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AN EFFICIENT APPROACH FOR THE LIVER LESION DETECTION FROM THE CONTRAST ENHANCED US IMAGES

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ABSTRACT: *This paper proposes an automatic classification method based on machine learning in Ultrasonography of focal liver lesions using image processing techniques. There are different techniques used for the segmentation of lesions from the image. Active contour is one of the active models in segmentation techniques, which makes use of the energy constraints and forces in the image for separation of a region of interest. Active contour defines a separate boundary or curvature for the regions of the target object for segmentation. This method can yield spatial and temporal features based on a discrete wavelet transform. The lesions are classified as benign or malignant liver tumors using support vector machines (SVM) with a combination of selected texture features. The experimental results are consistent with guidelines for diagnosing FLLs.*

I - INTRODUCTION

The differential diagnosis of focal liver lesions includes a broad spectrum of benign, malignant, and infectious etiologies. Focal liver lesions in humans include neoplasms, metastatic lesions, inflammatory masses, and cysts (congenital or acquired); primary neoplasms – both benign and malignant – are 1%-2% of all tumors. Many studies suggest that benign neoplasms are less frequent than malignant tumors. Primary liver neoplasms are in third place, in order of frequency, among malignant intra-abdominal masses in the pediatric population, after Wilms tumors and neuroblastomas, with an incidence of 5-6%.

Although liver tumors are the most frequent malignant GI tumors, they are less than 2% of all malignant processes. Most humans with benign or malignant liver masses come into a physical exam with palpable masses. Other symptoms include pain, anorexia, jaundice, paraneoplastic syndromes, hemorrhages, and congestive heart failure. Several factors help when making a differential diagnosis, such as the age of the child, characteristics of the images taken, clinical presentation, levels of alpha-fetoprotein, and whether it is a single or multiple lesions.

Liver tumors associated with high serum levels of alpha-fetoprotein include hepatoblastoma and hepatocellular carcinoma. Infantile hemangio endothelioma may have high levels in a minority of lesions (< 3%). The presence of multiple lesions suggests metastatic disease, infantile hemangioendothelioma, abscesses, cat-scratch disease. Adenomas or lymphoproliferative diseases in predisposing conditions, such as Fanconi's anemia or Gaucher's disease. Clinical presentation may suggest a specific diagnosis.

Several computer-aided diagnosis (CAD) techniques that improve the objectivity of diagnosing FLLs with CEUS have been proposed. For classifying FLLs into four classes (HCC, hepatic hemangioma, FNH, and liver metastasis) using a support vector machine (SVM) with parameters obtained from a TIC analysis of the arterial phase. A neural network with four parameters obtained from a TIC and achieved 93.4% sensitivity and 89.7% specificity for 112 cases. Their method used 43 parameters obtained from max-hold images in CEUS and classified FLLs with six neural networks in a cascade. The method for classifying FLLs as benign or malignant using an enhancement pattern of a differential TIC between the FLL and parenchyma ROIs obtained by ROI tracking based on the scale-invariant feature transform (SIFT) key points detector. The proposed system correctly classified 13 lesions out of 14 cases. a method of benign and malignant classification using TICs of FLL and parenchyma ROIs obtained by ROI tracking based on Compact and Real-time Descriptors (CARD) and mean shape estimation of ROI based on a Generalized Procrustes Analysis (GPA). This method achieved 91.6% accuracy for 107 cases.

II - RELATED WORK

In [1], M. Danila, et al., proposed a single-center experience concerning the use of contrast-enhanced ultrasound (CEUS) in the characterization of FLL and to find when one can avoid using other expensive imaging modalities such as contrast-enhanced CT or MRI. A CEUS examination was considered conclusive if the FLL had a typical enhancement pattern according to the EFSUMB guidelines. CEUS was conclusive in approximately 80% of the FLLs and the benign or malignant character of a lesion was demonstrated in about 90% of cases.

