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SEGMENTATION AND TRACKING OF CORONARY ARTERIAL WALL

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SUMMARY

In this paper, we present a segmentation and tracking method based on hidden Markov model (HMM) to detect the outer coronary arterial wall in intravascular images. The proposed method tracks a set of hidden states representing the border location on a set of normal lines obtained from the previous frame. The border observation is derived from a classification-based cost function and a shape prior model. The emission probability is defined based on two Gaussian probability distributions for the vessel border and background. The transition probability is learned by using the Baum-Welch algorithm. The optimal sequence of the hidden states is obtained by using Viterbi algorithm. The proposed method shows promising results on tracking and segmenting the arterial wall.

Key words: *IVUS segmentation, HMM, Viterbi algorithm*

1 INTRODUCTION

Intra-Vascular Ultrasound (IVUS) is a catheter-based technology that shows 2D cross-sectional images of the coronary. IVUS has been widely used as a complementary tool of angiography for better diagnosis of coronary disease in which it provides a characterization of the atherosclerotic plaques, detects plaque rupture, ensures the stent position. The media-adventitia border represents the outer coronary arterial wall located between the media and adventitia. Here, image segmentation is the process of delineating the inner and/or the outer vessel wall, which is important for clinicians in order to assess the stenosis size and plaque morphology and can also be later used to reconstruct in 3D.

Image segmentation and defect detection have been extensively researched in the field of computer vision, e.g. [5, 8, 6, 12]. There are many techniques that can be used to solve the segmentation and tracking problems simultaneously, e.g. active contour [13] and hidden Markov model. Hidden Markov model (HMM) is a stochastic model in which the Markov property is assumed to be satisfied in finite set of states in which these states are hidden. Many applications have demonstrated the advantage of HMM to deal with the time-varying signals such as speech recognition [9], classification [7], and tracking [2, 10]. In [7], authors use HMM to classify the local wall motion of stress echocardiography to normal or abnormal. They build two HMM models one for each class and used the forward algorithm to compute the probability of the observations data given each model. In [4], HMM used in conjunction with the particle filter to track hand motion. Particles filter used to estimate the region that most likely the hand will appear on it. HMM estimated the hand shape using Viterbi algorithm where the state is a set of quantized pre-learned exemplars [11]. However, the number of exemplar can grow exponentially regarding the complexity of the object. In [1], authors used Kalman filter with P2DHMM to track person. P2DHMM (pseudo 2-dimensional HMM) is a nested 1D HMM in which a number of superstates (i.e. 1D HMM) modeling image's columns, each of them contains a number of normally hidden states. Viterbi algorithm is used to find the best sequence of states that classify the image to object and background. This measurement is used by Kalman to predict the rectangle box containing the person in the next frame. However, the system will become more complex and time-consuming with the increasing of the object size. In [2], incorporate region and edge features with HMM. The contour is sampled into a set of discrete points, and the features are extracted along the normal lines that pass through each contour point. Ellipse shape is fitted based on the contour and unscented Kalman filter used for tracking. In [10], authors extend the previous idea to deal with variable length open contour problem. They used Hessian matrix to extract local ridges features and investigate more about using arc emission instead of traditional state emission for defining the observation probabilities of the HMM. The optimal contour is identified by using Viterbi algorithm.

In this paper, an HMM-based border tracking method is presented. The emission probabilities are defined based on two probability distributions for the arterial border and background that are derived directly from both the classification-based cost function and the shape prior model. The training of the transition probability is achieved by using the Baum-Welch algorithm. The optimal sequence of the hidden states corresponds to RBFs of the border and is obtained by using the Viterbi algorithm.

2 PROPOSED METHOD

The border of interest is approximated by using the RBF functions where the hidden states of the HMM are referring to the RBF centers. The contour is equally sampled into M points. At each point, a line segment (with N points) is drawn perpendicular to the tangent line to the contour. The index of the contour RBF centers is $\phi = 1, \ldots, M$ and the index of each normal line is $\psi = 1, \ldots, N$ where N is an odd number. The initial RBF centers are defined from the previous frame and located as the center of the normal line $\psi = (N+1)/2$. The normal line actually restricts the search space for the predicted contour to be within $(N-1)/2$ point distance from the initial contour.

