Registration Methods for IVUS: Transversal and Longitudinal Transducer Motion Compensation

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Abstract—Objective: Intravascular ultrasound is a fundamental imaging technique for atherosclerotic plaque assessment, interventionalist guidance and, ultimately, as a tissue characterization tool. The studies acquired by this technique present the spatial description of the vessel during the cardiac cycle. However, the study frames are not properly sorted. As gating methods deal with the cardiac phase classification of the frames, the gated studies lack motion compensation between vessel and catheter. In this work, we develop registration strategies to arrange the vessel data into its rightful spatial sequence. Methods: Registration is performed by compensating longitudinal and transversal relative motion between vessel and catheter. Transversal motion is identified through MLE optimization, while longitudinal motion is estimated by a neighborhood similarity estimator among the study frames. A strongly coupled implementation is proposed to compensate for both motion components at once. Loosely coupled implementations (DLT and DTL) decouple the registration process, resulting in more computationally efficient algorithms in detriment of the size of the set of candidate solutions. Results and Conclusions: The DTL outperforms DLT and coupled implementations in terms of accuracy by a factor of 1.9 and 1.4, respectively. Sensitivity analysis shows that perivascular tissue must be considered to obtain the best registration outcome. Evidences suggest that the method is able to measure axial strain along the vessel wall. Significance: The proposed registration sorts the IVUS frames for spatial location, which is crucial for a correct interpretation of the vessel wall kinematics along the cardiac phases.

Index Terms—Ultrasound, Registration, IVUS, Correlation, Optimization.

I. INTRODUCTION

INTRAVASCULAR ULTRASOUND (IVUS) is an imaging technique widely used for the atherosclerotic plaque assessment. During the acquisition, a piezo-electric sensor records the cross-sections of the vessel at a constant known velocity. Although a spatial arrangement of vessel cross-sections is available after an IVUS procedure, the heart contraction imprints an undesired motion between the transducer and the vessel (usually referred to as cardiac dynamic component), misleading that frame location during non-diastolic phases as well as the position and rotation with respect to the transducer. The transducer motion can be decomposed into two spatial components, the transversal (or in-plane) motion and the longitudinal (or axial) motion. The former produces the translation and rotation of the structures from one image to the other, while the latter induces a proximal/distal displacement additional to the pullback. As consequence, the reconstruction of the vessel wall is hindered for non-diastolic phases since vessel cross-sections are not equally spaced in the longitudinal direction and the transversal motion pollutes the geometrical description of the vessel wall. This affects the processing of image-derived quantities either for diagnosis or for input of computational models such as those used in CFD simulations or in tissue characterization (e.g. virtual histology, elastographies or palpographies).

Early approaches for IVUS study registration have focused only in the transversal motion component. The goal of these works was the improvement of vessel structures alignment to improve elastography outcomes. The main problem for IVUS registration is to deal with low signal-to-noise ratio of the ultrasound (US) and the speckle noise characteristics. Early works ([1]–[4]) performed a rigid registration of two adjacent images using the radiofrequency (RF) data of the IVUS study and block matching strategies with different maximum likelihood estimators (MLE) such as sum of absolute differences (SAD) ([1], [2], [4]), sum of square differences (SSD) ([1], [4]) or normalized cross-correlation (NCC) ([1], [3]). Subsequent approaches focused on IVUS image data which are available from traditional ultrasonic equipments. Several works applied SAD ([5], [6]), SSD ([7]), NCC ([8]–[10]) and mutual information ([8]) as MLE to match tissue patches between different IVUS images. Although these approaches deliver an improvement for registration, the MLE used are not suitable for speckle noise tracking. This issue can be circumvented by using US specific estimators as proposed in [11], which account for the log-compressed multiplicative noise within the images. Other approaches perform the transversal registration by aligning the centroids of the lumen in the two images ([9], [12]–[18]). To estimate the lumen centroid, a segmentation of the lumen is needed which is a time consuming task difficult to automatize. To overcome this, some authors proposed to approximate the lumen centroid as a gray intensity centroid ([15]) or the centroid of a simplified lumen geometry ([16], [17]). Some cross-sections registration may present inaccurate results due to substantial variations in the lumen geometry (inaccuracy in lumen estimation, sites of branching or stent...
Three strategies are considered to solve the problem. Particularly, [15], [17] estimated the rotation component of the rigid motion using a Fourier analysis, resulting in a higher robustness against centroid variations. Non-rigid registration approaches were also developed in [5], [6], [19]–[26]. Amores et al. ([19]–[21]) proposed the use of a 3D correlation scheme to analyze local and global features of the image and its gradient field to find the best correspondence between frames, although it requires a segmentation of the lumen. Kautozian et al. ([22]) presented a Markov random field discrete multi-labeling scheme to match histological and IVUS image data. Other authors ([5], [6], [23]–[26]) formulated an optimization problem to find the displacement field that maps the reference frame to the target one. Finally, a comparison study between different transversal registration approaches (rigid transformation, affine transformation, B-spline-based non-rigid free form deformation and demons) was presented in [27], assessing their performances to map calcified lesions.

In turn, the longitudinal motion component has usually been neglected. In [28], an average axial displacement from 1.5 ± 0.8 mm in a 0.016 mm interface acquisition has been observed. Due to the catheter migration, the cross-sectional region observed in systolic phases is more proximal than expected (a mean offset of 93.75 frames) and, in the context of elastography, the derivation of associated strains occurring in the arterial wall can become extremely inaccurate because of the changes in the topological and tissue composition at these sites. Works that tackle longitudinal registration are presented in [29]–[32]. In [29] a method for rigid longitudinal motion is proposed which aligns each cardiac phase against the diastolic phase of the study. Non-rigid approaches based on dynamic time warping (DTW) are proposed such as the extremes path search ([30], [31]) and minimal variance matching ([32]) methods.

More complete schemes that treat both motion components were presented in [10], [13], [14], [18], [33]. These works perform longitudinal prior transversal registration of two cardiac phases of the study. The longitudinal registration in [13], [14], [18], [33] requires user interaction to determine the frames at carina bifurcations (landmarks used to pair the frame bifurcations) and assumes a linear fitting for the remaining frames. The first non-rigid longitudinal registration method was proposed in [10] using a 3D graph path finding process where the segmentation of the lumen and external elastic membrane is a compulsory step.

