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Abstract. Analysis of intravascular optical coherence tomography (IVOCT) data has potential for real-time *in vivo* plaque classification. We developed a processing pipeline on a three-dimensional local region of support for estimation of optical properties of atherosclerotic plaques from coronary artery, IVOCT pullbacks. Using realistic coronary artery disease phantoms, we determined insignificant differences in mean and standard deviation estimates between our pullback analyses and more conventional processing of stationary acquisitions with frame averaging. There was no effect of tissue depth or oblique imaging on pullback parameter estimates. The method's performance was assessed in comparison with observer-defined standards using clinical pullback data. Values (calcium $3.58 \pm 1.74 \text{ mm}^{-1}$, lipid $9.93 \pm 2.44 \text{ mm}^{-1}$, and fibrous $1.96 \pm 1.11 \text{ mm}^{-1}$) were consistent with previous measurements obtained by other means. Using optical parameters (μ_t , $\langle I \rangle$, I_0), we achieved feature space separation of plaque types and classification accuracy of $92.5 \pm 3\%$. Despite the rapid z motion and varying incidence angle in pullbacks, the proposed computational pipeline appears to work as well as a more standard "stationary" approach. © 2016 Society of Photo-Optical Instrumentation Engineers (SPIE) [DOI: 10.1117/1.JMI.3.2.024501]

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1 Introduction

Intravascular optical coherence tomography (IVOCT) is a catheter-based, high-resolution imaging method that has demonstrated considerable application for assessments of vascular disease due to its high resolution and contrasts. IVOCT is able to distinguish between lipid, calcium, and fibrous plaque,^{1–4} and aids in assessment of new coronary artery stent designs.^{3,5–7} Newer IVOCT systems can acquire more than 500 image frames in a single 2.5-s pullback scan, making it possible to image a complete artery volume in a few seconds.^{8,9} Although experts can classify tissue types using consensus rules,^{1,10} there are sometimes regions in vessels that can confound the experts, especially if only a single frame is viewed. Moreover, it takes considerable training to become an expert reader, and there is significant potential for inter-reader variability, especially across sites and time. As a result of the volume of IVOCT data and difficulty in interpretation, it can be very difficult to interpret live-time in the catheterization suite or to analyze manually offline for research applications. We are developing computational methods for automatically classifying tissue. Our methods employ both the physics of image formation and image analysis to compute tissue optical features from three-dimensional (3-D) regions within the IVOCT pullback

volume, which can then be employed for automated tissue classification.

There have been previous studies relating to tissue identification and classification in OCT images.^{1,4,11,12} Yabushita et al.¹ published a qualitative plaque classification scheme where fibrous plaques are characterized by homogeneous, signal-rich regions; calcium plaque by well-delineated, signal-poor regions with sharp borders; and lipid-rich plaques by signal-poor regions with diffuse borders. These descriptions later were accepted as the consensus¹⁰ and are used in our research. Kume et al.¹¹ demonstrated *in vivo* evaluation of the different types of plaques with IVOCT but argue that interpretation of OCT images based on qualitative criteria alone might be ambiguous. Xu et al.⁴ used transverse imaging of *ex vivo* arteries using a high-resolution OCT microscopic system. They imaged fixed tissue sections of coronary arteries and calculated attenuation and backscattering coefficients based on an average of 400 lines over time. Using single scattering light model, they performed least squares fitting of log transformed data. They were able to discriminate numerically between the different plaque types. Using a catheter based system and a stationary acquisition, Van Soest et al.¹² measured μ_t in both *in vivo* and *ex vivo* specimens. They corrected for the nonideal imaging system, used a linear attenuation model on log transformed data,

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and applied an elegant algorithm to determine separate homogeneous regions along an A-line. In a preliminary study, we used 3-D spiral pullback acquisitions rather than stationary acquisitions, obtained during a single blood clearing operation to estimate optical properties of atherosclerotic plaques within 3-D volumes of interest (VOIs).^{13,14} These reports are encouraging, and we extend investigation of optical property estimation in this paper.

