Classification of hepatic metastasis in enhanced CT images by dipolar decision tree

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Résumé – Cette étude a pour but de réaliser une classification des métastases hépatiques, en imagerie scanner. Les régions d'intérêt analysées représentent du tissu sain, et quatre types de métastases. Pour chaque patient, trois acquisitions sont réalisées (sans injection de produit de contraste, aux phases artérielle et portale après injection). La méthode comporte une première étape de caractérisation par analyse de texture, suivie d'une classification des régions. La méthode de classification utilisée est basée sur les arbres de décision dipolaires. Dans cette méthode, chaque nœud de l'arbre correspond à un test multivariable (hyperplan). La recherche de l'hyperplan optimal est basée sur la séparation des dipôles (paire de vecteurs de paramètres de l'ensemble d'apprentissage). Les résultats préliminaires montrent que la qualité de classification augmente quand le temps d'acquisition des images est pris en compte, et qu'elle est supérieure à celle obtenue par d'autres méthodes de classification.

Abstract – In the paper, computer-aided decision support system for hepatic metastasis diagnosis based on dynamic CT scans is presented. Analyzed image database contains 4 types of pathological lesions and normal tissue in typical acquisition time moments of dynamic CT of the liver: without contrast material and after injection, in arterial and portal phases. In the proposed approach, texture analysis of drawn ROI-s is combined with a new classification method - dipolar decision tree. In this method, each node of the binary tree corresponds to a multivariate test (hyper-plane). Searching for an optimal position of the hyper-plane is based on separation of mixed dipoles (pairs of input feature vectors from different classes). Experimental results show that the proposed approach allowed obtaining the competitive classification quality. Furthermore, it could be improved by taking into account the acquisition time of CT images.

1 Introduction

Medical imaging (CT, ultrasound, MRI) is now used in clinical routine to aid diagnosis of abdominal organs. Visual analysis of images often enables to detect lesions and to assess their size. Exact pathology differentiation is a much more complicated process. In many cases, e.g. when a tumor is suspected, the needle biopsy is performed as a definitive test. In such cases, this invasive technique could be avoided by applying computer-aided methods for detailed analysis of acquired scans. One of the most informative element of medical images is their texture.

Texture analysis [8] is a very useful tool to describe homogeneous areas of images. In medical applications, it consists in extracting a set of parameters, to characterize Regions Of Interest (ROI) defined in the concerned organs. These features are generally derived from simple (e.g. histogram-based and gradient-based statistics) or more sophisticated (for example, based on run-length and co-occurrence matrices) statistical properties of the image. Another possibility is to apply model-based approaches (e.g. Markov fields), transform methods (e.g. based on wavelet) or mathematical morphology operations. Combined with classification methods, texture analysis is known to be a very sensitive tool in discrimination of pathologies [3]. Such approaches were successfully applied in a broad range of imaging modalities and diagnostic problems ([11], [9], [4]).

In this paper, we concentrate on texture-based classification of hepatic lesions from CT images. First application of texture analysis to liver scans was presented by Mir *et al.* [12]. They showed that values of gray level distribution derived from run-length matrix are significantly different in normal and malignant tissue. Chen *et al.* [5] proposed an automatic diagnostic system using artificial neural network based on fractal and co-occurrence features. This system was able to differentiate two major liver tumors. A similar approach (co-occurrence descriptors and sequentially placed feed-forward neural network) was presented in [7]. All aforementioned applications consider non-enhanced CT images and deal only with primary tumors of the liver. In this paper, for the first time contrast-enhanced scans are used to classify lesions. Recent simulation research [10] on CT images evolution over time after injection of contrast material confirmed discrimination potential of texture features.

Liver, beside their specific tumors, is very often affected by metastasis coming from other organs. In some situations, only detection of tumoral changes in the liver, allows to start searching for original sources of pathology. It should be clear that differentiation and finding source of metastasis is a vital clinical problem [1]. In this paper, for the first time texture classification is applied to support diagnosis of metastasis type.