S. Bakaset al., [3] proposed a methodology for tracking a hypo- or hyper-enhanced focal liver lesion (FLL) and a healthy liver region in a video sequence of a Contrast-Enhanced Ultrasound (CEUS) examination. The outcome allows the differentiation between benign and malignant cases, by characterizing FLLs of typical behavior, according to their Time-Intensity curves. The task is challenging mainly due to intensity changes caused by contrast agents. Initially, the ultrasound mask is automatically localized and then the FLL and parenchyma regions are tracked, assuming affine transformations on the image plane, employing the point-based registration technique of Lowe's scale-invariant feature transform (SIFT) key points detector.

X. Liang, et al.,[4] this work is to provide an automatic computational framework to assist clinicians in diagnosing Focal Liver Lesions (FLLs) in Contrast-Enhancement Ultrasound (CEUS). We represent FLLs in a CEUS video clip as an ensemble of Region-of-Interests (ROIs), whose locations are modeled as latent variables in a discriminative model. Different types of FLLs are characterized by both spatial and temporal enhancement patterns of the ROIs. The model is learned by iteratively inferring the optimal ROI locations and optimizing the model parameters.

M. Schneider et al., [5] this work was to develop a new parametric imaging technique, aimed at mapping the DVP signatures into a single image called a DVP parametric image, conceived as a diagnostic aid tool for characterizing lesion types. The methodology consisted of processing a time sequence of images (DICOM video data) using four consecutive steps: (1) pre-processing combining image motion correction and linearization to derive an echo-power signal, in each pixel, proportional to local contrast agent concentration over time; (2) signal modeling, utilizing a curve-fitting optimization, to compute a difference signal in each pixel, as the subtraction of adjacent parenchyma kinetic from the echo power signal; (3) classification of difference signals; and (4) parametric image rendering to represent classified pixels as support for diagnosis.

III - PROPOSED SYSTEM

To propose an automatic classification method based on machine learning in contrast-enhanced ultrasonography (CEUS) of focal liver lesions (FLLs) using the contrast agent SonazoidR. To segment the lesion region based on active contour technique, it defines a separate boundary or curvature for the regions of a liver lesion for segmentation. To extracts spatial and temporal features in three phases (arterial phase, portal phase, and post-vascular phase) and max-hold images of focal liver lesions from SonazoidR CEUS images. Benign and malignant tumors are classified by using the SVM classifier.

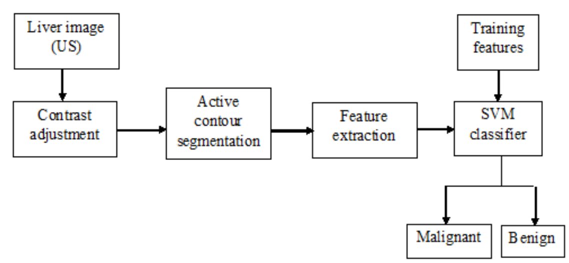


Fig 1. Proposed block

The proposed (fig 1) work is having the following functions:

- Contrast adjustment
- Active contour segmentation
- Feature extraction
- Support vector machine (SVM) classifier

A. Pre-Processing Techniques

Liver ultrasound images are degraded during the process of imaging due to image transmission and image digitization by noise and the existence of extracranial tissues.

Pre-processing is a procedure to eliminate these noises and extra-cranial tissues from the liver ultrasound and alters the heterogeneous image into a homogeneous image. Though there are lots of filters that have been used for filtering the images, some of them corrupt the miniature details of the image and some conventional filters will process the image incessantly (smoothing) and consequently harden the edges of the image. Hence, the proposed pre-processing steps namely De-noising and skull stripping provide better Image clarity.

B. Contrast Adjustment

Contrast adjustment remaps image intensity values to the full display range of the data type. An image with good contrast has sharp differences between black and white.

The first step is to calculate a contrast correction factor which is given by the following formula:

$$F = \frac{259(C+255)}{255(259-C)}$$

For the algorithm to function correctly the value for the contrast correction factor (F) needs to be stored as a floating-point number and not as an integer. The value C in the formula denotes the desired level of contrast.

