Development of a Support Vector Machine – Based Image Analysis System for Focal Liver Lesions Classification in Magnetic Resonance Images

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Abstract. Purpose: The design and implementation of a computer-based image analysis system employing the support vector machine (SVM) classifier system for the classification of Focal Liver Lesions (FLLs) on routine non-enhanced, T2-weighted Magnetic Resonance (MR) images. Materials and Methods: The study comprised 92 patients; each one of them has undergone MRI performed on a Magnetom Concerto (Siemens). Typical signs on dynamic contrast-enhanced MRI and biopsies were employed towards a three class categorization of the 92 cases: 40-benign FLLs, 25-Hepatocellular Carcinomas (HCC) within Cirrhotic liver parenchyma and 27-liver metastases from Non-Cirrhotic liver. Prior to FLLs classification an automated lesion segmentation algorithm based on Marcov Random Fields was employed in order to acquire each FLL Region of Interest. 42 texture features derived from the gray-level histogram, co-occurrence and run-length matrices and 12 morphological features were obtained from each lesion. Stepwise multi-linear regression analysis was utilized to avoid feature redundancy leading to a feature subset that fed the multiclass SVM classifier designed for lesion classification. SVM System evaluation was performed by means of leave-one-out method and ROC analysis. Results: Maximum accuracy for all three classes (90.0%) was obtained by means of the Radial Basis Kernel Function and three textural features (Inverse-Different-Moment, Sum-Variance and Long-Run-Emphasis) that describe lesion's contrast, variability and shape complexity. Sensitivity values for the three classes were 92.5%, 81.5% and 96.2% respectively, whereas specificity values were 94.2%, 95.3% and 95.5%. The AUC value achieved for the selected subset was 0.89 with 0.81 – 0.94 confidence interval. Conclusion: The proposed SVM system exhibit promising results that could be utilized as a second opinion tool to the radiologist in order to decrease the time/cost of diagnosis and the need for patients to undergo invasive examination.

1. Introduction

Focal liver lesions (FLL) have been considered as very difficult task faced by gastroenterologists and hepatologists. The increasing and widespread use of contemporary imaging modalities has led to an increase in incidental FLL detection. Thus, the identification of not only malignant liver lesions, but benign solid and cystic liver lesions (such as hemangioma, focal nodular hyperplasia, hepatocellular adenoma, and hepatic cysts) as well is crucial in differential diagnosis [1]. The majority of FLLs

present in non-cirrhotic livers are considered benign. Hemangiomas, focal nodular hyperplasias (FNH), and adenomas (HCA) are the most commonly encountered solid benign lesions. On the other hand, the most commonly encountered malignant lesions in noncirrhotic livers are metastases. Hepatocellular carcinoma (HCC) and intrahepatic cholangiocarcinoma (ICC) also occur in cases of chronic liver disease [2].

Specificity and accuracy optimization of cross-sectional imaging in the context of these incidental liver lesions is of importance in avoiding unnecessary biopsies, which may portend a post-procedural morbidity of 2.0% to 4.8% and mortality of 0.05%. Ultrasound, computed tomography (CT), and magnetic resonance imaging (MRI) are the main liver imaging modalities. A meta-analysis comparing contrast-enhanced ultrasound, CT, and MRI in evaluating incidental FLLs demonstrated similar diagnostic performance with specificities ranging from 82%-89% and no significant differences in the receiver operating characteristic analysis between modalities. Given the lack of ionizing radiation and relative non availability of ultrasound contrast in the U.S., Magnetic resonance imaging (MRI) is considered a sensitive diagnostic method towards characterization of hepatic cirrhosis that competes or outperforms the diagnostic utility of liver biopsies. However, hepatic MRI has some shortcomings in detection and classification of focal liver lesions without the need for administration of contrast media, despite its superior tissue contrast and the combination of different pulse sequences [3]. A comprehensive liver protocol evaluates the parenchyma, vasculature, and biliary system. This in MRI is accomplished by way of a combination of single-shot T2-weighted fast spin-echo, gradient echo T1-weighted in- and opposed-phase, fat suppressed T2-weighted, dynamic pre- and post-contrast T1-weighted imaging and potentially subtraction of pre from post-contrast image sets [3].