We denote to all sequence of hidden states by $S = \{s\}$ where $s = \{s_1, \ldots, s_\phi, \ldots, s_M\}$ is a possible state sequence and s_ϕ is the state on the normal at ϕ. These sequences are corresponded to a possible RBF centers location. The HMM observations $O = \{O_1, \ldots, O_\phi, \ldots, O_M\}$ is extracted from the normal lines. HMM [9] is specified by three probability measures $\lambda = (A, B, \pi)$, where A, B and π are the probabilities for the transition, emission and the initial state. The transition between states s at two normals ϕ and $\phi+1$ is governed by set of probabilities called transition probabilities $P(s_\phi | s_{\phi+1})$ and any state can only be observed by an output event according to associated probability distribution called emission probabilities $P(O_\phi | s_\phi)$. Here, the output event is the image features extract from each state at the normal.

In this work, we proposed to extract image observation from a classification-based cost function and shape prior model. The optimal sequence of states s^* can be efficiently found by the Viterbi algorithm. The correspondence real sequence of RBF centers c_t in the image domain is defined based on a mapping function of the optimal states s^* and the initial RBF centers c_{t-1} that computed in the previous frame. The final border is interpolated by using Thin-plate RBF function.

2.1 Emission & Transition Probabilities

Image observations are modeled by two probability density function (PDF) one for the border and the other for the background. Let $O_\phi = \{o_{\phi,1}, \ldots, o_{\phi,\psi}, \ldots, o_{\phi,N}\}$ is a set of features along the normal ϕ and $o_{\phi,\psi}$ is one feature extracted from point ψ on the line. $P(o_{\phi,\psi}|FG)$ and $P(o_{\phi,\psi}|BG)$ represent the probability of that feature to belong to the contour and the background respectively. The emission probability is defined as the following

$$P(O_\phi | s_\phi) \propto P(o_{\phi,\psi}|FG) \prod_{\psi \neq s_\phi} P(o_{\phi,\psi}|BG). \quad (1)$$

The likelihood of the observed variables O_ϕ from a state s_ϕ is achieved by measuring the likelihood of each feature $o_{\phi,\psi}$ at index ψ of the line ϕ to belong to the contour and all the rest of features on that line belong to the background. From a set of training data with manually labeled contour, we extract features that correspond to the contour and the background and used it to learn the parameters mean and variance of two Gaussian distribution FG and BG.

Baum-Welch and Viterbi training are popular estimation methods for the HMM parameters (A, B, π). The Viterbi training is an approximation of the Baum-Welch method and is computationally much faster. However, it may perform less compared to the Baum-Welch method. In this work, we use the Baum-Welch (Forward-Backward) algorithm [9] to define both the transition and prior probabilities.

2.2 Cost Function

The location of RBF centers is not known and is represented by HMM states. The inference of these hidden states can be archived with the help of a set of observations. RBF centers can be observed by determining the potential position of the contour. In an imaging application, the observation can be varied from using just pixel intensity or detecting some features such as edge, ridges, or incorporating prior information such as the color distribution of the object or more advanced shape prior model.

The cost function is defined on the image domain in which it is inversely proportional to the likelihood of each pixel to belong to the contour. Here, two probability distribution FG and BK are estimated from the cost function of the normal lines of the training data. The observation of the state-emission $o_{\phi,\psi}$ is extracted from a cost function ζ as the following:

$$o_{\phi,\psi} = \zeta(\mathbf{x}_{\phi,\psi}) \tag{2}$$

Where $\mathbf{x}_{\phi,\psi}$ is the correspondence index on the image domain for state defined on the normal ϕ at index ψ. The cost function is normalized by unit variance and can be combined with each other depending on the application.

In this work, we proposed multi-cost functions based on a classification result to overcome the obstacles of detecting and tracking the arterial wall. The image is unwrapped from the center point to polar coordinates. Each column is classified to set of labels $\mathcal{L}$ where each of which has a distinct feature. The proposed cost function can be defined as a combination of costs $SC_l(x, y)$ that is defined based on the label l:

$$\zeta(x, y) = \bigcup_{l \in \mathcal{L}} \bigcup_{p \in \mathcal{N}_l} SC_l(x_p, y_p) \tag{3}$$

Where $\mathcal{N}_l$ is a set of columns p in polar coordinates that classified as label l. The cost $SC_l(x, y)$ can have various forms based on not only edge or region costs, but also it can be a specific design cost to handle any obstacles in the object.

