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Characterization of Primary and Malignant Liver Lesions using Texture Analysis

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Abstract

Texture analysis can be used as a classification approach to describe microscopic changes in the liver. In our study, a total of 260 patients aged 4 to 90 underwent successful liver ultrasound examinations using a General Electric ultrasound machine (21045-87) with a 3.5MHz curve-linear transducer, typically used to scan the liver. The liver was scanned in multiple planes (transverse, sagittal, and oblique) to analyze the lesion based on shape, position, size, and echogenicity. Then the pictures were retrieved and classified into 5 categories: normal, a liver cyst, a hydatid cyst, hepatocellular carcinoma (HCC), and liver metastases. All pictures were 512 x512 pixels with 8-bit gray-level and were encoded in DICOM format; then three FOS features (mean, entropy, and energy, obtained from the intensity function of the images) were calculated for each ROI through all images using a 3x3 window size, and the data were processed for stepwise linear discriminant (SW-LD) analysis. The classification matrix of the original and predicted groups, using the discriminant function, presents the classification accuracy of each class in which 99.2% of normal liver was correctly classified and 75.6%, 81.4%, 100.0%, and 100.0% classification sensitivity for liver cyst, HCC, hydatid cyst, and liver metastases, respectively, with the highest predictive overall accuracy of 89.1%.(**International Journal of Biomedicine. 2023;13(1):111-114.**)

Keywords: liver • focal liver lesions • ultrasound • texture analysis • first order statistics

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Abbreviations

FOS, first order statistics; **FLL**, focal liver lesions; **HCC**, hepatocellular carcinoma; **ROI**, region of interest.

Introduction

Focal liver lesions are described as solid or liquid-containing masses that are not part of the normal anatomy of the liver and may be distinguished from it utilizing imaging techniques.[1,2]

They might be benign, cancerous, or metastatic. Benign lesions that are commonly found include pyogenic liver abscess, localized nodular hyperplasia, simple cyst, hydatid cyst, and hemangioma.[3] Due to the prevalence of a wide diversity of sonographic appearances, even within certain classes of focal liver lesions (FLL), differential diagnosis in FLL patients using B-mode (US) images is extensive.[4,5]

Even so, B-mode ultrasonography[6] is the preferred method for characterizing FLL due to its non-radioactive, non-invasive, low-cost, and real-time imaging characteristics. There is a particular disadvantage associated with using B-mode ultrasound for the FLL diagnosis, namely limited sensitivity for detecting small FLL developed (less than 2cm) in the cirrhotic liver, which is already nodular and coarse textured.[7]

The sonographic appearance of HCC, a typical hemangioma, and typical metastases are highly overlapping; the sonographic appearance of cystic metastases and a typical cyst often overlap.[8] Even for seasoned radiologists, distinguishing tumor-affected tissue is a difficult task. The definitive diagnosis frequently necessitates invasive treatments such as needle biopsy or even surgery, which can be dangerous. New computer-aided image-processing technologies (particularly texture analysis) combined with effective classification algorithms can significantly enhance diagnosis accuracy. Those approaches, which extract information not generally recognized by the human eye, could reduce or even eliminate the need for intrusive procedures.[9] One of the most important issues to address when performing computer-aided image analysis is the objective and explicit categorization of image regions. The texture of studied image regions could be one of the most valuable sources of information.[10] The texture analysis entails obtaining a set of numerical parameters (referred to as texture characteristics) to characterize the ROI specified in the organs under investigation. Each texture parameter reflects a specific texture property, such as coarseness, homogeneity, or local contrast. A wide range of approaches to extracting texture features has been researched thus far.[11] Texture analysis is an important aspect of picture processing. It is a collection of mathematical strategies for quantifying the different gray levels in an image in terms of intensity and distribution. The texture is the spatial organization of gray levels in pixels in a location. As a result, it can be classified into two types: periodic texture and random texture. As a result, we can distinguish between structural and statistical techniques to calculate a number of mathematical factors that characterize texture. The study of periodic or regular textures lends itself better to structural techniques. Statistical methods, on the other hand, are employed to describe fine and non-homogeneous structures with no apparent regularity. As a result, this approach is commonly used in medical imaging.[12] A texture is perceived as a quantitative measure of the organization of intensities in an area via a statistical approach. Based on the number of pixels required to define the feature, statistical methods are classified as first-order, second-order, higher-order, and spectral statistics.[13]