In this paper, we propose an improved processing pipeline for estimating optical properties from 3-D IVOCT pullbacks. We introduce multiple enhancements as compared to previous reports from others^{4,12,15–17} and our own report.^{13,14} Improvements include, speckle noise reduction, baseline signal computation, and catheter eccentricity correction. Due to noise in a single A-line from a pullback, we estimate parameters from a collection of A-lines nearby in space, both within a polar ($r - \theta$) image and across image frames in z . We evaluate the methodology using both a silicon-matrix vascular phantom and clinical pullback data. In experiments on homogenous phantoms, we compared results from stationary and pullback acquisitions, evaluated precision and accuracy of measurements, and investigated potential effects of oblique sensor orientation and distance from the lumen on parameter estimates.

2 Algorithms and Data Analysis

We describe our processing pipeline and algorithms for estimating optical properties in 3-D IVOCT pullbacks. Starting with raw (linear) data in the ($r - \theta$) view, the processing pipeline consisted of the following steps.

1. Reduce speckle noise using the enhanced Lee (ELEE) filter that accounts for the statistical distribution of noise.
2. Estimate and subtract the intensity baseline.
3. Correct for nonideal imaging system response.
4. Segment lumen border using dynamic programming as described elsewhere.¹⁸
5. Spatially adjust pixels to account for catheter eccentricity.

6. Apply natural logarithm of intensities to linearize exponential attenuation.
7. Estimate optical parameters using 3-D robust least square fitting technique.

Some are described in more detail below.

2.1 Speckle Noise Characterization and Reduction

We filtered IVOCT images to reduce speckle, multiplicative noise,^{19,20} a major challenge in the analysis of optical properties.^{21,22} We used an ELEE filter on IVOCT images, which accounts for the multiplicative nature of speckle noise.^{23,24} The ELEE filter is an adaptation of the Lee filter and uses local statistics within a processing window to filter adaptively. We used a rectangular window in ($r - \theta$), with the width along $\theta \geq 2$ times the width in r . We compared results to those from the traditional Lee filter used by us previously.¹³ The traditional LEE assumes normally distributed multiplicative noise.²⁵ It replaces the center pixel of the kernel with the average of the pixel values within 2σ of the center pixel value. For the IVOCT application, LEE suffers from two drawbacks: that (for a case with mean = 4) the original 2σ range would shift the original mean value to μ_{norm} , a value smaller than the true mean, causing an intensity underestimation. Thus, if one realizes that as the intensity level is higher, then the under estimation is higher (Fig. 1), it is clear that it has direct impact on the attenuation values: It is especially apparent with lipid since lipid-rich plaques start with very high intensity rapidly decreasing to signal-poor region. To illustrate, if the start of a 0.14-mm long A-line within a lipid VOI has intensity value of, say, 4095, and at the end of the A-line the intensity value is 1000, then using Eq. (1), we compute the attenuation to be 10.7 mm^{-1} . However, if the underestimation at the start of the VOI causes us to estimate it at, say, 3500, and at the end of the VOI we still estimate it at 1000, then the attenuation would be computed as 8.94 mm^{-1} . The second major drawback of the traditional Lee filter is that regions with very small variation in intensity (small sigma) are not filtered. In the extreme case, of zero intensity, the sigma range is zero, and the pixel would remain unfiltered. These two problems are addressed by ELEE. Within the

Fig. 1 Bias of Lee filter that is fixed with the enhanced version. (a) Probability density function (pdf) of image data from an IVOCT acquisition with Rayleigh distribution mean, $\mu_{\text{ray}} = 4.0$. Assumption of a normal distribution ignores values in the Rayleigh tail and gives a $\mu_{\text{norm}} = 3.2$. (b) Variation in normal and Rayleigh means as a function of intensity.

window, each pixel is put into one of three classes, which are treated as follows:

- Homogeneous: The pixel value is replaced by the average of the filter window.
- Heterogeneous: The pixel value is replaced by a weighted average.
- Point pixel: The pixel value is not changed.