The classification can be achieved by many methods such as support vector machine, adaptive boosting, and random Forest. Here, we use the random forest (RF) classifier to arrange the image columns $\mathcal{N}$ into a set of group depend on the labeling result. RF is an ensemble of decision trees in which each tree is trained on randomly sampled data and features variables used to make a decision at each node is also randomly selected. Haar-like features are used as features for the classifier. For each column, Haar-like features are extracted from a 1D window in both vertical and horizontal direction at different scales to highlight edge and bar features.

The shape prior is also incorporated into the cost function using a non-parametric density estimation of the similarity between the initial segmentation and a set of shape templates as described in [3].

3 RESULTS

The IVUS dataset contains 10 in vivo pullbacks acquired by a 40 MHz transducer Boston Scientific ultrasound machine. We randomly select 2 pullbacks for HMM training and 8 pullbacks for testing (i.e., 26,390 images) and the evaluation were carried out on every 10th frame. The normal lines have a length of 101 pixels with 51 RBF centers in polar coordinates. Four evaluation metrics are used. The proposed method performance based on labeled groundtruth can be summarized as: 19.06 Hausdorff distance, 94.78% area overlap, 96.73% sensitivity and 97.71% specificity for detecting the outer vessel wall. Figure 1 shows the longitudinal view of two IVUS pullbacks.

4 CONCLUSION

We presented a segmentation and tracking method based on HMM to detect the outer coronary arterial wall in IVUS images. The method searches for the border along a set of normal lines based

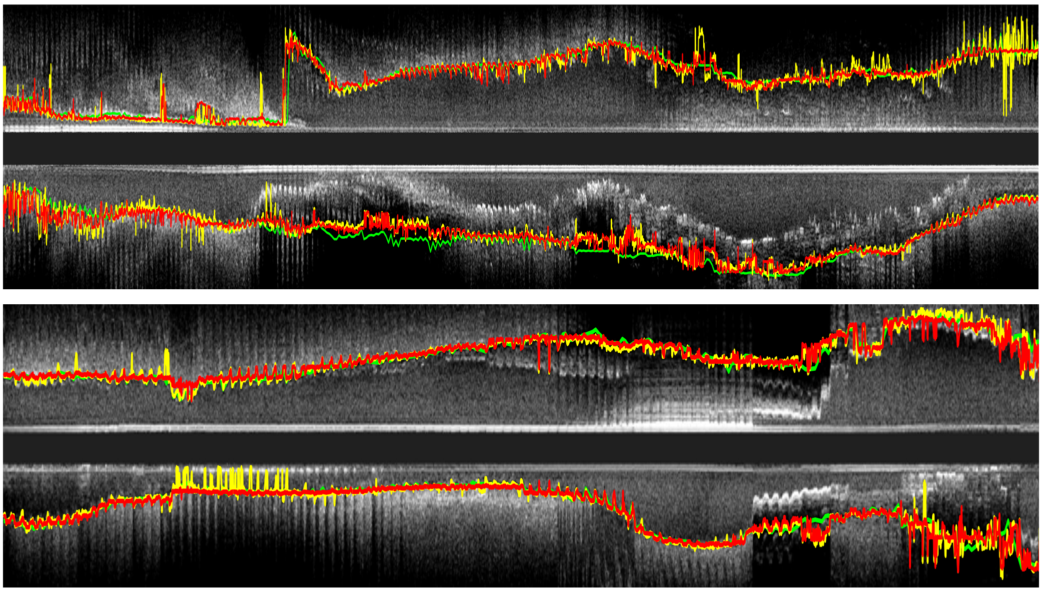

Figure 1: Longitudinal view of two different IVUS pullbacks, the proposed HMM (red), the classification-based method (yellow) and groundtruth (green).

on the segmentation of the previous frame. The proposed method shows a good result despite the segmentation challenges of acoustic shadowing and image artifacts.

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