In the present work we address the problem of transversal and longitudinal registration so that both motion components can be suitably compensated by using MLE specifically tailored for US speckle noise (see [11], [34]). Transversal registration is performed through the formulation of an optimization problem for which the rigid transversal motion identified is the one that maximizes a given cost functional depending on the MLE. In addition, longitudinal registration is performed with a weighted MLE function that allows to align two different IVUS cardiac phase sub-sequences. Three strategies are considered to solve the problem. The first one is a strongly coupled (computationally demanding) method in which both motion components (transversal and longitudinal) are obtained simultaneously. The second and third strategies solve both motion components in a decoupled manner (resulting in a computationally cheaper procedure), either considering first the longitudinal and then the transversal registration problems, or first the transversal and just then the longitudinal. Preliminary results of the decoupled approach (which performs longitudinal and posterior transversal registration with a normalized cross-correlation function as MLE) were briefly reported in [35]. All strategies are compared in terms of performance and accuracy on in-vivo patients, and descriptions of transducer longitudinal displacement along the IVUS acquisition are discussed. The results obtained by these strategies shown that no segmentation of the vessel wall is needed for the registration process, which improves reproducibility.

The article is structured as follows. In Section II the framework for IVUS transversal and longitudinal registration is presented. In Section III, computational cost and accuracy of the registration implementations is assessed using in-vivo IVUS studies. Also, longitudinal motion between the diastolic and systolic cardiac phases is characterized by dividing the IVUS studies population by different criteria. In Section V, we outline the conclusions of the present work. To ease the reading of this article, a list of symbols is included in Section C of the Supplementary Material.

II. METHODOLOGY

In this section, we introduce the mathematical framework for the registration process. This is composed by the IVUS preprocessing, the longitudinal registration and the transversal registration. Firstly, we define the region of interest (ROI) used during the registration process. The subsequent stages deal with the longitudinal and transversal components of the transducer motion.

Then, through the integration of these stages, three registration algorithms are proposed. Two decoupled strategies are tested, namely solving first the longitudinal registration and then the transversal (DLT technique), and inverting the registration stages (DTL technique). A fully coupled strategy is finally addressed. More details are given in Section II-D.

A. IVUS preprocessing

The arterial wall is better characterized by the structures lying in the region between the lumen and the external elastic lamina [36], [37]. However, the identification of this region through any image segmentation procedure requires, to some extent, manual setting and is also time-consuming, moreover the development of robust and reproducible computational methods to accomplish this task is still an open problem [38]. Therefore, to analyze the sensitivity of the registration with respect to the vessel wall specificity, we define two ROIs: (i) a manually segmented vessel wall region (VWR) and (ii) the full image region (FIR) which does not require segmentation whatsoever. The manual segmentation for the VWR ROI is performed by an specialist to obtain an accurate and robust
description of the vessel wall, which may not be guaranteed by automatic segmentation methods.

Let $J_k$ be the $k$-th frame of the IVUS study ordered according to the original acquisition sequence. The ROI for the $k$-th frame $J_k(x,y)$, is defined as a binary mask $M_k(x,y)$ with the same size of an IVUS frame. Each value of $M_k$ indicates whether the associated pixel in $J_k$ belongs to the ROI or not. Similarly, we define $M^{\text{DR}}_k(x,y)$ and $M^{\text{GW}}_k(x,y)$ as the binary masks associated to the down-ring and the guidewire artifacts. These masks contain 1s at the positions where the artifact is found and 0s at remaining locations. The construction of the artifact masks is detailed in the section A of the supplementary material.

The FIR for the $k$-th frame is defined as
\[ M^{\text{FIR}}_k = \neg (M^{\text{DR}}_k \vee M^{\text{GW}}_k), \tag{1} \]
where $\neg$ and $\vee$ are the logical operators NOT and OR respectively.

The VWR requires the elimination of regions outside the external elastic lamina and inside the vessel lumen from the ROI defined above. For this task, the user manually performs a segmentation of the EEM and lumen areas by picking points which are then interpolated with a cubic spline curve. To avoid lack of pixels in the mask, especially in healthy wall cross-sections, the EEM curves are radially displaced by 20 pixels. Then, we create a mask, $M^{\text{VWR}}_k$, where the area comprised between the EEM and lumen has value of 1, and 0 otherwise. Thus, the VWR is defined as
\[ M^{\text{VWR}}_k = M^{\text{FIR}}_k \wedge M^{\text{VW}}_k. \tag{2} \]
where $\wedge$ is the logical operator AND. The resulting masks for a given frame in an IVUS study are shown in Fig. 1.

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{fig1.png}
\caption{Binary masks used for each ROI: (top left) original IVUS image; (top right) $M^{\text{FIR}}_k$; (bottom left) $M^{\text{VWR}}_k$; (bottom right) $M^{\text{VWR}}_k$ overlapped with the original IVUS image.}
\end{figure}

\section*{B. Transversal Registration}

The transversal registration consists in finding the rigid motion that better aligns the structures between two frames, say $J_n$ and $J_m$. To properly specify a mechanism for registration, we define a similarity function based in estimators presented in [11], [34] that measures the structures alignment between a pair of frames. For the given frames $J_n$ and $J_m$ of the IVUS study and the corresponding ROIs $M^{\text{Z}}_n$ and $M^{\text{Z}}_m$, $Z \in \{\text{FIR}, \text{VWR}\}$, we define the common ROI between these images as
\[ M^{\text{Z}}_{n,m} = M^{\text{Z}}_n \wedge M^{\text{Z}}_m. \tag{3} \]

Using this common ROI we identify the set $\mathcal{A}^{Z}_{n,m} = \{(x,y), M^{\text{Z}}_{n,m}(x,y) = 1 \}$ and its cardinality $|\mathcal{A}^{Z}_{n,m}|$. Then, we modify the similarity function presented in [11], [34] as
\[ c(J_n, J_m)|_{\mathcal{A}^{Z}} = \frac{1}{|\mathcal{A}^{Z}_{n,m}|} \sum_{(x,y) \in \mathcal{A}^{Z}_{n,m}} \left\{ J_n(x,y) - J_m(x,y) - \log \left( \exp \left( 2(J_n(x,y) - J_m(x,y)) \right) + 1 \right) \right\} \tag{4} \]
which models the multiplicative log-compressed Rayleigh noise present in $J_n$ and $J_m$ and compares only the common ROI, $\mathcal{A}^{Z}_{n,m}$.