Computer-aided diagnostic (CAD) systems that include quantitative lesion description and classification can provide radiologists or physicians an alternative second opinion towards optimization of the diagnostic procedure. The need to strengthen the diagnostic value of non-enhanced T1 and T2 sequences, Mayerhoefer et al. has tried to apply texture analysis for an automatic classification of liver cyst and hemangiomas showing promising results [4]. A study with more cases including more types of lesions is needed though to establish this method as a reliable non-enhanced tool for differential diagnosis. In this study, the feasibility of Computer Aided Diagnosis system for the classification of Focal Liver Lesions (FLLs) on routine non-enhanced, T2-weighted Magnetic Resonance images is evaluated.

The design and implementation of a computer-based image analysis system employing the support vector machine (SVM) classifier system for the classification of Focal Liver Lesions (FLLs) on routine non-enhanced, T2-weighted Magnetic Resonance (MR) is presented in this study.

2. Materials and Methods

2.1. Clinical Data

Clinical material includes 30 – benign FLLs, 19 – Hepatocellular Carcinomas (HCC) within Cirrhotic liver parenchyma and 22 – liver metastases from Non-Cirrhotic liver. All three classes' diagnosis was established by means of typical signs on dynamic contrast-enhanced MRI and biopsies.

2.2. FLLs Detection

The lesion detection – segmentation procedure comprise an initialization step that combines the edge information derived from Dyadic Wavelet Transform (DWT) and the clustering properties of unsupervised Fuzzy C-means (FCM) clustering algorithm followed by Marcov Random Fields (MRF) segmentation for final lesion extraction.

Wavelet transform is a multiresolution analysis technique that has been developed and applied in various fields, such as astronomy, finance, quantum physics, signal processing, video compression, and image processing. Throughout this study, the 2D redundant DWT was employed for multiresolution analysis [5]. The Dyadic Wavelet Transform (DWT) of a function $f(x,y) \in L^2R^2$ is the set of functions $W_{2^j}^1 f(x,y), W_{2^j}^2 f(x,y)$ which are respectively the partial derivative along the

horizontal and vertical orientation of the convolution of $f(x,y)$ by the smoothing function $\theta(x,y)$, dilated along a dyadic sequence $(2^j)_{j\in Z}$ and is given by:

$$\begin{pmatrix} W_{2^j}^1 f(x,y) \\ W_{2^j}^2 f(x,y) \end{pmatrix} = f \cdot \begin{pmatrix} \psi_{2^j}^1 \\ \psi_{2^j}^2 \end{pmatrix} = 2^j \begin{pmatrix} \frac{\partial}{\partial x}(f \cdot \theta_{2^j})(x,y) \\ \frac{\partial}{\partial y}(f \cdot \theta_{2^j})(x,y) \end{pmatrix} \tag{1}$$

where $\psi_{2^j}^1$ and $\psi_{2^j}^2$ are the analyzing wavelets and j the dyadic scale. We performed the wavelet analysis with the DWT using Mallat's filters [5].

The FCM algorithm is an iterative clustering algorithm in which each data point is assigned to a cluster to a degree specified by a fuzzy membership grade. The procedure for assigning each cluster is considered an iterative optimization procedure that minimizes a cost function when pixels close to the centroid of their clusters are assigned to high membership values [6].

Let $V = \{v_1, \ldots, v_n\}$ be the set of n image pixels and let C be the number of clusters. The cost or objective function for FCM is described as follows:

$$Q_{fcm} = \sum_{j=1}^{n}\sum_{i=1}^{C} u_{ij}^m \left\| v_j - \mu_i \right\|^2 \qquad 1 \le m < \infty \tag{2}$$

subject to:

$$\sum_{i=1}^{C} u_{ij} = 1, \forall \; j = \{1,\ldots,n\} \tag{3}$$

where, $m \in (1, \infty)$ controls the fuzziness of the resulting partition, u_{ij} denotes the membership of data pixel v_j to fuzzy cluster i whose value is between $[0,1]$; μ_i is the cluster center of fuzzy cluster i, and $\left\| v_j - \mu_i \right\|^2$ represents the Euclidian distance between the pixel v_i and the cluster center μ_i.

The FCM cost function is minimized when high membership values are assigned to pixels whose intensities are close to the centroid of their clusters and low membership values are assigned when the point is far from the centroid. The membership degrees and the cluster centers are updated according to the following formulas:

$$u_{ij}^m = \frac{1}{\sum_{k=1}^{C}\left(\frac{\left\| v_j - \mu_i \right\|}{\left\| v_j - \mu_k \right\|} \right)^{\frac{2}{m-1}}} \tag{4}$$

$$\mu_i = \frac{\sum u_{ij}^m v_i}{\sum_{i=1}^{n} u_{ij}^m} \tag{5}$$

Starting with an initial guess for each cluster center, the FCM converges to a solution for μ_i representing the local minimum or a saddle point of the cost function. Convergence can be detected by comparing the changes in the membership function or the cluster center at two successive iteration steps.