C. ACTIVE CONTOUR SEGMENTATION ALGORITHM

Active Contours or Snakes can be generalized as curves described in an image domain that can shrink or grow due to the Internal and External Forces.

Internal forces are defined within the curve itself, whereas the External forces arise from the image data. These forces ensure that the snake is confined to object boundaries or any other feature in the image.

1. Implementation of the active contour model (ACM).

For a closed parametric curve (s) = $[(s), (s)]$, $s\in$ [0,1], ACM defines the energy function:

$$E = \int_0^1 \frac{1}{2}(\alpha|X'(s)|^2 + \beta|X''(s)|^2) + E_{ext}\big(X(s)\big)ds, \quad (1)$$

where$\alpha$and $\beta$are the weighting parameters of contour elasticity and rigidity, respectively, $X'(s)$and $X''(s)$denote the first and the second derivatives of $X(s)$ to s, and $E_{ext}\big(X(s)\big)$is the external energy derived from image and constraint forces so that it has a smaller value near the object boundary and bigger value in the other areas.

The minimization of Emust satisfy the Euler equation:

$$\alpha X''(s) - \beta X''''(s) - \nabla E_{ext} = 0 \ (2)$$

Which can be regarded as a force balance equation:

$$F_{int} + F_{ext} = 0 \ (3)$$

where $F_{int} = \alpha X''(s) - \beta X''''(s)$, $F_{ext} = -\nabla E_{ext}$, internal force F_{int} discourages both stretching and bending, external force F_{ext} pulls the active contour to the desired image edges, and finally, the curve stops at the position with force balance.

To solve (2), the active contour is taken as a function of time $t$and parameter s; that is, $(s,\ t)$ and the solution of (2) become the solution of:

$$X_t(s,t) = \alpha X''(s,t) - \beta X''''(s,t) - \nabla E_{ext} \ (4)$$

2. Implementation of gradient vector flow (GVF).

There are two major challenges with the Active Contour. First, the initial snake must be close to the edge to be detected and snakes have difficulty converging in the concave regions.

To overcome these challenges a new external force was introduced, whose fields are called GVF fields, and the snake that uses the GVF field is called GVF snake. This GVF field pulls the snake towards the object boundary when the snake is closer to the boundary and can converge the snake into concave regions.

The GVF based ACM defines a new external force field $F_{ext}^g = V(x,y)$, and the new external force field is named gradient vector flow force field. From(4), there is

$$X_t(s,t) = \alpha X''(s,t) - \beta X''''(s,t) + \nabla(x,y)(5)$$

An edge map $(x,\ y)$ is calculated from the original image $(x,\ y)$, and the value of the edge map is larger at positions near the image edges. Edge map can be obtained from gray-level images or binary images as

$$f(x,y) = -\nabla E_{ext}^i(x,y) \ (6)$$

where$i$ = 1, 2, 3, or 4. Edge map has three characteristics: the gradient vector of edge map, that is, ∇f, should point to and be perpendicular with the object boundary; the gradient vector of edge map has a larger value at object boundaries; in the smooth region of the image where little change with the value of $I(x,\ y)$, $\nabla f$is close to 0.

The gradient vector flow force field can be expressed as $(x,\ y)$ = $((x,\ y),\ \mathrm{V}(x,\ y))$, and its energy function is

$$\varepsilon = \iint \mu(u_x^2 + u_y^2 + v_x^2 + v_y^2) + |\nabla f|^2 |V - \nabla f|^2 dx\, dy \ (7)$$

The energy function follows a standard principle that, in the absence of a gradient vector field, the smoothness of active contour is ensured. When the value of $\nabla f$is small, the energy function is determined by the sum of the squares of partial derivatives of the gradient vector force field. When the value of $\nabla f$is large, the energy function is determined by $|\nabla f|2|V - \nabla f|2$ and is minimized by $V = \nabla f$. Therefore, Vnearly equals to the gradient of edge map where gradient value is large and changes little where gradient value is small. As the weighting parameter, $\mu$is set according to the proportion of noise in the image, that is, more noise with a larger value of μ.