Thus, we have to find the rigid motion that maximizes the similarity function between the two given frames. The rigid motion, called $\Xi$, is described by the horizontal and vertical displacements, $\tau_x$ and $\tau_y$, and a rotation around the center of the frame $\theta$. Then, $\Xi$ that registers $J_m$ to $J_n$ is defined as
\[ \Xi^n_m = \arg \max_{\Xi \in \mathcal{W}} \mathcal{F}(J_n, J_m) \]
\[ = \arg \max_{\Xi \in \mathcal{W}} c(J_n, J_m(x(\Xi), y(\Xi)))|_{\mathcal{A}^{Z}} \tag{5} \]
where $\mathcal{W}$ is the space of admissible rigid motions of the transducer and $J_m(x(\Xi), y(\Xi))$ is the frame $J_m$ after applying the rigid motion $\Xi$. Because of the acquisition sampling, the space $\mathcal{W}$ is discrete. The translations and rotations only make sense for multiples of one pixel and $\frac{2\pi}{256}$ radians, respectively. Furthermore, the transducer is confined to the lumen, which imposes bounds to the horizontal and vertical displacements. Thus, we characterize $\mathcal{W}$ as
\[ \mathcal{W} = \left\{ \Xi = (\tau_x, \tau_y, \theta); \theta = i \frac{\pi}{128}, i = 0, \ldots, 255; \right\} \]
\[ = \left[ \tau_x^{\text{MIN}}, \tau_x^{\text{MAX}} \right] \subset \mathbb{Z}; \tau_y \in \left[ \tau_y^{\text{MIN}}, \tau_y^{\text{MAX}} \right] \subset \mathbb{Z} \right\}. \tag{6} \]

Expression (5) involves the maximization of a non-convex functional. The lack of convexity arises from the presence of speckle noise and because of the partial (incomplete) matching of the aligned structures. Notice that, the space $\mathcal{W}$ is finite-dimensional, enabling the computation of the cost functional $\mathcal{F}$ for each element $\Xi \in \mathcal{W}$. For this reason, a brute force algorithm simplifies the solution for the maximization problem.

In turn, the regularity of $\mathcal{F}$ over $\mathcal{W}$ allows the maximization through less expensive strategies. As seen in Fig. 2, the streamlines across $\mathcal{F}$ (using as velocity field $\frac{d\Xi}{dt}$) yield
to the same area with the minima values (colored in red), showing the functional space adequacy for minimization by gradient methods. Also, the regularity of $\mathcal{F}$ enables to use a gradient method without the need of a regularization terms. To deal with the lack of convexity and multiple solutions, an heuristic method called multi-seed gradient ascend (MSGA) is proposed. Here, multiple initializations are used to ascend and the instance that reaches the highest value of $\mathcal{F}$ is retained as the solution for the maximization problem. A suitable trade-off between accuracy and performance is found for a 5-seed initialization procedure as described in Fig. 3 (see also Section III-B). Some considerations about this approach are presented in the section B of the supplementary material.

C. Longitudinal Registration

During IVUS pullback, cardiac contraction strongly affects the longitudinal motion of the transducer with respect to the vessel ([28], [39], [40]). For this reason, IVUS frame sequence is not spatially ordered from distal to proximal positions. Also, the estimation of each frame spatial location based on the pullback velocity, is not possible for frames acquired during cardiac contraction. To address this motion artifact, the study is gated to properly identify the frames in each cardiac phase. From the gating process [41], $P$ image sets are generated, where each set corresponds to a specific cardiac phase (see Fig. 4). Although the images within each set are longitudinally ordered, the displacements between the frames may not necessarily be homogeneous because of the large variability in the transducer motion. Particularly, the phase previous to the cardiac contraction, hereafter referred to as steady phase, is assumed to present the most homogeneous displacement field as a result of the reduced cardiac motion. Because frames during the cardiac contraction present blurring due to the motion of the ultrasonic transducer [41], [42], we quantify vessel movement as the negative sum of the intensity gradient along each image (proportionally inverse to the image sharpness). Then, from the $\mathcal{I}_i$, $i = 1, \ldots, P$ cardiac phases, we define the steady phase $\mathcal{I}_{st}$ as

$$\mathcal{I}_{st} = \arg \min_{i=1, \ldots, P} \mathcal{P}_{\text{motion}}(\mathcal{I}_i) = \arg \min_{i=1, \ldots, P} \left\{ -\frac{1}{N_{s}} \sum_{j=1}^{N_{s}} \sum_{y=1}^{W} \sum_{x=1}^{H} |\nabla I_j^{s}(x, y)| \right\}$$

(7)

where $I_j^{s}$ denotes the $j$-th frame of the IVUS study in the $i$-th phase, $N_{s}$ is the number of frames for that $i$-th cardiac phase, and $H$ and $W$ are the height and width of the images in the IVUS study.

As counterpart, we define the phase featuring maximal motion $\mathcal{I}_{mo}$ as the maximum of $\mathcal{P}_{\text{motion}}$ (see Fig. 5). Clearly, it will be denoted $I_j^{m}$ and $I_j^{mo}$ the frames of the steady phase and those in the maximal motion phase, respectively.

Assuming no motion by the cardiac contraction at the steady phase, the longitudinal location of its frames along the catheter is characterized as

$$s(I_{j}^{st}) = s_0 + \frac{j v_p}{f_s},$$

(8)

where $I_{j}^{st}$ is the $j$-th frame of the IVUS study in the steady frame $\mathcal{I}_{st}$, $s_0$ is the initial position of the transducer over the longitudinal axis, $v_p$ is the pullback velocity in $\text{mm} / \text{s}$ and $f_s$ is the framerate of the study in frames.

The steady phase $\mathcal{I}_{st}$, and the known spatial location of each frame $I_{j}^{st}, j = 1, \ldots, N_{st}$, is used to perform a non-linear longitudinal registration of the remaining phases, hereafter referred to as non-steady phases. The registration process consists in assessing the similarity of each non-steady phase frame against the steady phase frames. The most similar steady phase frame is used to place the non-steady one. For the $i$-th cardiac phase, the degree of similarity between the $i$-th and $j$-th steady phase frames is given by

$$\mathcal{C}_{w}(I_{j}^{i}, I_{k}^{st}) = \frac{\sum_{d=-w}^{w} \phi(d, \sigma_G) c(I_{j+d}^{i}, I_{k+d}^{st})}{\sum_{d=-w}^{w} \phi(d, \sigma_G)},$$

(9)

where $w$ is the longitudinal neighborhood width, $d$ is the frame index within that neighborhood, and $\phi$ is a Gaussian weight...
function with $\sigma_G$ standard deviation. The parameter $w$ defines the domain used by the estimator $c$ weighted by the value $\sigma_G$. Specifically, we want to neglect the contributions from frames whose weights are smaller than a factor $T$ of the maximum weight value $\phi(0, \sigma_G)$. This would allow a weighting function of compact support with low computational effort. Empirically, we set $T = 10^{-1}$ to approximate $c_w$. Then, $w$ is defined in terms of $\sigma_G$ and $T$ as

$$w(\sigma_G, T) = \left[ \sigma_G(-2\log(T))^{\frac{1}{2}} \right].$$

Once we choose a suitable tolerance, the only parameter left is $\sigma_G$. As the value of $\sigma_G$ is increased, information from adjacent frames is more relevant. Then, $\sigma_G$ should be small enough to be representative of the local structures and large enough to incorporate information about the longitudinal structure to achieve robustness. In this way, the function $\phi$ in (9) introduces a low-pass filter regularization in the longitudinal motion and $\sigma_G$ adjusts the low-pass frequencies to be included (the lower the $\sigma_G$ the more frequencies pass through the filter). The setup of this parameter is studied in Section III-D.