MRF modelling combines conditional (local intensity distribution) with contextual (intensity similarity within small neighborhoods) information under the Bayesian framework in order to estimate the true intensities of the image rather than those based only on the conditional information [7]. It assumes that the class probability of a pixel is only dependent on class membership of its spatial neighbors (also called lattice) which in turn reduces the possible influence of noise and overlapping structures. The

model assumption that the conditional distribution depends on the pixels in the near neighborhood is subject to the Bayesian framework which states that the decision rule for labelling an image pixel combines the conditional intensity distribution of an individual region with prior knowledge regarding that region.

Given the fact that the observed image y is a realization of a random field *Y*, x^* is the true unknown label of the observed pixel, and $\hat{x}$ indicates the estimate of x^*, the main objective of the MRF segmentation model is to find $\hat{x}$ given the observed image y. Let's assume that *P(X)* is our prior knowledge and *P(Y|X)* is the probability of realizing the observed image given the regions distribution in the image. Then, in accordance to Bayes theorem:

$$P(X \mid Y) = \frac{P(Y \mid X)P(X)}{P(Y)} \tag{6}$$

where, *P(X|Y)* is our posterior probability. The most widely used conditional intensity distribution is the Gaussian distribution, whose function, given the class x_s is given by:

$$P(Y = y \mid X = x_s) = \frac{1}{\sqrt{2\pi\sigma_s^2}} \exp\left(-\frac{(y-\mu_s)}{\sigma_s^2}\right) \tag{7}$$

Where, μ_s and σ_s are the distribution parameters of class x_s.

Then, $\hat{x}$ can be obtained by taking the posterior's probability natural logarithm and minimizing its negative resultant:

$$\hat{x} = \arg\min_{x}(-\log(\mathrm{P}(\mathrm{X} \mid \mathrm{Y}))) \tag{8}$$

In our case this optimization task is solved within the deterministic approach (iterated conditional mode – ICM). The ICM solves the minimization problem by sequentially updating (i.e. raster scanning the image) labels by minimizing the following equation at each pixel s:

$$\hat{x} = \arg\min_{x_s \in L} = \left\{\frac{(y-\mu_s)}{\sigma_s^2} + \frac{1}{2}\log(2\pi\sigma_s^2) + \beta \mathrm{U}(x_s)\right\} \tag{9}$$

Where, $U(x_s)$ is the number of pixels in the neighborhood that have color x_s. and β is a positive constant that controls the interaction between the pixels within the neighborhood.

An Edge Indicator Function (EIF) is computed from the wavelet image in order to locate the edge positions that correspond to local maxima in the wavelet domain (Figure 1c). The mean intensity value of the area between consecutive edges from the MR images is then calculated and fed as input to the FCM algorithm to acquire the initialization image (Figure 1d). The resulted image is applied as initial image to the Marcov – Random – Field (MRF) Model towards final lesion segmentation (Figure 1e).

2.3. Feature Extraction, Selection & Classification

For each lesion extracted by the aforementioned segmentation procedure, a single Region-of-Interest (ROI) was constructed on the image section depicting the maximum lesion diameter. 42 texture features derived from the gray-level histogram, co-occurrence and run-length matrices and 12 morphological features were obtained from each lesion [8-9]. Stepwise multi-linear regression analysis was utilized to avoid feature redundancy leading to a feature subset that fed the multiclass SVM classifier designed for lesion classification.

An SVM based classifier [10] is designed to work for two class problems and can be applied to linearly or nonlinearly separable data, with or without class data overlap. In the most difficult case of nonlinearly separable and overlapped data, which is often the case, data are first transformed from the input space to a higher dimensionality feature space, where classes are linearly separable. Then two parallel hyperplanes are determined with maximum distance between them and at the same time with minimum number of training points in the area between them (also called the margin). Finally, a third hyperplane through the middle of the margin is defined, which is the decision boundary of the two classes. SVM System evaluation was performed by means of leave-one-out method.