To calculate texture, first order statistics (FOS) measures are applied to the image histogram. The fundamental advantage of this strategy is its simplicity in characterizing data using standard descriptors. For any surface, or image, grey levels are in the range $0 \leq i \leq Ng - 1$, where Ng is the total number of distinct grey levels. If N (i) is the number of pixels with intensity i and M is the total number of pixels in an image, it follows that the histogram, or pixel occurrence probability, is given by $P(i)=N(i)/M$

Texture analysis techniques are commonly employed in image-processing disciplines such as classification, segmentation, and synthesis. Image classification aims to organize diverse images or image portions into distinct categories.[14] Texture analysis methods are particularly suited to this since they provide unique information on the texture, or spatial variation, of pixels of the region in question. Image segmentation problems aim to define boundaries between distinct image sections. Image texture synthesis is essential in 3D computer graphics applications, where the goal is to build highly complex and realistic-looking surfaces.[15] In general, seven characteristics are computed that are typically employed to define the qualities of the image histogram, and hence image texture. These are the following: mean, variance, coarseness, skewness, kurtosis, energy, and entropy.[16]

Materials and Methods

A total of 260 patients aged 4 to 90 underwent successful liver ultrasound examinations using a General Electric ultrasound machine (21045-87) with a 3.5MHz curve-linear transducer, typically used to scan the liver.

The study was conducted between 2016 to 2019. All participants provided written informed consent.

The liver was scanned in multiple planes (transverse, sagittal, and oblique) to analyze the lesion based on shape, position, size, and echogenicity. Then the pictures were retrieved and classified into 5 categories: normal, a liver cyst, hydatid cyst, hepatocellular carcinoma (HCC), and liver metastases. All pictures were 512 x512 pixels with 8-bit gray-level and were encoded in DICOM format; then three FOS features (mean, entropy, and energy, obtained from the intensity function of the images) were calculated for each ROI through all images using a 3x3 window size, and the data were processed for stepwise linear discriminant (SW-LD) analysis. Studies with normal liver texture were performed as a control group. The obtained results are shown in Table 1 and Figures 1-4.

Results and Discussion

FOS was used to extract characteristics from ultrasound images in this investigation. Characteristics, which included mean, energy, and entropy, revealed a significant association with the studied 5 classes. All of these parameters were calculated for all images. The data were then ready for discrimination, which was performed using a stepwise technique to select the most significant feature that can be used to classify the classes in ultrasound liver images.

The results show a high concentration of components around the class centers, resulting in a significant difference between the classes (Figure 1).

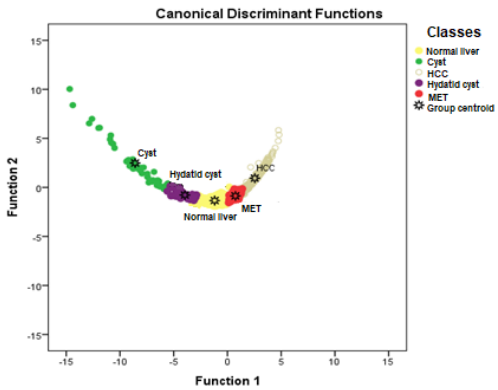

Fig. 1. *Scatter plot of the classes using discriminant function and center of classes.*

The classification matrix of the original and predicted groups, using the discriminant function, presents the classification accuracy of each class in which 99.2% of normal liver was correctly classified and 75.6%, 81.4%, 100.0%, and 100.0% classification sensitivity for liver cyst, HCC, hydatid cyst, and liver metastases (MET), respectively, with the highest predictive overall accuracy of 89.1% (Table 1).

Table 1.

The classification matrix of the original and predicted groups using the discriminant function.