For a more detailed description of the filter please see Lee et al.²⁵

We numerically analyzed the effect of ELEE as compared to LEE (see Sec. 4). The ELEE filter performance was evaluated using signal-to-noise ratio (SNR), an established speckle-reduction performance metric^{21,26,27} as defined by Gonzalez and Woods:²⁷ $SNR = 10 \log_{10} [\max(I^2)/\sigma^2]$, where I is the linear magnitude image and σ is the variance of I in a background noise region. To exemplify the improvement in the SNR, we created several background images (taken from the region beyond beam penetration) to create the noise standard deviation. We then created the same number of images from regions, which included meaningful information to get average intensity values (I).

2.2 Baseline

To find the value of the baseline intensity value, we arbitrarily selected a θ value and averaged all A-lines along the pullback direction (z) corresponding to this θ in a pullback. Using lumen segmentation as described later, we selected a segment beyond the beam penetration depth (>2 mm) in tissue. Any segment that was too short was ignored. The average intensity value within this ($r - z$) plane gave us the baseline. We expected some variation in the computed baseline value for different θ 's, therefore, in order to account for this variation; we repeated the above steps for several randomly selected θ values and picked the median value. The baseline value determined was subtracted from the OCT signal [see Eq. (1)], where any negative values were set to zero.

2.3 Intravascular Optical Coherence Tomography Signal Model and Catheter Correction

We used the commonly used equation below to describe the OCT measurement in presence of a nonideal imaging system.¹³ The OCT signal is attenuated from the initial value I_0 in an exponential fashion with the total attenuation constant, μ_t , and distance along the A-line, r .

$$I_d(r) = I_0 T(r) S(r) \exp(-\mu_t r) + I_b.$$

Remaining terms include I_b , the background floor intensity, $T(r)$, the confocal function, and $S(r)$, the Gaussian Coherence function,¹² accounting for the spectral coherence of the source in Fourier domain OCT. The form of these latter functions are shown below with parameters Z_w (representing the half-width of the intensity roll off) and Z_c (representing the center of the scan) as given below

$$T(r) = \left[\left(\frac{r - Z_0}{Z_R} \right)^2 + 1 \right]^{-1/2} \quad S(r) = \exp \left[- \left(\frac{r - Z_c}{Z_w} \right)^2 \right],$$

where Z_0 is the position of the beam waist and Z_R is the Rayleigh length. We estimated parameters from model fits to IVOCT imaging data obtained in a low lipid concentration solution where attenuation is negligible as described by Garghesha et al.¹³ Z_c and Z_w were obtained from the specifications of the light source and values were $Z_c = 0$ mm and $Z_w = 12$ mm. Estimated parameters for a typical catheter were $I_0 = 154.93$, $Z_0 = 10.57$ mm, and $Z_R = 0.59$ mm. Following subtraction of I_b and division by the imaging system response, we are left with the equation

$$I_d(r) = I_0 \exp(-\mu_t r). \quad (1)$$

2.4 Pixel Shift Correction for Oblique Incident Beam

In an IVOCT pullback, the catheter is often not at the geometric center of the lumen. This eccentricity gives rise to variations in the distance to the lumen boundary in the ($r - \theta$) view. Since we do 3-D processing rather than A-line processing, it is important to correct these variations to better align tissue structures. We segment the lumen border as suggested by Zhao et al.¹⁸ with a slight modification in which we make it a two-pass process: First pass, we implement the cost function as suggested by Zhao et al.¹⁸ along an A-line. In the second pass, we fine-tune the lumen segmentation by computing the same cost function along the line perpendicular to any lumen segment (found in the first pass) that is close to being a horizontal line (± 5 deg). This process has shown improvements mainly where the lumen appears as a close-to-horizontal line in the $r - \theta$ view. For each A-line, we record the distance from the catheter to the lumen border and then shift the A-line along r by an integer number of pixels to place the lumen border at $r = 50$. We use integer pixel shifting to avoid interpolation and record the distance so that we can recreate the actual distance from the catheter to any pixel in the IVOCT data set. The result of this process is a new image with a lumen border consisting of a straight vertical line.