Finally, the position in space of the frame $I_{ij}$, which belongs to a non-steady phase, i.e. $i \neq \text{st}$, is defined as

$$s(I_{ij}) = s(I_{\text{st}m}),$$

where

$$m = \arg \max_{k=1,\ldots,N_{\text{st}}} c_w(I_{ij}, I_{\text{st}k}).$$

Fig. 6 shows the longitudinal registration of an in-vivo IVUS study according to the proposed method. The estimated motion of the transducer resembles the motion pattern observed in-vivo. In [28], the longitudinal displacements of the transducer were studied for a group of 31 patients using angiographies and IVUS at coronary bifurcations. The obtained longitudinal displacements are within the experimentally recorded ranges [28]. Furthermore, a specific position in the longitudinal axis is represented by a set of frames in the different cardiac phases.

A formal definition for the set of frames located at the $n$-th frame position of the steady phase, is given by

$$\mathcal{R}_n = \{I^s_j; s(I^s_j) = s(I^s_n), j = 1, \ldots, N_s, i = 1, \ldots, P\}.$$ (13)

D. Implementations

The implementations described next, present three alternative longitudinal registration schemes, two decoupled and another coupled with the transversal registration. As input for these implementations, we provide the $N$ sets of gated volumes from the original IVUS study, i.e., $I_i$, $i = 1, \ldots, N$.

Then, the registration task is to transversally and longitudinally register all phases $I_{ij}, i \neq \text{st}$, against $I_{\text{st}}$.

For all implementations, the preprocessing of the study is performed either using the FIR or the VWR. The first decoupled implementation (DLT implementation), defines $\mathcal{R}_n$ sets through the longitudinal registration of all phases, as described in section II-C and then, performs the transversal registration in each $\mathcal{R}_n$ independently. The second decoupled
implementation (DTL implementation), performs the transversal registration of each set $\mathcal{Y}_i = \{I_j^i; i = 1, \ldots, P\}$ against $I^k_j$ and, then, performs the longitudinal registration of all phases. The coupled implementation, aligns the cross-sections prior to the calculation of the correlation presented in (12). Once the minimum is found it provides not only the longitudinal coordinates, but also the transversal motion that aligns the structures, leading to a fully coupled frame registration.

1) DLT implementation: The DLT implementation is composed of three serial and independent stages: the preprocessing, the longitudinal and transversal registration. As input the last stage receives the $\mathcal{X}_n$ sets from the longitudinal registration. Here for each one of these sets, the non-steady frames are registered against the steady frame. Formally, we define the transversal registration of the set $\mathcal{X}_n$ as

$$\Xi_n = \arg \max_{\Xi^* \in \mathcal{W}} \mathcal{F}(I^k_n, J_m)$$
$$= \arg \max_{\Xi^* \in \mathcal{W}} c(I^k_n, J_m(x(\Xi^*), y(\Xi^*))|_{|\mathcal{W}}$$

where $J_m \in \mathcal{X}_n$ and $J_m \neq I^k_n$. Finally, the aligned set of frames located at the $n$-th frame position of the steady phase, is given by

$$\mathcal{X}_n = \{ J_m(x(\Xi^*), y(\Xi^*)); J_m \in \mathcal{X}_n - \{I^k_n\} \} \cup \{ I^k_n \}. $$

2) DLT implementation: The DLT implementation is also composed of three serial and independent stages: the preprocessing, the transversal and longitudinal registration. The second step performs the transversal registration of the $j$-th frame across all phases ($\mathcal{Y}_i$) against the frame in $\mathcal{X}_n$. Formally, we define the transversal registration of the set $\mathcal{Y}_i = \{I^i_j; i = 1, \ldots, P\}$ as

$$\Xi^i_n = \arg \max_{\Xi^* \in \mathcal{W}} \mathcal{F}(I^k_j, I^i_j)$$
$$= \arg \max_{\Xi^* \in \mathcal{W}} c(I^k_j, I^i_j(x(\Xi^*), y(\Xi^*))|_{|\mathcal{W}}$$

where $I^k_j \in \mathcal{Y}_i$ and $I^k_j \neq I^i_j$. The transversally registered frames $I^i_j = I^i_j(x(\Xi^*_j), y(\Xi^*_j))$ are the inputs for the longitudinal registration in which the longitudinal position for each frame $I^k_j$ is given by

$$s(I^k_j) = s(I^k_n),$$

where

$$n = \arg \max_{k=1, \ldots, N_{st}} c_w(I^k_j, I^k_n).$$

Finally, the aligned set of frames located at the $n$-th frame position of the steady phase, is given by

$$\mathcal{X}^{\text{DTL}}_n = \{ I^k_j; s(I^k_j) = s(I^k_n), j = 1, \ldots, N_i, i = 1, \ldots, P \} \cup \{ I^k_n \}. $$

3) Coupled implementation: The coupled implementation is composed of two stages: the preprocessing and the coupled longitudinal and transversal registration. The second stage, performs the transversal registration prior the comparison presented in (9). In that manner, the position in space of the frame $I^j$, which belongs to a non-steady phase and the applied transversal rigid motion $\Xi^j$ to that frame are defined as

$$s(I^j(x(\Xi^j), y(\Xi^j))) = s(I^k_n),$$

where

$$n = \arg \max_{k=1, \ldots, N_{st}} c_w(I^j_j(x(\Xi^j), y(\Xi^j)), I^j_k).$$

and

$$\Xi^j = \arg \max_{\Xi^* \in \mathcal{W}} \sum_{d=-w}^{w} \mathcal{F}(I^k_n, I^j_{n+d}).$$

Note that the transversal registration performed in (22) is now coupled with the longitudinal registration due to (21). Evidently, this implementation is computationally more expensive. To decrease the computational cost, we confine the search space in (21) to $k \in [\max(j-11, 1); \min(j+11, N_{st})$ which represents longitudinal displacements until $\approx 5.5$mm forward and backward. According to [28], this range of displacement encloses those experimentally observed in vivo. The same optimization is performed for the decoupled implementation for an objective cost and accuracy comparison in the forthcoming sections.

Finally, the aligned set of frames located at the $n$-th frame position of the steady phase, is given by

$$\mathcal{X}^{\text{C}}_n = \{ I^j_j(x(\Xi^j), y(\Xi^j)); s(I^j_j(x(\Xi^j), y(\Xi^j))) = s(I^k_n), j = 1, \ldots, N_i, i = 1, \ldots, P \} \cup \{ I^k_n \}. $$
III. RESULTS

A. IVUS Data

The IVUS studies were acquired with the Atlantis™ SR Pro Imaging Catheter at 40 MHz synchronized with an ECG signal and connected to an iLab™ Ultrasound Imaging System (both by Boston Scientific Corporation, Natick, MA, USA), at the Heart Institute (InCor), University of São Paulo Medical School and Sírio-Libanês Hospital, São Paulo, Brazil.