The rest of the paper is organized as follows. In the next section, the proposed method of texture-based classification is presented. Collected database of hepatic CT images and obtained results of metastasis classification are described in section 3. In

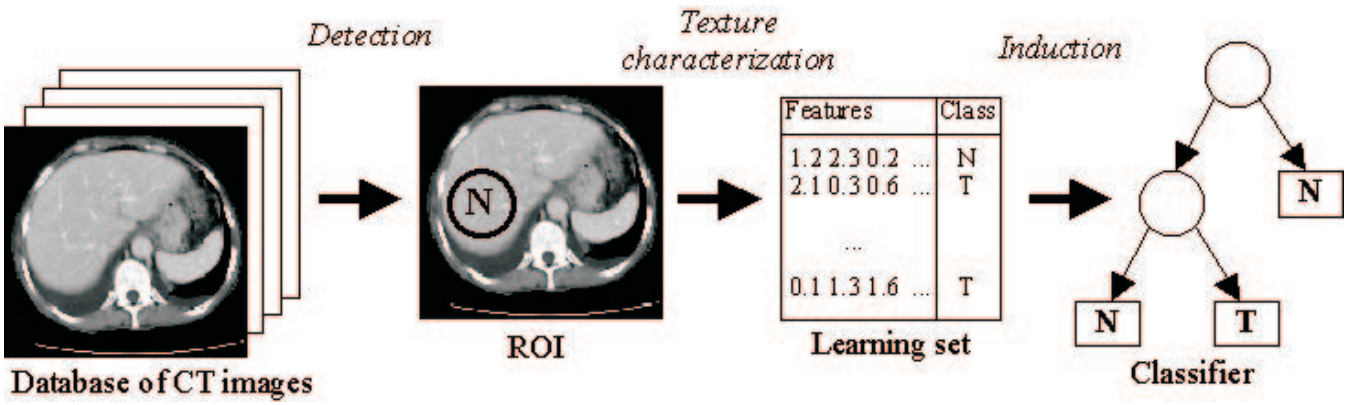

FIG. 1: Process of classifier induction based on learning set derived by texture analysis from gathered database of CT images with known diagnosis

the last part of the paper, short conclusions and future plans are presented.

2 Proposed approach

In figure 1, the process of designing a classifier, which can be used in computer-aided diagnosis, is summarized. After visual detection of pathological regions, ROI-s are manually drawn inside lesions. In questionable cases, when the radiological rapport does not precise enough the lesion location, the expert is asked to position the ROI. For normal organ, circular regions of radii 15-25 pixels are placed avoiding the biggest vessels.

In the next step, texture analysis is performed. The statistical textural features (histogram-, gradient-based and derived from co-occurrence and run-length matrices) are calculated for each ROI. Feature values obtained with different directions ($0°$, $45°$, $90°$ and $135°$) and distances (from 1 to 4) are averaged, which reduces the number of descriptors from almost 200 to 25. For each ROI, the learning set also includes the label (class) corresponding to the verified diagnosis.

As a classification method, an extended version of a dipolar decision tree introduced in [2] is utilized. The dipolar tree can be called *oblique* (*multivariate*) because at each non-terminal node, a linear decision function (hyper-plane) is used to split the data. Optimal hyper-plane position is searched by minimizing dipolar criterion function. The essential concept in this approach is *dipole*, which can de defined as a pair $(\mathbf{y}^i, \mathbf{y}^j)$ of feature vectors from the learning set. Two types of dipoles are distinguished: *mixed* (constituted of objects belonging to different classes) and *pure* (vectors from the same class). Hyper-plane $H(\mathbf{v})$ splits the dipole $(\mathbf{y}^i, \mathbf{y}^j)$ if and only if: $(\mathbf{v}\bullet\mathbf{y}^i)\cdot(\mathbf{v}\bullet\mathbf{y}^j) < 0$, where $\bullet$ denotes the inner product. It means that input vectors $\mathbf{y}^i$ and $\mathbf{y}^j$ are situated on opposite sides of the dividing hyper-plane. In terms of the dipole notation, the optimal hyper-plane should divide a possible high number of mixed dipoles and a possible low number of pure ones.