2.5 Estimation of Optical Properties

Following all processing above, we took the natural log of both sides of Eq. (1):

$$\ln[I_d(r)] = \ln(I_0) - \mu_t r$$

This gave a linear equation with unknowns $\ln(I_0)$ and μ_t . We applied a linear least squares fit to each separate A-line within a VOI. We computed medians and recorded this as our I_0 and μ_t estimates for the VOI. We termed this algorithm LSQM.

2.6 Plaque Classification

We performed an exploratory classification study. We applied a two-class support vector machine (SVM) classifier with Gaussian radial basis function kernel (RBF) which assigns a label, $y \in (\text{positive}, \text{negative})$. We used a one-versus-all approach for multiclass classification of the three plaque types (calcium, lipid, and fibrous).

We optimized SVM parameters, C and γ . The Gaussian kernel variance, γ , defines how far the influence of a single training example reaches, with low values meaning "far" and high values meaning "close." The regularization parameter, C , trades off misclassification of training examples against simplicity of

the decision surface. A low C makes the decision surface smooth, while a high C aims to classify all training examples correctly. We optimized these parameters using grid search and cross validation. Different pairs of (C, γ) values were tried and the one with the best cross-validation accuracy was selected. We found that exponentially growing sequences of C and γ gave a good, practical search, i.e., $C = 2^{-5}, 2^{-3}, \dots, 2^{15}$, $\gamma = 2^{-15}, 2^{-13}, \dots, 2^3$.

Following standard nomenclature, we use TP (true positives), FN, FP, and TN to make assessments of precision, $P = TP/(TP + FP)$, recall, $R = TP/(TP + FN)$, and $F_1 = 2PR/(P + R)$. F_1 is the harmonic mean of precision and recall and ranges between zero and one. That is, if R or P is zero, F_1 will be zero, and if both are one, F_1 will be one, the ideal value.

3 Experimental Methods

3.1 Image Acquisition

Clinical images were selected from the database available at the Cardiovascular Core Lab of University Hospitals Case Medical Center (Cleveland, OH), working with our institution. The images consist of 35 IVOCT pullbacks of the left anterior descending and the left circumflex coronary arteries of patients acquired prior to stent implantation. All OCT images used in this study were acquired by commercial Fourier domain OCT systems (C7-XRTM OCT Intravascular Imaging System, St. Jude Medical Inc., St. Paul, MN). It has axial resolution of about $15 \mu\text{m}$, yielding pixel size of approximately $4.96 \mu\text{m}$ in $(r - \theta)$ view. The scan characteristics of the system are: 50,000 lines/s, 504 lines/frame, yielding 100 fps and 20 mm/s pullback speed yielding a $200 \mu\text{m}$ frame interval. The pullback length was 54 mm.

The optical tissue phantoms used in this experiment were described previously.²⁸ The artery-like phantoms were

composed of cylindrical layers successively deposited on lathe setup. Each layer was made from a silicone matrix with specific concentrations of alumina and carbon black to provide specific absorption and scattering properties. For a typical healthy artery, the signal from the media was mimicked using concentrations of 14 mg/ml of alumina and 0.5 mg/ml of carbon black. For the adventitia, the signal was mimicked with 60 mg/ml of alumina. Since, the intima has normally higher scattering than the media, but also has lower attenuation, a concentration of 20 mg/ml of alumina, without carbon black, was chosen to approximate its optical properties. The fabrication process was adapted to allow inclusion of silicone/alumina/carbon black or polyurethane/alumina mixtures to mimic plaque structures. The optical properties of these mixtures were adjusted to provide OCT images with the typical signatures of the plaque structures.^{28,29} Three phantoms were used in this experiment, one each for lipid, fibrous, and calcium. For stationary imaging, the phantom was placed in a water bath and immobilized. The imaging catheter was moved along the lumen until the site of interest (containing phantom plaque) was identified. Then, the catheter sheath was held firmly on both sides to avoid any motion artifacts and five stationary acquisitions were obtained for each phantom. For pullback acquisitions, the same process as done with in-vivo acquisition as performed along the segment of phantom tissue.