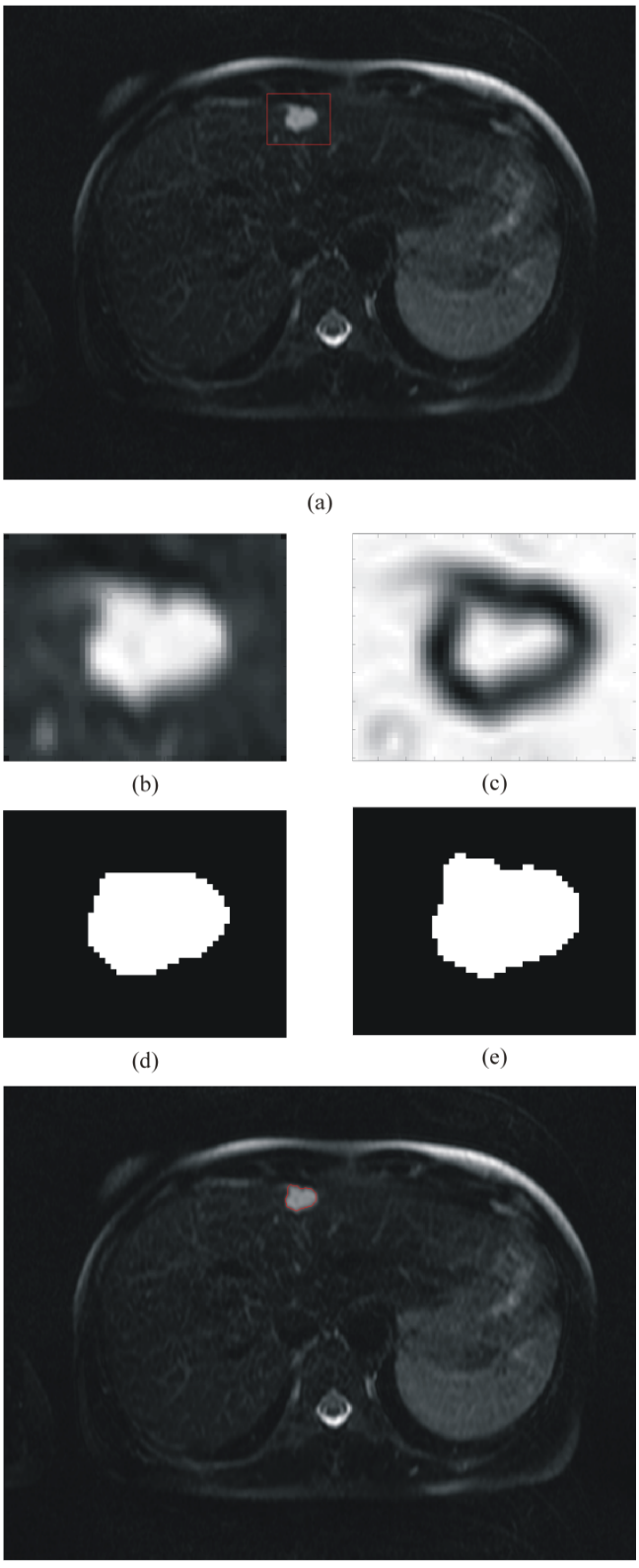

Figure 1. MRF segmentation with edge driven FCM initialization. (a) MR image with lesion selected, (b) Lesion cropped, (c) Edge Indicator Function, (d) FCM initialization, (e) MRF segmentation, (f) Lesion outlined.

3. Results

Maximum accuracy for all three classes (90.2%) was obtained by means of the Radial Basis Kernel Function and three textural features (Inverse-Different-Moment, Sum-Variance and Long-Run-Emphasis) that describe lesion's contrast, variability and shape complexity. Sensitivity values for the three classes were 92.5%, 81.4% and 96.0% respectively, whereas specificity values were 94.2%, 95.3% and 95.5%. The AUC value achieved for the selected subset was 0.89 with 0.81 – 0.94 confidence interval (Table 1).

Table 1 Confusion matrix of the SVM classifier employing the Inverse-Different-Moment, Sum-Variance and Long-Run-Emphasis best feature combination.

	Multi-Class SVM classification				
Verified FLLs	Benign	HCC	Metastases	Sensitivity/ Specificity	LOO precision
Benign	37	2	1	92.5 % / 94.2 %	92.5 %
HCC	3	22	2	81.5 % / 95.3 %	88.0 %
Metastases	0	1	24	96.2 % / 95.5 %	88.8 %
Overall accuracy					90.0 %

4. Discussion & Conclusion

The proposed SVM system exhibit promising results that could be utilized as a second opinion tool to the radiologist in order to decrease the time/cost of diagnosis and the need for patients to undergo invasive examination.

5. References

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