Dipolar criterion function, inspired by perceptron, was defined to enable an efficient and robust realization of the above general postulate. With each input vector $\mathbf{y}^j$, a positive penalty functions, $\varphi_j^+(\mathbf{v})$, and a negative one, $\varphi_j^-(\mathbf{v})$ can be associated:

$$\varphi_j^+(\mathbf{v}) = \begin{cases} \delta^j - (\mathbf{v} \bullet \mathbf{y}^j) & \text{if } (\mathbf{v} \bullet \mathbf{y}^j) < \delta^j \\ 0 & \text{if } (\mathbf{v} \bullet \mathbf{y}^j) \geq \delta^j \end{cases}, \tag{1}$$

$$\varphi_j^-(\mathbf{v}) = \begin{cases} \delta^j + (\mathbf{v} \bullet \mathbf{y}^j) & \text{if } (\mathbf{v} \bullet \mathbf{y}^j) > -\delta^j \\ 0 & \text{if } (\mathbf{v} \bullet \mathbf{y}^j) \leq -\delta^j \end{cases}, \tag{2}$$

where δ^j ($\delta^j \geq 0$) is the margin. Depending on which of the functions is used, the hyper-plane $H(\mathbf{v})$ is forced to position with $\mathbf{y}^j$ on its positive or negative side. The penalty function associated with the dipole is a sum of two functions associated with its feature vectors. For the mixed dipole, two functions with opposite signs are used, because we are interested in cutting it. In case of a pure dipole, functions with the same signs are used, to avoid dividing it. The corresponding penalty functions can be defined as follows (for simplicity reason we do not consider orientation of dipoles):

$$\varphi_{ij}^m(\mathbf{v}) = \varphi_i^+(\mathbf{v}) + \varphi_j^-(\mathbf{v}), \tag{3}$$

$$\varphi_{ij}^p(\mathbf{v}) = \varphi_i^+(\mathbf{v}) + \varphi_j^+(\mathbf{v}). \tag{4}$$

The dipolar criterion function $\Psi(\mathbf{v})$ is a weighted sum of all penalty functions associated with dipoles:

$$\Psi(\mathbf{v}) = \sum_{(i,j)\in I_p} \alpha_{ij} \cdot \varphi_{ij}^p(\mathbf{v}) + \sum_{(i,j)\in I_m} \alpha_{ij} \cdot \varphi_{ij}^m(\mathbf{v}), \tag{5}$$

where α_{ij} is relative importance of the dipole $(\mathbf{y}^i, \mathbf{y}^j)$ and I_p and I_m are sets of pure and mixed dipoles. The dipolar criterion function, as a sum of convex and piece-wise linear functions, is also such a function, and the basis exchange algorithm, close to linear programming methods, is an efficient tool for minimizing it.

Furthermore, the algorithm was extended to enable feature selection during the optimization process. A new feature is chosen based on a correction vector and is added (forward selection scheme) to linear combination only if a sufficient drop in the value of the criterion function is obtained. The embedded feature selection mechanism takes also into account the problem of underfitting the training data [6], which is especially important in lower parts of the decision tree, when the number of feature vectors is lower.

After the growing phase of the decision tree induction the resulting classifier can be over-fitted with the learning data. This is the well-known problem in learning any decision structures (e.g. neural networks or decision rules). In case of decision trees the over-fitting is solved by post-pruning procedures.

When the classifier is created, it can be applied to new, not diagnosed images in computer-aided medical decision support.

