Improved Rigid Registration of Vessel Structures using the Fast Radial Symmetry Transform

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Abstract. Intravascular UltraSound (IVUS) imaging is unique in the possibility to explore internal vessel structures of the coronary wall, being a powerful tool for diagnosis. The coronary vessel is moving due to the periodical contraction and expansion of heart muscles, thus the acquired images present different artifacts. This instability, among other problems, makes harder the analysis of data in the longitudinal cut, especially for the visual evaluation of length and size of vessel structures, like e.g. calcium plaques. In this paper, we propose important improvements to an algorithm for rigid vessel structures alignment. We improve the estimate of vessel's center using the Fast Radial Symmetry Transform; then we perform the rotation estimation focusing only on the vessel boundary thus improving the alignment of vessel structures. A quantitative and qualitative comparison on 9 pullback is presented.

1 Introduction and previous work

The Intracoronary UltraSound imaging is a powerful technique for diagnosis of coronary diseases [1]. Unfortunately, the catheter and heart motion artifacts affect its usability in different ways. The induced longitudinal movement affects the interpretation of longitudinal cuts and the computation of reliable volumetric measurement; research is ongoing to devise efficacious and efficient proper gating algorithms. Moreover, the apparent roto-translation that affects the short axis view also makes harder the visual inspection of longitudinal cuts and affects the performance of automatic or semi-automatic methods for area and volume measurement. This paper focuses on the reduction of short axis roto-translation of a non-gated pullback by rigid registration of subsequent pullback frames.

Two excellent reviews on medical imaging registration can be found in [2] and [3]. However, despite a total amount of about four hundred cited papers, in these two reviews no paper has been found regarding IVUS images alignment. There is an evident need for ad-hoc solutions designed to adapt to the nature of IVUS images (heavy textured and with multiplicative noise), to estimate strong and fast apparent movement and rotation between subsequent frames while tackling the large amount of data in a pullback (thousand frames each). In [4] the authors present a sophisticated method for non-rigid alignment of IVUS image. It is based on the use of rich local and global (contextual) descriptors and, at the same time, using cooperative-iterative strategy in order to get a good set of correspondences as well as a good final transformation. In [5] the authors present a method to suppress the IVUS image rotation based on a kinematic approach. The method is based on the assumption that the vessel wall can be described as a discrete structure which kinematics temporal evolution can be followed by a trained Neural Network, during at least one heart cycle. In [6] authors present an alignment algorithm that estimates the vessel center based on center of mass computation, followed by the estimation of rigid rotation with center in the previously obtained center of mass. The most important lack of this method is that the estimation of rigid rotation (second step of the algorithm) heavily depends on the correct estimation of translation (first step of the algorithm). To compute the rigid roto-translation between subsequent frames the authors use the center of mass as a method to estimate the center of the rotation; then computing the translation just by coordinate subtraction. While this is robust with respect to noise and changes in image texture, it performs poorly if the vessel structure is changing due to e.g. a bifurcation or a calcium plaque. Moreover, an unbalanced position of the catheter with respect to the real center of the vessel produces a heavily unbalanced spatial distribution of gray scale values in the image due to the effect of image reconstruction from radio frequency data; i.e. vessel structures far from the catheter appear darker than the ones close to the catheter. In this case, even without important changes in the vessel structure, the estimation of translation using the center of mass can be very poor. In [7] the authors present a method based on the scale-space optical flow algorithm with a feature-based weighting scheme. The algorithm has been demonstrated on a tissue-mimicking phantom, subjected to controlled amount of angular deviation.

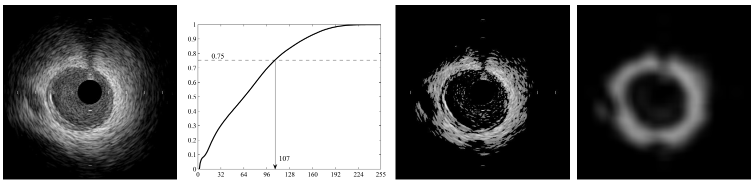
2 Rigid registration using the Fast Radial Symmetry Transform

The proposed method is an extension of the method presented in [6]. We estimates the rotation, that was demonstrated to be effective and sufficiently robust, as in [6], but we propose to change the estimation of vessel center. We start with the assumption that the vessel boundary on the short axis can be approximated as a circle. This assumption is quite simplistic since usually a better, and well accepted, approximation is to describe it as an ellipse [5]. To support this decision, we have two main reasons. (1) Our assumption is necessary because an elliptic model can be easily "cheated" by the deformation of vessel boundary caused by a bifurcation. In these cases, an elliptic model will estimate the center of the vessel with an important error in the direction of the bifurcation. (2) The algorithm we are going to use for detecting the center of the vessel, highlights any possible radial symmetry in the image, thus it is not easy to identify an elliptic shape.

Using this vessel model, we adapted the Fast Radial Symmetry Transform [8] (FRST) to be able to estimate the center of the vessel. IVUS images are far more complex than real world images, so we designed a pre-processing step and modified the FRST according to our needs. Moreover, we force the rotation estimation to work only on the part of the image that represents the vessel boundaries. The following subsections explain the method in detail.