Classes	Predicted Group Membership					Total
	Normal liver	Cyst	HCC	Hydatid Cyst	Metastasis	
Normal liver	99.2%	0.0	0.0	0.0	0.8	100.0
Cyst	0.0	75.6%	0.0	24.4%	0.0	100.0
HCC	0.0	0.0	81.4%	0.0	18.6	100.0
Hydatid Cyst	0.0	0.0	0.0	100.0%	0.0	100.0
Metastases	0.0	0.0	0.0	0.0	100.0%	100.0

There was a high concentration of features around the class centers, resulting in a significant disparity across the 5 classes. From the standpoint of discriminant power in terms of applied characteristics, entropy, like the mean, can successfully discriminate between all classes. The mean and entropy can successfully distinguish cysts and HCC from the rest of the tissue. Still, they are ineffective in distinguishing metastases and HCC since they have comparable average group levels. Textural heterogeneity and overlaps are observed.

Finally, the energy emphasizes HCC more than the other tissue types (Figures 2-4).

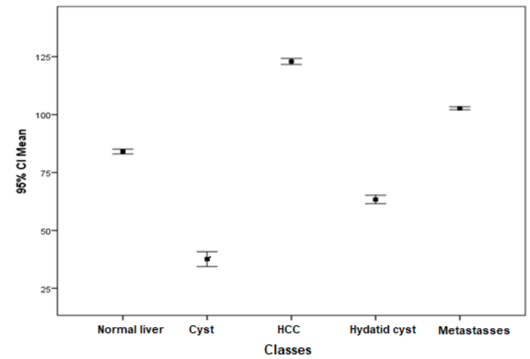

Fig. 2. *An error bar of 5 classes using the mean feature with the standard error.*

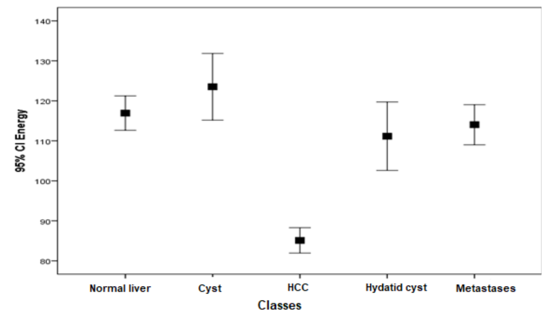

Fig. 3. *An error bar of 5 classes using the energy feature with the standard error.*

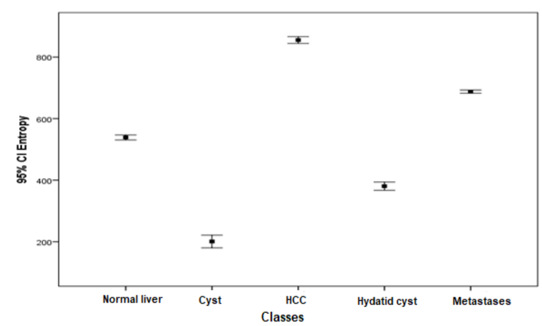

Fig. 4. *An error bar of 5 classes using the entropy feature with the standard error.*

Conclusion

Based on textural features, excellent discrimination between benign and malignant liver lesions can be achieved, and this serves as a secondary method for further characterization of the lesion. The texture reveals a different underlying pattern in the normal liver than do benign and malignant liver lesions, with an overall classification accuracy of 89.1%. Texture analysis can be used as a classification approach to describe microscopic changes in the liver. To summarize the findings of this study, the following equation should be used to classify liver tissue as normal, cyst, HCC, hydatid cyst, or liver metastases (MET), with the highest value receiving the most votes.

Normal liver = (35.6 × mean) + (0.2 × Energy) + (-4.2 × Entropy) -365.8

Cyst = (25.7 × mean) + (0.19 × Energy) + (-3.1 × Entropy) - 185.4

HCC = (35.8 × mean) + (0.17 × Energy) + (-4.2 × Entropy) - 411.0

Hydatid cyst = (32.95 × mean) + (0.185 × Energy) + (-3.95 × Entropy) - 303.19

MET = (36.4 × mean) + (.205 × Energy) + (-4.31 × Entropy) - 400.4

Competing Interests

The authors declare that they have no competing interests.

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