D. Feature Extraction

The pattern recognition, machine learning and, image processing, the extraction of feature starts from an initial set of measured data and builds derived values (features) intended to be informative and non-redundant, facilitating the subsequent learning and generalization steps, and in some cases leading to better human interpretations. Feature extraction is related to dimensionality reduction.

The algorithms input data is very large to be processes and it is anticipated to be redundant then it can be transformed into a reduced set of features (also named a features vector). This process is called feature selection. The features which are selected is expected to contain the relevant information from the input data such that the desired task can be performed by using this reduced representation instead of the complete initial data.

In order to describe a large set of data, the Feature extraction is involved with reducing the number of resources required. When performing analysis of complex data one of the major problems stems from the number of variables involved. Analysis with a large number of variables generally requires a large amount of memory and computation power, also it may cause a classification algorithm to overfit to training samples and generalize poorly to new samples. Feature extraction is a general term for methods of constructing combinations of the variables to get around these problems while still describing the data with sufficient accuracy.

The transformation of an image into its set of features is known as feature extraction. Useful features of the image are extracted from the image for classification purposes. It is a challenging task to extract a good feature set for classification. There are many techniques for feature extraction e.g. texture Features, Gabor features, feature based on wavelet transform, principal component analysis, minimum noise fraction transform, discriminant analysis, decision boundary feature extraction, non-parametric weighted feature extraction, and spectral mixture analysis. We are using the texture feature for our proposed system.

E. Support Vector Machine Classification

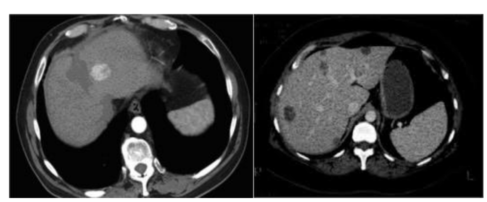
Support vector machines (SVMs) are a set of supervised learning methods used for classification, regression, and outlier detection. More formally, a support vector machine constructs a hyperplanes or set of hyper planes in a high- or infinite-dimensional space, which can be used for classification, regression, or other tasks. Intuitively, a good separation is achieved by the hyperplane that has the largest distance to the nearest training-data point of any class (so-called functional margin), since in general the larger the margin the lower the generalization error of the classifier.

SVM Algorithm

Classifying data is a common task in machine learning. Suppose some given data points each belong to one of two classes, and the goal is to decide which class a new data point will be in. In the case of support vector machines, a data point is viewed as a p-dimensional vector, and we want to know whether we can separate such points with a (p-1)-dimensional hyperplane. This is called a linear classifier. Many hyperplanes might classify the data. One reasonable choice as the best hyperplane is the one that represents the largest separation, or margin, between the two classes. So we choose the hyperplane so that the distance from it to the nearest data point on each side is maximized. If such a hyperplane exists, it is known as the maximum-margin hyperplane and the linear classifier it defines is known as a maximum margin classifier; or equivalently, the perceptron of optimal stability.

IV – SIMULATION RESULTS

The following figure represents the sample liver CT images tested with this proposed work. The images are downloaded from the UCI database.



