. Haralick parameters characterization:Correlation Matrices

TheHaralickfeatures [34] are representative of theinformation of the ultrasound image textures and are calculated fromthecorresponding GLCMs. In this workthe fourteenfeatureslisted in table 3 are considered.

Table3.Haralick textural features [34]

Textural feature	**Symbol**
Energy or Angular Second Moment	f_1
Contrast f_2	f_2
Correlation f_3	f_3
Variance f_4	f_4
Inverse Difference Moment	f_5
Sum Average	f_6
Sum Variance	f_7
Sum Entropy	f_8
Entropy	f_9
Difference Variance	f_{10}
Difference Entropy	f_{11}
Information Measures of Correlation I	f_{12}
Information Measures of Correlation II	f_{13}
Maximal Correlation Coefficient	f_{14}

After the features in table 3 are calculated for all the GLCMs related to the image test set, the inter-correlation betweenthemis provided by means of a Correlation-Matrix (CorMat) representation,depending on the different patterns, cell size, contrast and speckle noise levels.EachCorMatprovides the interdependence between the 14 features and highlights whichof them are most significant within the main classes.In figure 5 an example of CorMatis reported: thematrixis evaluated for the chessboard pattern with 1-pixel cell size and speckle noise level 3.

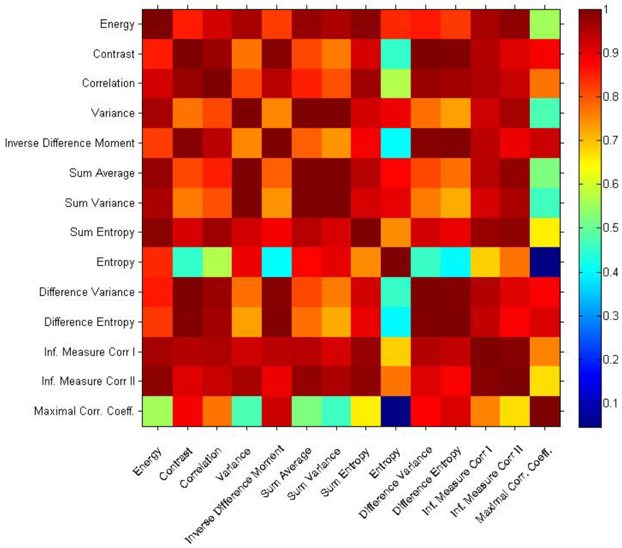


Fig. 5. Example of correlation matrix of the Haralick Featuresfor the chessboard class (pattern of size 1 and speckle noise level 3)

III. RESULTS AND DISCUSSIONS

In this study we focused our attention on the influence of pattern size and speckle noise level.

Taking in consideration the pattern cell size variation, thestudy ofCorMatsuggest that there aresome independent features over all classes:*Entropy*, *Energy*, *Sum Entropy* and *Information Measures of CorrelationII*.Nevertheless,lessuncorrelated features have been foundfor the speckle noised patterns, i.e. the *Entropy* and the *Maximal Correlation Coefficient* are the most independent features, with some differences among classes.In conclusion, among features that shows significant sensitivity to pattern characteristics (i.e. significant variations depending on cell size and noise level), our preliminary results suggest that thefollowing have significant independence respect to the others: *Entropy*, *Energy*, *Sum Entropy* and *Information Measuresof Correlation II* and *Maximum Correlation Coefficient*. Therefore, the above features should be preferredwhenpattern analysisby means of GLCM methods is applied to quality assessment of the ultrasound image.

IV. CONCLUSIONS

In the application of pattern analysis to ultrasound image quality assessment by means of Gray Level Co-occurrence Matrices, some issues should be taken into account on GLCM calculus and Haralick features selection. In particular some criterionsare needed for GLCM direction and inter-pixel distancechoice, as well as fordetermining the most significant Haralick features, becauseall of them influence the image pattern characterization and analysis.To this aim a study on the selection of the significantHaralick parameters by means of correlation matrices is here proposed. The work is subdivided into three sections: (a) Image test set definition:4 different class of textures are processed in order to obtain 576 test images with different pattern size, contrast and speckle noise (b) GLCM calculus, by means of direction and inter-pixel distance determination (c) Haralick features evaluation and characterization by means of Correlation Matrices.

Preliminary results are limited todifferent pattern cell size and speckle noise levelbutsuggest that *Entropy, Energy, Maximal CorrelationCoefficient*and *InformationMeasures of Correlation II* should be taken into account because of their sensitivity to pattern characteristics and statistical independence from the others. Further tests are going to be arranged for a detailed and more robust characterization of the features and their application to ultrasound image quality assessment.

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