3.2 Volume of Interest Selection

After acquiring both phantom and clinical images, we asked an expert (a cardiologist at our partner hospital) to label volumes of interest (VOIs) as belonging to one of the three plaque types in the images. The expert marked the VOIs of a particular plaque type using freehand brush strokes. On the clinical images, the expert annotated 311 VOIs (roughly equal number from each plaque type) on a total of 287 clinical images. On the phantom

Fig. 2 Appearance of atherosclerotic tissue types. Region enclosed in red regions denotes the plaque where the top row are clinical images where (a) is calcium, (b) is lipid, and (c) is fibrous (asterisk denotes the guidewire). On the bottom row, phantom images are shown where (d) is calcium, (e) is lipid, and (f) is fibrous (note that there is no guidewire when acquiring phantom images).

images, he marked 20 VOIs of each type taken from 15 phantom pullbacks. VOIs were of various sizes and shapes. Most consisted of 2–5 image frames, 50–200 A-lines, and 20–50 sample points in each A-line.

4 Results

Processing pipeline parameters were chosen in exploratory experiments. The dynamic programming, hard connectivity constraint, basically the maximum change in r allowed between adjacent A-lines¹⁸ was 25. With this value, phantom data were always segmented correctly and clinical data were correct in over ~98% of frames, and any small errors did not negatively affect results. ELEE parameters were window size = 11×7 pixels in the θ and r directions, respectively, and damping factor, $D = 1.0$, which controls the smoothing of the algorithm. This window size aspect ratio embodies the idea that the data along the θ direction changes less than that in the r direction.

Example phantom and clinical IVOCT images are shown in Fig. 2. Clinical images show the classic characteristics of tissue types where calcium shows sharp edges, low reflectivity and low attenuation, lipid shows diffuse edges, high reflectivity and high attenuation and fibrous shows high reflectivity and low attenuation. Phantom images have features similar to the clinical images. However, they are less noisy with reduced speckle noise owing to homogeneity of the phantoms.

The baseline intensity level, I_b , was quite consistent. It was determined to be 6.7 ± 3.8 over 15 pullbacks on the same number of different catheters. We modeled the OCT signal as Lambert–Beer exponential decay function, with the addition of baseline I_b to account for noise and other sources that elevate the expected signal value [Eq. (1)]. The justification for using this model is exemplified in Fig. 3.

Visual inspection of the images before and after filtering (Fig. 4) shows clear impact. The SNR for the filtered image was calculated to be 15.604 db and that of the image prior to filtering was calculated to be 12.03 db. To evaluate the model assumptions for clinical IVOCT data, we created a histogram of intensity values in an $(r - \theta)$ frame of a clinically obtained pullback. Statistical analysis confirmed that the distribution from the pullback was negative exponential distribution.^{19,20,30}

Fig. 4 (a) Clinical image before filtering (SNR = 12.03 db) (b) after filtering (SNR = 15.604 db). A significant visual improvement after speckle reduction using the enhanced Lee filter.

We first measured IVOCT optical parameters using the same approach (to enable comparison) where an expert annotated VOIs on individual sequential frames of both phantom stationary acquisitions and phantom pullback frames. After going through the preprocessing steps as described above, parameters estimated from different VOIs and data acquisitions were quite consistent (Fig. 5 and Table 1). In this controlled setting, we also assessed potential effects of the angle of the beam incidence, θ_i , and depth in tissue, as measured by the distance to the lumen, on μ_t estimates (Fig. 6). Plots show little effect and statistical tests indicated no significant effect of angle or tissue depth. In Fig. 5, histograms of pullback measurements show that the spread of μ_t estimates is greater than that for stationary data. Since the parameter estimation was done in a similar fashion we can assume that the small difference between the two types of acquisition is probably due to the pullback.

As an additional validation paradigm, we compared our μ_t results to estimates obtained in the standard way from stationary acquisitions (Table 1). In the standard approach, we acquired five data sets from each of the three phantoms and averaged over 100 frames in each instance. We marked five VOIs in the piecewise homogeneous phantoms, and estimated parameters from the low noise VOIs. Means across different VOIs were very similar, indicating no bias, and a student t-test has indicated insignificant differences between the new and standard method.

