Conditional Random Fields for image segmentation in Intravascular Ultrasound

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***Abstract*—We present a Conditional Random Fields based approach for segmenting Intravascular Ultrasound (IVUS) images. The presented method uses a contextual discriminative graphical model to deal with the presence of distortions and artifacts in IVUS images, that turns the segmentation of interesting regions into a difficult task. An accurate lumen segmentation on IVUS longitudinal images is achieved.**

I. Introduction

The accurate segmentation of IVUS images is still an open problem. The presence of noise, distortions and artifacts, caused by the guide-wire presence, the ring-down effect and the shade produced by calcifications make the detection of interesting tissues a difficult task. Physicians usually overcome this difficulty by exploiting the contextual information extrapolated from the image itself, thus considering spatial relationships among different tissues. In order to take profit of such contextual information in the automatic segmentation process, we propose to formulate the labeling process of each point of the IVUS image as a conditioned probability provided by Conditional Random Fields models [1]. CRFs are in fact discriminative sequential graphical models able to model a conditional probability that takes into account the context of the observed domain. Several CRF models have been proposed in literature in the last decade [2], [3], [4]. In particular, the extension to 2D domain of CRF is defined Discriminative Random Fields (DRF) [5]. A common approach for modeling neighborhood relationships in DRF consists in defining a-priori pairwise potential function. Given the difficulty of segmenting IVUS data, relationships strictly based on data observation are required instead. For this reason, we propose a novel formulation of potential functions for DRF where the transition event between adjacent states is considered as an independent classification problem. Hence, an effective and observation-related pairwise potential is achieved.

Given the commonly large combination of possible states $(K \geq 4)$ assumed by observation nodes, the pairwise potential formulation is turned into a multi-class problem. We use then the Error-Correcting Output Codes (ECOC) [6] framework to reduce the multi-class problem to a set of simple binary problems. The proposed method is applied to the lumen segmentation, providing a most accurate results when compared with the standard state-of-the-art DRF formulation.

II. Materials and methodology

Ten IVUS pullbacks have been acquired at the University Hospital German Trias i Pujol (Badalona, Spain). Longitudinal cuts have been extracted from each sequence (0,45,90 and 135 degree) and lumen area has been segmented by two experts. Common segmentation areas have been used as ground truth. The DRF model requires a graphical representation $G = (S, E)$ of data, where S indicates each block (node) of the graph and E indicates interconnections among nodes (edges). For each cut, features are first extracted from the whole image, then a feature vector $\mathbf{x}_i$ is assigned to each node $S_i \in S$ by considering the median value of features for each block. As in [7], a 10-dimensional observation vector is computed for each node.

The set of extracted features represents a sequence $\mathbf{X} = \{\mathbf{x}_1, \dots, \mathbf{x}_M\}$ of IVUS data observations in the graphical model. Hence, the conditional probability of its labels field Y can be modeled as a DRF [1], [5] as

$$P(Y|\mathbf{X}) = \frac{1}{Z(\mathbf{X})} \prod_{i=1}^{M} \psi_i \prod_{j \in \mathcal{N}_i} \psi_{ij},$$

where (i, j) are indexes of nodes in the graph, $\mathcal{N}_i$ is the neighborhood of the i^{th} node and $Z(\mathbf{X})$ is a normalization function. The terms ψ_i and ψ_{ij} are the node potential and edge potential.

The novelty of the proposed approach consists in designing the two potential functions by using generic margin classifiers for segmenting IVUS images. Each potential function can be seen in fact as a classification problem, and a margin classifier can be used to solve it. A generic binary margin classifier h_n is trained to model the conditional probability $p(y|\mathbf{x})$. For each classified data point with feature vector $\mathbf{x}$, a *margin* value $m_n = h_n(\mathbf{x})$ is obtained. This margin value represents the distance, in the feature space, from the point to the decision boundary. The idea is to convert the margin value into a potential value for both node and edge potential definition.

In this sense, while the formulation of the node potential derived from margin is quite immediate, the edge potential requires the definition of meta-classes. We can in fact define a new meta-label $\tilde{y} = (y_i - 1)\sqrt{K} + y_j$ (*"label trick"*) for each pairwise transition and a new feature vector $\tilde{\mathbf{x}} = f(\mathbf{x}_i, \mathbf{x})$ for each pair of adjacent nodes. In this way, the probability