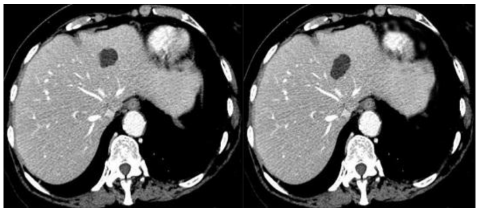


Figure 1. Sample liver CT images

Figure 2. Sample test liver image

Figure 3.Liver seed region

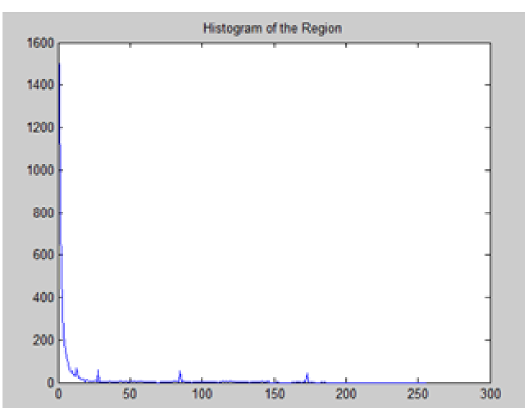


Figure 4. Histogram of liver region

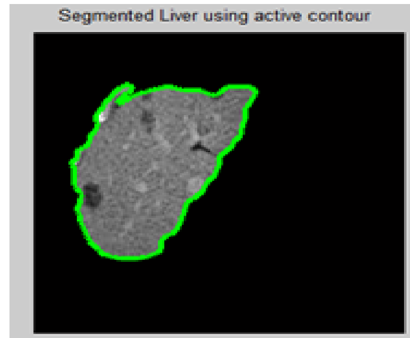


Figure 5.Segmented liver boundary

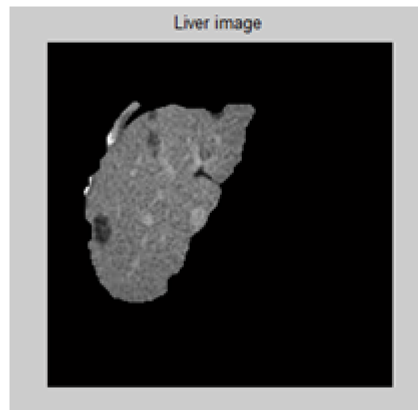


Figure 6.Segmented liver ROI

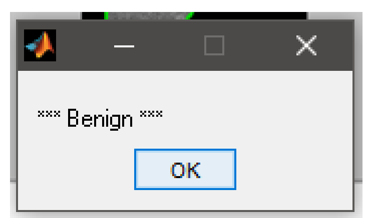


Figure 10 Classifier result

(I) Performance Measure

The performance is evaluated for images the performance measure includes accuracy, sensitivity,precision,recall, and specificity.Maximumaccuracy is obtained in the SVM method. The accuracy obtained for SVM is 75% and KNN 60%. The specificity obtained for SVM is 93% and KNN 75%. The sensitivity obtained for SVM is 93% and KNN 86%. The precision obtained for SVM is 78% and KNN 50%. Fig 4.35 gives the overall performance graph for accuracy, sensitivity, precision, specificity.The accuracy is high and it signifies that the system is an efficient system for segmenting the tumor.

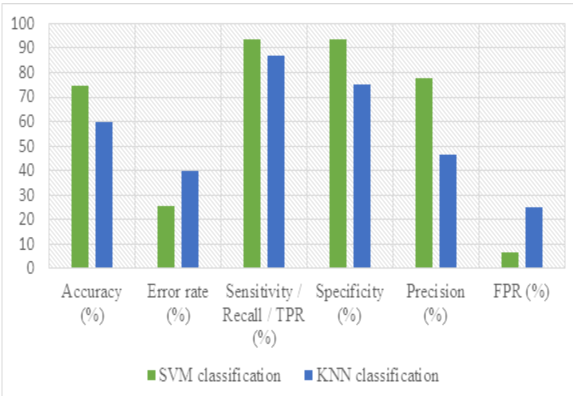


Fig 7: Perfomance evaluation graph

V - CONCLUSION

In this paper, we proposed an automatic classification method using machine learning techniques for focal liver lesions. The results indicated that combining the features from the liver ROI was important for classification methods based on machine learning US images. Our investigation of the operator dependence associated with ROI specification in our method showed that the intra-operator agreement was moderate and the inter-operator agreement was fair to good. The liver region is segmented based on the active contour segmentation technique. The segmented liver region is given into the feature measurement. The texture and spatial features are extracted from the liver region and the test features are classified with the help of a support vector machine classifier.

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