The procedure was performed during a diagnostic or therapeutic percutaneous coronary procedure. Vessels were imaged using automated pullback at 0.5 mm/s. Overall, multiple runs were performed on 28 patients leading to 52 IVUS studies with synchronized ECG signal. We analyzed images from different coronary arteries (Left Anterior Descending - LAD, 27 studies; Left Circumflex Artery - LCx, 12 studies; Right Coronary Artery - RCA, 10 studies; and other coronary arteries, 3 studies) spanning different mean cardiac frequencies (from 65 BPM to almost 90 BPM) including cases with severe stenoses and deployment (22 studies) or not (30 studies) of stents.

After the procedure, a specialist performed a manual offline ECG gating of the studies. Specifically, an operator marked the frame number at each R-wave peak in the IVUS study aided by the synchronized ECG signal. Hence, images in a specific cardiac phase (the R-wave peak phase) can be identified. Then, we use the criteria presented in [41] to decompose the IVUS study in several cardiac phases.

B. Computational Cost

The computational cost is proportional to the number of seeds used in the gradient ascend method for transversal registration. For this reason, we analyzed the trade-off between seeds used in the gradient ascend method for transversal registration. For this reason, we analyzed the trade-off between seeds used in the gradient ascend method for transversal B. Computational Cost study in several cardiac phases.

we use the criteria presented in [41] to decompose the IVUS cardiac phase (the R-wave peak phase) can be identified. Then, we use the criteria presented in [41] to decompose the IVUS study in several cardiac phases.

Fig. 7. Initialization patterns over the space $\mathcal{U}$. The dashed box is aligned with the $\tau_x$, $\tau_y$, $\theta$ axes.

the brute force and the MSGA method (hereafter assumed as MSGA error) is defined as follows

$$
\varepsilon = \sqrt{\left(\frac{\tau_x - \hat{\tau}_x}{\mu_{\hat{\tau}_x}}\right)^2 + \left(\frac{\tau_y - \hat{\tau}_y}{\mu_{\hat{\tau}_y}}\right)^2 + \left(\frac{r_{eq} (\theta - \hat{\theta})}{\mu_{\hat{\theta}}}\right)^2}
$$

(25)

where $\tau_x$, $\tau_y$, $\theta$ and $\hat{\tau}_x$, $\hat{\tau}_y$, $\hat{\theta}$ triplets are the rigid motion estimated with MSGA and brute force method, respectively, $r_{eq} = \sqrt{A_l/\pi}$ is the equivalent radius for the lumen in the analyzed frame, $A_l$ is the area of the lumen in the analyzed frame and $\mu_{\hat{\tau}_x}, \mu_{\hat{\tau}_y}, \mu_{\hat{\theta}}$ are the means of $\hat{\tau}_x$, $\hat{\tau}_y$ and $r_{eq} \hat{\theta}$ for the 52 cases analyzed. The normalization applied by the factors $\mu_{\hat{\tau}_x}$, $\mu_{\hat{\tau}_y}$, and $\mu_{\hat{\theta}}$ equalizes the three motion components contribution to $\varepsilon$.

From the analysis (see Fig. 8), it is confirmed that the accuracy improves as more seeds are added in the initialization process. The 3-seed pattern have shown that $\tau_x$ is the dimension that requires more initialization to minimize the optimization error because of the local minima in the functional produced by the partial matching of the structures registered. Note that the 7 seeds and the 15 seeds patterns present the same error $\varepsilon$ in terms of mean and standard deviation, although the computational cost of 15-seed doubles the one of the 7-seed pattern (see Fig. 9). For this reasons, we use the 7-seed pattern in the following analysis because it presents the better trade-off between accuracy and computational cost.

Lastly, we assess the performance of the decoupled and coupled implementations. We do not differentiate the two decoupled alternatives because their computational complexity in terms of frames registrations and comparisons (quantity of transversal registration and frame comparisons performed with the proposed MLE within a study) is the same and its computational cost does not present significant variations. In this
case, we choose to parallelize the implementations to judge their potential use in medical practice. The implementations coded in C++ compiled with GNU compilers were parallelized at frame level with OpenMP. Each execution was parallelized across the 16 threads of the aforementioned processors. The registration was carried along the 52 studies using the FIR ROL, $\sigma = 0.4$ and the MSGA with 7-seed pattern for both implementations. Results show that the decoupled implementation is 134 times faster than the coupled implementation (see Fig. 10) with an execution time per study of $562 \pm 233$ sec and $75521 \pm 35356$ sec, respectively. As the execution times suggests, the decoupled implementation is capable to assess longitudinal motion during medical procedure meanwhile the coupled implementation is necessarily an offline method.

C. Validation of Transversal Registration

To validate our method, we construct a ground truth based on registrations performed by medical image experts. Thus, two specialist perform the rigid registration of 30 distinguishable anatomical landmarks (each landmark is characterized by a pair of IVUS frames at the same cross-section in different cardiac phases) such as bifurcations, extreme points of stent or calcified regions. We study the intra- and inter-observer variability for this ground truth in terms of Bland-Altman limits of agreement (LA) and intervals of cross-correlation (ICC, only for inter-observer analysis).

The intra-observer variability (see Table I) shows that manual registration (here performed twice for each landmark) is a hardly reproducible task even for image experts ($p$-value $> 0.33$ for the Bland-Altman mean). The identification at pixel precision of landmarks within an image was not entirely successful (LA smaller than 11 pixels for translations and 2.25 radians for rotations). Causes of these inaccuracies include the poor SNR, polar-to-cartesian interpolation within the image and the blurring of landmark structures provoked by heart contraction.

The inter-observer variability was estimated by comparing the average of the two manual registrations performed by each observer at each landmark ($\bar{\Omega}$). Table II presents a good agreement between the specialists in the identification of $\tau_x$ and $\theta$ (ICC of 0.93 and 0.87 with $p$-value of $2 \cdot 10^{-10}$ and $3 \cdot 10^{-7}$, respectively) and a low correlation in the identification of $\tau_y$ (ICC of 0.49 with $p$-value of $4 \cdot 10^{-2}$). The LA show lower inter-observer than intra-observer variation.