Fig. 3 Linearity of A-line averaged over 121 frames in a stationary acquisition from a phantom. (a) Linear data is processed with all the steps including catheter correction, baseline subtraction, and (b) log, giving the result. Data in (b) is well fit by the linear model used in our analysis (red line) with $\mu_t = 12.24 \text{ mm}^{-1}$. Data were obtained from a homogeneous “lipid” region in the phantom image.

Fig. 5 Comparison of μ_t estimates of the phantom as estimated using stationary and pullback acquisitions. Mean values for simulated calcium, lipid, and fibrous tissues are similar. The stationary acquisition gives a tighter distribution of values and smaller standard deviation than pullback acquisitions. The values are shown to belong to the same distribution (using t -test, p -values are shown in Table 1). Vertical axis is the fraction of A-lines with attenuation value given on the x-axis.

We, then, compared the phantom pullback estimates with clinical pullback estimates (Table 2). We observed that estimates from clinical dataset were consistent with phantoms, but with a larger spread.

We plotted a feature space of optical properties (μ_t , I_0 , $\langle I \rangle$) obtained by running our proposed processing pipeline on a set of 311 VOIs from 35 clinical pullbacks (Fig. 7). In the feature space plot, we observe good separation of the three plaque

Table 1 Results of attenuation coefficient estimates (mean of the median estimates) along with uncertainty estimates (standard deviation) computed for phantom stationary acquisition and phantom pullback. The p -values of a t -test indicate insignificant difference.

	Stationary	Pullback	t -test
	$\mu_t \pm \sigma$	$\mu_t \pm \sigma$	p -value
Calcium	3.56 ± 0.13	3.64 ± 0.35	0.64
Lipid	9.9 ± 0.18	9.97 ± 0.18	0.53
Fibrous	1.94 ± 0.23	2.17 ± 0.50	0.76

types identified with the three colors. In order to quantify this visual separation we trained and tested an SVM classifier as described in Sec. 3. We ran 5-fold cross validation on the 311 VOIs and calculated the accuracy measures as described in Sec. 3. These results are shown in Table 3, showing that the F_1 -score is very close to 1 for all plaque types. This indicates that VOI-based classification is very close to perfect for this somewhat contrived dataset.

5 Discussion

We have created a computational pipeline for estimating optical parameters from 3-D IVOCT pullback data and first evaluated it on realistic OCT vascular phantoms.²⁸ Because the phantom is locally homogeneous, it presents a unique opportunity for testing consistency of IVOCT measurements. We obtained μ_t estimates ($3.58 \pm 1.74 \text{ mm}^{-1}$, $9.93 \pm 2.44 \text{ mm}^{-1}$, $1.96 \pm 1.11 \text{ mm}^{-1}$ for calcium, lipid, and fibrous, respectively), which were within the ranges specified for the phantom. We carefully compared our pullback analysis method to a more conventional stationary analysis where the catheter was not moving along the length of an artery. Means were insignificantly different for all three phantom types, indicating no bias of measurements, even though in a pullback data comes from a catheter rapidly spiraling along the vessel at a linear rate of 20 mm/sec. To assess precision, we compared data spread, as measured by standard deviation, of measurements over at least 600 (Five stationary acquisitions for each type) samples for each plaque type. Pullback data had only slightly higher standard deviations for calcium and fibrous the same for lipid (Fig. 5). The barely statistically significant (Table 1) differences might have been due to mechanical instabilities between A-lines. Finally, we also determined that the angle of incidence insignificantly affected μ_t estimates. This reassures us that the pullback does not introduce an additional confound even though each angle of incidence will be somewhat different for each A-line under consideration in the pullback. Similarly, when we analyzed volumes of interest at different depths in tissue, we found no significant difference in μ_t estimates for calcium and fibrous. (There was insufficient depth of signal to do this in the case of lipid.). Results of calcium and fibrous are consistent with good single exponential fits (Fig. 6). Together, these experiments suggest that our clinically practical, 3-D pullback method yields accurate, precise results, as good as stationary analysis.