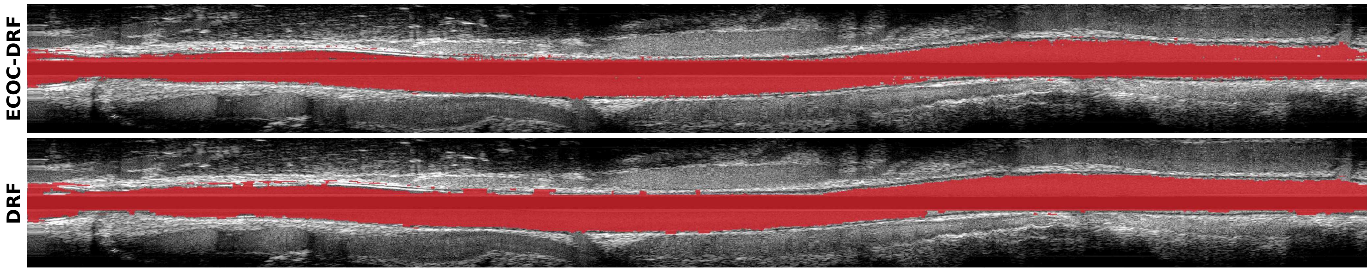

Fig. 1. Lumen segmentation results in longitudinal IVUS image by using the ECOC-based proposed approach (top) compared with the standard state-of-the-art approach (bottom)

TABLE I
LUMEN SEGMENTATION RESULTS FOR ECOC-DRF AND DRF.
A = ACCURACY; DR = DETECTION RATE; FR_r = FALSE POSITIVE RATE.

	$ECOC$	DRF
A	76.82%	74.67%
DR	74.39%	62.43%
FP_r	0.26%	0.3%

$p(\tilde{y}|\tilde{\mathbf{x}})$ can be modeled as a combination of margin classifiers, and the proposed approach is still applicable. Since the set of possible states transition is $(K \geq 4)$, at least 4 meta-labels are required, defining a multi-class problem. For this reason, we use the Error-Correcting Output Codes (ECOC) [6] framework to reduce the multi-class problem to a set of simple binary problems. The set of margins represents then a point in the ECOC space and expresses the similarity of each observation to one of the classes; in the specific lumen segmentation case, the classes are $\{lumen, not-lumen\}$. In order to compute the similarity, each margin value is scaled into a $-1 \leq \mu \leq 1$ range. Then, by the decoding process, a distance vector $\mathbf{d} = [d_1, \ldots, d_K]$ between the margin codeword $\vec{\mu}$ and each k^{th} row of the ECOC matrix is computed, where $0 \leq d_k \leq d_{max}$ and d_{max} is a known value depending on the coding and decoding techniques. The conversion from distance to potential value is done by means of the function $f_\alpha(d) = e^{-\alpha d}$, where α is a problem-specific parameter. Finally, both node and edge potential can be defined as: $\psi_i(y_i, \mathbf{x}_i) = e^{-\alpha_N \mathbf{d}(y_i, \mathbf{x}_i)}$ and $\psi_{ij}(y_i, y_j, \mathbf{X}) = e^{-\alpha_E \mathbf{d}(y_i, y_j, \tilde{\mathbf{x}})}$, where the distances are now expressed as function of the feature vector and label of a data observation; as in DRF [5], [3] we define here $\tilde{\mathbf{x}} = |\mathbf{x}_i - \mathbf{x}_j|$. The DRF model resulting from this approach is named ECOC-DRF.

III. RESULTS

The performance of the ECOC-DRF applied to the lumen segmentation are compared with DRF [5], [3]. The margin classifier used for ECOC-DRF is AdaBoost [8] with Decision Stumps as weak learner; training parameters have been set to T = 50 rounds, OneVsOne coding and Attenuated Euclidean Distance decoding. DRF has been trained by Stochastic Gradient Descent (SGD) as described in [3]. In both cases the inference is performed by Belief Propagation (BP) (nIter = 1000). It is worth noting that ECOC-DRF outperforms the DRF model in each considered performance parameters with a difference in detection rate of around 12% (see Table I). Furthermore, the low FP_r value is due to the use of ad-hoc features descriptors for the specific problem, that allow the ECOC-DRF to correctly define state transition, thus resulting in a highly precise blood area border definition (see Fig.1), while letting some undetected isolated nodes inside the area. The smoothness constraint is imposed by DRF instead, thus producing a continuous blood area definition, at the cost of detection error in the border. For this reason, the ECOC-DRF model is extremely suitable for the automatic lumen detection in IVUS images.

IV. DISCUSSION AND CONCLUSIONS

A novel method for defining potential functions for DRF as classification problems has been presented. The method embeds the capability of powerful discriminative margin classifiers to model complex dependencies among features in both node and edge potentials, while requiring a fast and easy training process. Furthermore, a novel interpretation of state transition event as a meta-class is provided, allowing to effectively model real state transitions. This technique demonstrates to outperform standard state-of-the-art DRF method in the lumen segmentation problem. Finally, it is easily extendable to multi-class segmentation problem as well, being thus suitable to be applied to even more complex segmentation problems in IVUS.

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