Lastly, we extended the observations of one specialist ($\bar{\Omega}_1^E$) from 30 to 50 landmarks, to obtain a bigger set for comparison against the proposed MSGA method. As result (see Table II) it is seen that the specialist 1 presents a higher correlation against the MSGA (ICC of 0.89, 0.94 and 0.93) than against specialist 2 (ICC of 0.93, 0.49 and 0.87). Moreover, the LA are narrower in the case $\bar{\Omega}_1^E$ vs $O_{MSGA}$ for $\tau_y$ (LA $< 2.3$ pixels) while $\tau_x$ and $\theta$ remain within the same limits as in $\bar{\Omega}_1^E$. 

![Fig. 8. Standard deviation (whiskers) and mean (bars) of the MSGA error for the 7 initialization patterns along 52 bifurcation frames registrations. The normalization factors are $\mu_{\tau_x} = 5.827$, $\mu_{\tau_y} = 4.769$, $\mu_{\theta} = 0.152$.](image1)

![Fig. 9. Standard deviation (whiskers) and mean (bars) computational cost of the proposed MSGA initializations and the brute force method for 52 bifurcation frames registrations.](image2)

![Fig. 10. Standard deviation (whiskers) and mean (bars) computational cost per study of the parallelized decoupled and coupled implementations. The wall-clock times were estimated using the 52 IVUS studies.](image3)
In the previous two sections, we have defined the optimal parameters for our registration method. Then, we have applied the DTL strategy with \( w = 5 \) using a FIR mask and MSGA with 7 seeds to two in-vivo IVUS study. As seen in Fig. 11, the gated systolic volume is degraded by both longitudinal and transversal motion components. We have chosen two IVUS studies highlighting different scenarios: i) large transversal misalignments; ii) large longitudinal misalignment. In the scenario i) presented in the left column of Fig. 11, it is seen that the rotations due to the transversal registration aligned the bifurcations and vessel wall (e.g. the bifurcation highlighted in the yellow square area and the lumen at the beginning of the pullback). In the scenario ii) presented in the right column, a red vertical line indicates the plane at the bifurcation carina. It is seen that the carinas are displaced between phases \( \mathcal{S}_t \) and \( \mathcal{S}_m \) due to the longitudinal motion of the transducer. After the registration of \( \mathcal{S}_m \) against \( \mathcal{S}_t \) the anatomical structures are successfully aligned.

### E. Registration qualitative assessment

To analyze the factors that contribute to the appearance of longitudinal motion, we compare groups of IVUS studies using...
TABLE III
MEAN AND STANDARD DEVIATION OF THE LONGITUDINAL REGISTRATION ERROR MEASURED AT 212 LANDMARK SITES ALONG 52 IN-VIVO IVUS STUDIES.

<table>
<thead>
<tr>
<th>( \sigma )</th>
<th>( w )</th>
<th>DLT Implementation ( \varepsilon ) with FIR ( \varepsilon ) with VWR (mean ± SD)</th>
<th>DTL Implementation ( \varepsilon ) with FIR ( \varepsilon ) with VWR (mean ± SD)</th>
<th>Coupled Implementation ( \varepsilon ) with FIR ( \varepsilon ) with VWR (mean ± SD)</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.4</td>
<td>0</td>
<td>0.78 ± 1.72 0.83 ± 1.94</td>
<td>0.42 ± 0.78 0.45 ± 0.85</td>
<td>0.49 ± 1.26 1.82 ± 2.99</td>
</tr>
<tr>
<td>0.8</td>
<td>1</td>
<td>0.69 ± 1.74 0.68 ± 1.77</td>
<td>0.38 ± 0.85 0.54 ± 1.14</td>
<td>0.51 ± 1.42 1.38 ± 2.78</td>
</tr>
<tr>
<td>1.2</td>
<td>2</td>
<td>0.64 ± 1.68 0.67 ± 1.78</td>
<td>0.32 ± 0.75 0.67 ± 1.46</td>
<td>0.45 ± 1.36 1.02 ± 2.24</td>
</tr>
<tr>
<td>1.6</td>
<td>3</td>
<td>0.62 ± 1.65 0.67 ± 1.84</td>
<td>0.30 ± 0.63 0.69 ± 1.33</td>
<td>0.51 ± 1.54 1.08 ± 2.43</td>
</tr>
<tr>
<td>2.0</td>
<td>4</td>
<td>0.58 ± 1.63 0.70 ± 1.97</td>
<td>0.31 ± 0.68 0.83 ± 1.84</td>
<td>0.42 ± 1.22 1.18 ± 2.51</td>
</tr>
<tr>
<td>2.4</td>
<td>5</td>
<td>0.57 ± 1.52 0.72 ± 1.97</td>
<td>0.33 ± 0.73 0.90 ± 1.90</td>
<td>0.42 ± 1.15 1.06 ± 2.44</td>
</tr>
<tr>
<td>2.8</td>
<td>6</td>
<td>0.64 ± 1.69 0.69 ± 1.87</td>
<td>0.33 ± 0.66 0.99 ± 2.02</td>
<td>0.52 ± 1.45 1.03 ± 2.27</td>
</tr>
</tbody>
</table>

TABLE IV
BLAND-ALTMAN (BA) MEAN (\( \mu_{BA} \)) AND LIMITS OF AGREEMENT (LA) FOR LONGITUDINAL REGISTRATIONS WITH THE PROPOSED IMPLEMENTATIONS AGAINST THE EXPERT GROUND TRUTH (212 ANATOMICAL LANDMARKS USED AS SAMPLES).

<table>
<thead>
<tr>
<th>( \sigma )</th>
<th>( w )</th>
<th>DLT Implementation ( \mu_{BA} ) ± LA</th>
<th>DTL Implementation ( \mu_{BA} ) ± LA</th>
<th>Coupled Implementation ( \mu_{BA} ) ± LA</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.4</td>
<td>0</td>
<td>0.13 ± 3.69 0.17 ± 4.13</td>
<td>0.19 ± 1.71 0.23 ± 1.84</td>
<td>−0.07 ± 2.66 0.27 ± 6.85</td>
</tr>
<tr>
<td>0.8</td>
<td>1</td>
<td>0.14 ± 3.67 0.17 ± 3.71</td>
<td>0.12 ± 1.80 0.09 ± 2.47</td>
<td>−0.08 ± 2.96 0.29 ± 6.07</td>
</tr>
<tr>
<td>1.2</td>
<td>2</td>
<td>0.11 ± 3.53 0.22 ± 3.72</td>
<td>0.06 ± 1.60 −0.02 ± 3.16</td>
<td>−0.09 ± 2.82 −0.04 ± 4.83</td>
</tr>
<tr>
<td>1.6</td>
<td>3</td>
<td>0.09 ± 3.46 0.28 ± 3.80</td>
<td>0.00 ± 1.38 −0.06 ± 2.94</td>
<td>−0.14 ± 3.18 −0.33 ± 5.18</td>
</tr>
<tr>
<td>2.0</td>
<td>4</td>
<td>0.05 ± 3.39 0.12 ± 4.11</td>
<td>−0.01 ± 1.46 0.13 ± 3.96</td>
<td>−0.18 ± 2.51 −0.19 ± 5.43</td>
</tr>
<tr>
<td>2.4</td>
<td>5</td>
<td>0.00 ± 3.19 0.09 ± 4.11</td>
<td>−0.02 ± 1.58 −0.14 ± 4.13</td>
<td>−0.10 ± 2.40 −0.50 ± 5.13</td>
</tr>
<tr>
<td>2.8</td>
<td>6</td>
<td>−0.01 ± 3.55 0.04 ± 3.91</td>
<td>−0.01 ± 1.45 −0.24 ± 4.39</td>
<td>−0.19 ± 3.01 −0.36 ± 4.85</td>
</tr>
</tbody>
</table>