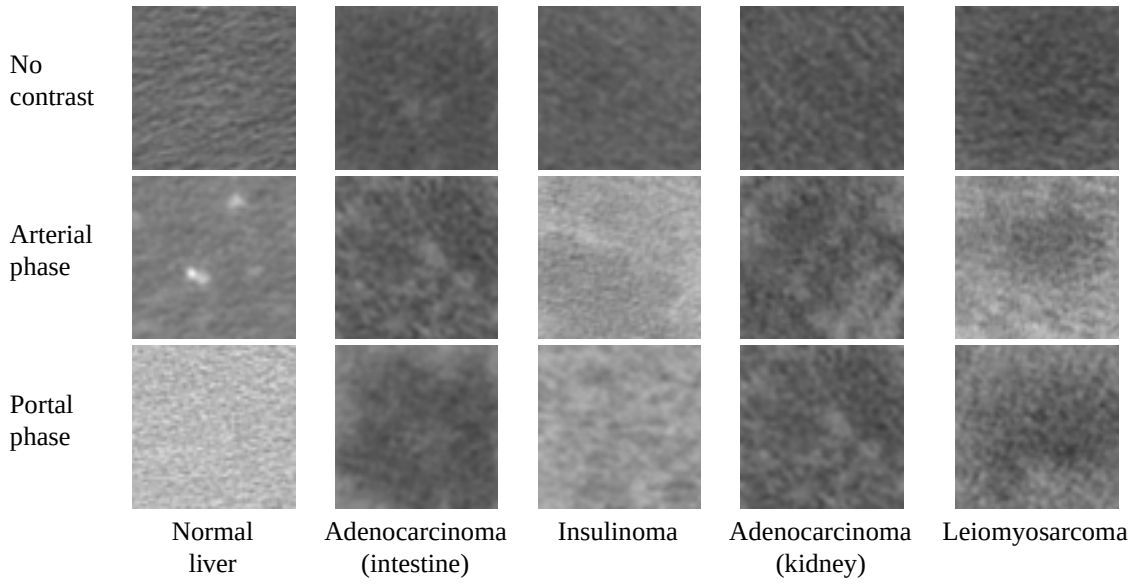

FIG. 2: Examples of analyzed textures (normal tissue and 4 types of metastasis) extracted from dynamic CT images acquired before injection of contrast product and during its propagation (arterial and portal phases)

Any suspected ROI is characterized by the same textural features, which were used during the classifier induction. Then, the features vector is presented to the classifier and a decision (diagnosis) is proposed.

3 Results

In the framework of the described approach, two applications were used. The first one, Texture Analysis enables i) to calculate texture descriptors and then, ii) to create learning sets used as input for a classifier. The second program, DDT (Dipolar Decision Tree) was implemented as a universal data mining tool and can be used in any classification problems. Both applications were developed in C++ on PC.

Analyzed database of images was gathered by Dr. Y. Rolland and his co-workers from University Hospitals and Cancer Treatment Center in Rennes. It consists in 291 tomographic images acquired in clinical conditions with 2 types of CT device: Somaton (Siemens) and HiSpeed CT (GE Medical Systems). The standardized acquisition protocol was used: helical scanning, with slice thickness 8-10 mm for non-enhanced CT and 7-8 mm for contrast-enhanced ones. For each patient, appropriate amount of contrast material was chosen (about 100 ml), and injection was performed at 4 ml/s. All images had a size of 512x512 pixels with 8-bit gray levels and were represented in DICOM format. The database contains scans of normal liver and 4 types of metastasis: 2 types of adenocarcinoma (from intestine and kidney), insulinoma (pancreas) and leiomyosarcoma.

The 5-times repeated 10-fold cross-validation procedure was applied to estimate classification quality of the proposed approach. Two experiments were performed. In the first one, all images were treated without taking into account the acquisition moment, and in the second one three groups of images were separately analyzed: non-enhanced images and acquired after contrast injection, in arterial (only arterial network is enhanced) and portal phases (30-40 seconds later when the contrast material arrives also in the portal vein). These phases are usually distinguished by radiologists in clinical practice. Table 1 presents numbers of drawn ROI-s corresponding to analyzed tissue classes and acquisition moments. In figure 2 examples of treated textures are presented.

TAB. 1: Numbers of Regions Of Interest associated with analyzed types of tissue in corresponding acquisition conditions

Tissue type	No contrast	Arterial phase	Portal phase
Normal	71	39	82
Insulinoma	33	29	64
Adenoarc. (kid.)	56	20	28
Adenocarc. (int.)	35	24	48
Leiomyosarcoma	19	19	30
	214	131	252

Table 2 presents the accuracy obtained by the dipolar decision tree. The classification quality was generally high and it was improved when the grouped images were analyzed. The highest accuracy (84%) was observed in the arterial phase, but it was the smallest group (only 131 ROI-s), so this result could be biased.

TAB. 2: Classification accuracy obtained by dipolar decision tree

All images	No contrast	Arterial phase	Portal phase
77.6 ± 1.3	78.5 ± 2.9	83.8 ± 2.6	80.4 ± 1.2

Beside the dipolar classifier, other methods were studied for validation purpose. The learning set containing all ROI-s was analyzed. Statistical methods like linear discriminant analysis and k-NN gave only 73.3% and 73.5% (the best result for k=3) respectively. An artificial neural network (multi-layered perceptron with 10 neurons in a hidden layer) was slightly worst

(75.8%) than the decision tree, but probably optimization of the network structure could lead to better accuracy.

4 Conclusion

In this paper, it is shown that hepatic metastasis diagnosis could profit from texture classification of CT images. The induction of multivariate decision trees using the dipolar criteria provides a promising quality of classification, compared to other classical methods. Moreover, we noticed that considering the acquisition moment, when dynamic CT images are analyzed, improves the classification quality. Furthermore, it seems that new techniques based on the evolution of texture in time could allow increasing the overall accuracy.

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