Analyses on clinical pullback data were equally encouraging. When comparing phantom pullback estimates to clinical pullback results (Table 2) we observed that estimates were consistent with phantoms, but with a larger spread. Another thing to

Fig. 6 Independence of μ_t estimates on angle of incidence, θ_i (a) and depth, measured from the lumen (b) for a stationary acquisition dataset. The (approximately) horizontal lines indicate that regardless of the independent variable's value (i.e., distance or angle), the μ_t remains constant. In the case of fibrous tissue, due to the plaque's narrow width it was not possible to select VOIs at varying distances from the lumen, thus, it appears as highly aggregates cluster. Furthermore, in (a) there appear to be two clusters. This is because incident angles (positive and negative) were always in the indicated range.

note is that the calcified and lipid plaques (in both, clinical and phantom) exhibited a much lower average intensity (signal poor regions) than that of the fibrous; however, the high attenuation of the lipid and the low attenuation of the calcium helped us to distinguish between the two easily. The high value of the average intensity of the fibrous indicates that it is signal rich region. The classification metric shows that the F_1 -score approaches 1.0 as desirable for an accurate and efficient classification method.

The pipeline has some novel aspects, which can be compared to previous reports in the literature. It was applied to clinical 3-D data, which is aimed at improving the robustness of optical parameter estimation. In this study, we better account for noise in the acquired images. We also note that each 3-D

VOI consists of 50–400 A-lines with different angles of rotation (θ) and different axial positions along the artery, posing many challenges including eccentricity of the catheter relative to the lumen surface, catheter motion, and so on. We meet these challenges by applying the processing pipeline steps including pixel shifting, noise reduction, lumen segmentation using dynamic programming as described in Ref. 18, and better statistics for robust and resource-efficient estimation. Furthermore, our method of analyzing the results of phantom stationary acquisition, phantom pullback and clinical pullback is a good framework enabling efficiency of processing and classification. Our results have indicated an improved feature space clustering that will aid in automated learning.

Our preliminary classification results (Table 3 and Fig. 7) are promising and indicate an improvement over previously reported classifications results by Ughi et al.³¹ and Lambros

Table 2 Estimates on a clinical dataset of 311 VOI's from 35 pullbacks. Values compared are the average values of the attenuation coefficient.

	Estimated values		
	$\mu_t \pm \sigma$	$\langle I \rangle$	I_o
Calcium	3.58 ± 1.74	37.81	38.46
Lipid	9.93 ± 2.44	82.79	139.39
Fibrous	1.96 ± 1.11	162.23	195.83

Table 3 SVM classification results: The overall classification accuracy was 92.5%, however, since we could not ensure that the data is not skewed, the F_1 -score is also given [F_1 -Score = $2PR/(P + R)$].

	Precision (P)	Recall (R)	F_1 -score
Calcium	94.3%	86.8%	0.904
Lipid	89.3%	96.2%	0.926
Fibrous	93.3%	96.6%	0.949

Fig. 7 Feature space of $(\mu_t, \bar{I}, I_o)$ created by applying the proposed LSQM method on 311 VOI's of all atherosclerotic tissue types after preprocessing pipeline. VOI's were derived from 35 clinical IVOCT pullbacks. We observe a good separation of plaque types even though only the three features $(\mu_t, \bar{I}, I_o)$ were used.

et al.³² However, the datasets used in this experiment were carefully manually selected to be clearly one tissue type or another, probably giving an overestimation of classification accuracy. Moreover, it is not really possible to compare classification statistics between publications since different data sets and methods are used. Nevertheless, our approach is quite appropriate for evaluation and optimization of methods for estimating optical parameters. Optical parameters will be only one set of features for a more realistic and clinically useful application of plaque classification.

In conclusion, the proposed computational pipeline appears to work as well as a more standard “stationary” approach. This is important, as it will be difficult to justify stationary acquisitions for routine clinical work. We believe that when optical parameters are combined with other features, it would further improve these results.

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