Fig. 11. Comparison between two IVUS studies, before and after registration: (First row) stentless phase \( \mathcal{I}_{st} \); (Second row) moved phase \( \mathcal{I}_{mo} \) before registration; (Third row) moved phase \( \mathcal{I}_{mo} \) after registration. (Left column) Panels highlight (yellow square) the improvement brought by the transversal registration in terms of the alignment of the bifurcations, particularly in the proximal bifurcation; (Right column) Panels highlight (red lines) the improvement in the longitudinal alignment in terms of the bifurcation carinas.
different criteria. As we map the systole frames to the diastole frames whose locations are known, we use this mapping as a non-linear description of the longitudinal motion between the diastole and systole, i.e., the vessel displacement between $I_{st}$ and $I_{mo}$. Then, we define the longitudinal motion in mm units at the $k$-th frame as follows

$$d_k = |s(I_{st}^k) - s(I_{mo}^k)|,$$  \hspace{1cm} (27)

where $s$ is the function of frame space location defined in (8) and (11). Then, we define three longitudinal motion features: the fraction of the study with a pre-defined motion ($p_d$), the motion mean ($\mu_d$) and the motion standard deviation ($\sigma_d$). The $p_d$ feature is calculated as

$$p_d = \frac{\sum_{k=1}^{N} m^i(d_k)}{N},$$ \hspace{1cm} (28)

where $m^i(d_k)$ is 1 if $d_k \geq i$ otherwise is 0, and $N$ is the amount of heartbeats in the study such that contains the phases $I_{st}$ and $I_{mo}$. We decide to measure the rate that represents the fraction of the study that spans with longitudinal displacement of $i = 0.6$ mm or more. The use of 0.6mm as threshold for longitudinal motion is given by the fact that $I_{st}$ frames are spaced by $\approx 0.5$ mm and errors of this magnitude are expected for the discretization of $s(I_{mo}^k)$. Then, we choose to add 0.1mm to avoid the oscillations of the discretization error to guarantee the motion detection. The remaining features, $\mu_d$ and $\sigma_d$, are trivially defined as the mean and standard deviation of $d_k \geq 0.6$ mm in the study.

In the first analysis, we grouped the studies by coronary arteries. Additionally, the studies where separated by presence or not of a stent to avoid that longitudinal motion effects caused by stent deployment, which may interfere with coronary artery local effects. According to the results reported in Table V, a general reduction of motion was seen in all the features for the cases in which there was stent deployment. Here, a minor portion of the study presented longitudinal motion and even in the locations where the motion persisted, a reduction in the mean and standard deviation was observed. In the case with no stent deployment, it was seen that as the longitudinal motion was less frequent (smaller values of $p_d$), the intensity of the motion also decreased ($\mu_d$ and $\sigma_d$). Particularly, LAD arteries presented the lower longitudinal motion, followed by the RCA and LCx. All these results are consistent with those reported by [28] using different IVUS and AX imaging techniques for longitudinal displacement estimation.

In the second study, we choose 5 patients with multiple IVUS studies on different arteries to assess whether the longitudinal motion is related to a specific patient, or not. The analysis did not show a clear correlation between the patient and the longitudinal motion. A study with a bigger patient population is necessary to evaluate this issue.

A last study is performed for patients before and after stent deployment to assess the influence of the arterial longitudinal stiffening and the longitudinal motion. To visualize the longitudinal displacement provoked by the heart contraction, we subtracted the pullback longitudinal displacement. As result, we observed (see Fig. 12) that the stenting procedure suppressed the longitudinal displacement at the stent location and its surroundings. Also, the bifurcations outside the stent moved towards the stent center as well as some of the motion patterns (e.g. Case 2 in the distal half).

<table>
<thead>
<tr>
<th>Case</th>
<th>$p_d$ (in mm)</th>
<th>$\mu_d$ (in mm)</th>
<th>$\sigma_d$ (in mm)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.16</td>
<td>0.51</td>
<td>0.47</td>
</tr>
<tr>
<td>2</td>
<td>0.89</td>
<td>2.20</td>
<td>1.98</td>
</tr>
<tr>
<td>3</td>
<td>0.16</td>
<td>0.58</td>
<td>0.31</td>
</tr>
<tr>
<td>4</td>
<td>0.85</td>
<td>0.90</td>
<td>0.15</td>
</tr>
<tr>
<td>5</td>
<td>0.24</td>
<td>1.81</td>
<td>1.41</td>
</tr>
</tbody>
</table>

TABLE VI

LONGITUDINAL MOTION FEATURES FOR 5 DIFFERENT CASES BEFORE AND AFTER STENT DEPLOYMENT. THE FEATURES WERE ONLY COMPUTED ALONG THE VESSEL PART WHERE THE STENT HAS BEEN DEPLOYED.

G. Longitudinal Motion Characterization

The insights given by the longitudinal motion before and after stent deployment, suggest that the observed longitudinal motion is directly related to the longitudinal vessel strain. As known, the estimated longitudinal motion represents the relative displacement between the vessel wall and the IVUS transducer. If longitudinal motion were to be dominantly determined by the transducer migration, the expansion of the lumen would increase the longitudinal motion. Instead, the five cases presented in Fig. 12 have shown the opposite phenomenon (see Table VI. This behavior is compatible with the hypothesis that longitudinal motion is connected to the longitudinal strain (i.e. the longitudinal displacement of the vessel wall), which was suppressed by the stenting deployment. Even more, the results reported in Table V show a reduction of longitudinal motion for arteries with stent and similar results are reported by [28] with different IVUS and AX imaging techniques. All these evidence is also compatible with the previous hypotheses.

By assuming this hypotheses to hold, the presented method becomes more than a mere longitudinal registration solution for IVUS. As a matter of fact, it allows the estimation of longitudinal strain distribution along the vessel. With this data at hand, added to proper tissue characterization methods, the longitudinal stress over atherosclerotic lesions can be inferred once suitable constitutive models for the vessel wall are available. Also, we will be able to predict areas more susceptible to stent fracture which is a late adverse event related to local shear forces [43].

Finally, the suppression of the longitudinal motion at the stenting area may be a temporal effect linked with the angioplasty procedure. Is well known that during angioplasty the arteries tends to contract as response to the balloon inflation [44]–[46] and so could be the lack of axial strain. In a study by Togni et al. [45], implantation of a bare-metal stent does not affect physiologic response to exercise proximal and distal to the stent. However, sirolimus-eluting stents are associated with exercise-induced paradoxic coronary vasoconstriction of the adjacent vessel segments, although vasodilatory response to nitroglycerin is maintained. These observations suggest (drug-induced) endothelial dysfunction as the underlying mechanism. To better characterize the absence of longitudinal motion...
in stenting areas, longitudinal studies with pre-stent, post-stent and follow up IVUS acquisitions need to be performed.

### IV. DISCUSSION

Several authors base their registration strategies on the segmentation of the whole arterial wall to obtain a more reliable representation of the vessel, although the outcomes of the present study suggest that this task is ineffective and, moreover, does a disservice to the registration. In contrast, the inclusion of perivascular tissue to the ROI aids the identification of the location of the vessel cross-section. In that sense, the ROI FIR avoids the segmentation task which is time consuming and, in some cases, questionable (e.g. bifurcations or calcium rings). Circumventing this task is fundamental towards achieving automation of the registration procedure, as in the present approach when using the FIR mask. In this last point, studies with guidewire artifact may demand the artifact segmentation (see Supplementary material, Section A) which is the only not fully automatic task, although it is far less time demanding than the vessel wall segmentation.

The transducer motion model is such that the fully coupled and the DTL decoupled strategies render similar results, being slightly better the latter technique. Both strategies, substantially outperform the DLT strategy, pointing out the importance of performing transversal registration prior longitudinal registration. Remarkably, the frames that rendered better results with DTL than with the coupled implementation feature significant variation of the cross-section geometry between systole and diastole, e.g. bifurcations, and other neighboring contours attained a major MLE value than the expected (correct) frame. The use of transversal non-rigid registration may improve these cases, although it is important to highlight that the registration error was acceptably low even in these cases. The reason for DTL to slightly outperform the coupled implementation is that successive frames of the same phase present a similar transversal motion from diastolic phase, then DTL favors the longitudinal registration against near location frames which in most cases present the correct solution. On the contrary, the coupled implementation performs transversal

<table>
<thead>
<tr>
<th>Artery label</th>
<th>$&lt;\mu_d&gt;$</th>
<th>$&lt;\sigma_d&gt;$</th>
<th>$S$</th>
<th>$&lt;\mu_d&gt;$</th>
<th>$&lt;\sigma_d&gt;$</th>
<th>$S$</th>
</tr>
</thead>
<tbody>
<tr>
<td>LAD</td>
<td>0.09</td>
<td>1.10</td>
<td>7.5</td>
<td>0.16</td>
<td>1.33</td>
<td>9.6</td>
</tr>
<tr>
<td>LCx</td>
<td>0.20</td>
<td>1.74</td>
<td>5.0</td>
<td>0.32</td>
<td>2.25</td>
<td>6.2</td>
</tr>
<tr>
<td>RCA</td>
<td>0.08</td>
<td>1.03</td>
<td>3.0</td>
<td>0.18</td>
<td>1.66</td>
<td>7.5</td>
</tr>
</tbody>
</table>

**TABLE V**  
Mean longitudinal motion features for different coronary arteries with and without stent deployment. The $S$ value stands for the amount of samples in the population used for the calculation and $<\cdot>$ is the mean of $\cdot$ for the $S$ samples.

**Fig. 12.** Longitudinal displacement estimated before and after stent deployment in 5 different patients. The bold $\times$ marks the bifurcation used for rigid registration of the studies. The black arrows depict the longitudinal displacement of the remaining bifurcation due to stenting deformations in the vessel.
registration against each one of the longitudinal candidate frames, which gives the best alignment to near or far frames without favoring any in particular. When the correct frame matches with low MLE value due to non-rigid deformations, the coupled implementation may result in bigger errors than the DTL.

Another interesting insight from the registration analysis was the poor reproducibility of registration results obtained from medical imaging experts. This is consequence of the poor quality of US images which hinders the registration task for the human inspection. The computational models, as here proposed, ensure reproducibility, giving less uncertainty to the quality of the registration. Also, we demonstrated that the transversal error was competitive with the experts alignment and that mean longitudinal error was smaller than a single frame. These results indicate that our registration approach (particularly DTL) is less time consuming, offering reproducibility and high accuracy, which makes it more convenient for medical practice than manual registration by experts.

In Section III-F, we have shown the capabilities of using the proposed method to measure local longitudinal strains along the vessel, which were in agreement with previously reported observations ([28]). This application of the method may help for the characterization of the vessel properties and a better understanding of the vessel deformation for different scenarios.

As final remark, our previous approaches used normalized cross-correlation (NCC) instead the MLE presented in 4 (CD2 as proposed in [11], [34]). The NCC MLE have rendered larger errors for both registrations (transversal and longitudinal) than CD2. CD2 estimator models the Rayleigh multiplicative noise as log-compressed which is the case of these US images. As result, the MLE is less sensitive to this noise along the registration process, improving the similarity measurements across the vessel structures.

V. CONCLUSIONS

Methods for longitudinal and transversal registration and longitudinal motion estimation have been proposed. Insights from applying the methodology before and after stenting procedures, suggest that the longitudinal motion is associated with the longitudinal strain of the vessel wall which can benefit the construction of new culprit plaque indicators adding physical magnitude.

From the proposed methods, it have been shown that a decoupled scheme of transversal prior longitudinal registration is the best option in terms of accuracy and computational cost. To reduce even more the computational cost involved in the transversal registration stage, the so-called MSGA method has been developed and exhaustively tested. Also, it is concluded that the best choice of ROI used for registration is the one that makes use of both vessel wall and perivascular tissue.

Estimation of longitudinal motion across 52 IVUS studies showed that stent areas suppress the local longitudinal motion and the overall motion within the study. In arteries without stent, LAD arteries present the minor amount of longitudinal motion, followed by LCx and RCA.

VI. FUTURE WORKS

From our point of view, medical research aided by the proposed method requires the study of a larger population of patients in order to characterize motion of vessel structures in each coronary artery for different scenarios, namely plaque types and stent materials. Also, longitudinal studies with several follow-ups after stent deployment will definitely bring an insight about the axial remodeling of the vessel in terms of their strains.

Conflict of Interest: The authors declare that they have no conflict of interest.

Ethical approval: For this type of study formal consent is not required.

REFERENCES