2.1 Pre-processing for optimal FRST performance

Since the detection of a circle performed in [8] is done computing the image gradient, we need to highlight the vessel boundaries by preprocessing the IVUS image reducing, at the same time, both the noise and the texture. Identifying a circle that fits well with the vessel is difficult since gradients that represent the vessel boundary are not well defined and bright areas far from the vessel center generate important gradients not correlated to the vessel shape. We compute the cumulative probability density function (cpdf) of gray scale values with the goal to identify a good threshold to remove lower values (no signal or blood) and keep high values (vessel tissues). Thus we suppose that vessel tissues are represented by the pixels that contribute to the cumulative cpdf between 0.75 and 1 (see figure 1 (b)). These parameters have been set empirically but the fact that they act on the cpdf, and not on the pdf directly, makes the method less sensitive to variations of contrast and image average value. The next step is to remove the



(a) (b) (c) (d)

Fig. 1. From left to right: (a) the input image; (b) the cumulative probability function of gray scale values, note that the 0.75 percentile, in this case, give a threshold of 107; (c) the image after thresholding and (d) after gaussian smoothing.

texture and noise. The anisotropic diffusion can be an excellent filtering method, but it is extremely computationally expensive even using recent fast approach. Thus, we apply a strong Gaussian filter ($\sigma = 0.4mm$). This procedure smooths the texture and removes the noise (see figure 1 (d)); nevertheless, a remaining problem is that the outer boundary of the pre-processed image can be interpreted as a circle by the FRST. This has been tackled by modifying some part of the FRST as discussed in the next section.

2.2 Fast Radial Symmetry Transform

The Fast Radial Symmetry Transform has been developed to detect points of interest in an image that correspond to center of radially distributed image features (in our case to detect the center and the radius that approximate the vessel). Let us assume that we examine the detection of a radial symmetry generated by a circle of radius r. Given an input image $I(\boldsymbol{p})$, we can easily compute the gradient $\boldsymbol{G}(\boldsymbol{p})$, thus for each point $\boldsymbol{p}$ we can compute the unit vector of the gradient as $\boldsymbol{D}(\boldsymbol{p}) = \frac{\boldsymbol{G}(\boldsymbol{p})}{\|\boldsymbol{G}(\boldsymbol{p})\|}$. Now, for each pixel $\boldsymbol{p}$, we can define the center of the symmetry (as a pixel $\boldsymbol{q}$) that potentially generated its gradient $\boldsymbol{G}(\boldsymbol{p})$ (e.g. a circle). The coordinates of this pixel are computed as $\boldsymbol{q}_r(\boldsymbol{p}) = \boldsymbol{p} - r\boldsymbol{D}(\boldsymbol{p})$. To obtain the transform, a set of r matrices, O_r and M_r are instantiated with the same size of I and zero values and, while exploring every point $\boldsymbol{p}$ and radius r, are updated following the equations:

$$O_r(\boldsymbol{q}_r(\boldsymbol{p})) = O_r(\boldsymbol{q}_r(\boldsymbol{p})) + 1 \tag{1}$$

$$M_r(\boldsymbol{q}_r(\boldsymbol{p})) = M_r(\boldsymbol{q}_r(\boldsymbol{p})) + \|\boldsymbol{G}(\boldsymbol{p})\| \tag{2}$$

Intuitively, if in the image I there exists a circle with radius $\tilde{r}$ and center $\tilde{\boldsymbol{p}}$, the edges representing the circle will have gradients that point opposite to the center of the circle. This means that $O_{\tilde{r}}(\tilde{\boldsymbol{p}})$ will have a value conspicuously greater than in other pixel positions. For a similar reason, if the edges were strong, the $M_{\tilde{r}}(\tilde{\boldsymbol{p}})$ will be very high, because it collects a lot of important gradient magnitudes. Finally, since the transformation can span over different radii, a possible synthetic bi-dimensional result can be expressed as follows:

$$S(\boldsymbol{p}) = \sum_{r \in \Omega} L_r(\boldsymbol{p}) = \sum_{r \in \Omega} \left(\frac{O_r(\boldsymbol{p})}{\max_p O_r(\boldsymbol{p})} \right)^{\alpha} \cdot \frac{M_r(\boldsymbol{p})}{\max_p M_r(\boldsymbol{p})} \tag{3}$$

where Ω represents the set of radii spanned by the transform and α can define how strictly the radial symmetry property has to be computed. As an example, $\alpha = 3$ will produce less relevant points with respect to $\alpha = 1$. This is easily understandable since α is the parameter of a power function with base in the range [0 1]. Essentially, once computed $S(\boldsymbol{p})$, positions with high values represent highly probable centers of radial symmetries, thus searching for the maxima in $S(\boldsymbol{p})$ means searching for the more prominent symmetry in the image.

2.3 Modified Fast Radial Symmetry Transform

We modified the FRST to force the algorithm to find only the inner circle that fits into the pre-processed image. This ensures that a bad (non circular) outer boundary of vessel does not affect the algorithm performance. Moreover, to improve the performance, almost without increasing the computational cost, we implemented sub-pixel precision both in the detection of the center and radius.

Imposing inner circle detection constraint The vessel boundary cannot cross the center of the image, since it represents the catheter and thus it is physically impossible that the boundary can cross it. Taking advantage of this, we can know if the gradient $\boldsymbol{G}(\boldsymbol{p})$ at position $\boldsymbol{p}$ is produced by the inner or outer edges of vessel. Being $\boldsymbol{c}$ the center of the image, $\boldsymbol{d} = \boldsymbol{p} - \boldsymbol{c}$ represents the vector starting from $\boldsymbol{c}$, pointing to $\boldsymbol{p}$. We can compare the vector $\boldsymbol{D}(\boldsymbol{p})$ (gradient direction at point $\boldsymbol{p}$) and $\boldsymbol{d}$ simply by taking the dot product. If $\boldsymbol{D}(\boldsymbol{p}) \cdot \boldsymbol{d} < 0$, it means that the gradient $\boldsymbol{D}(\boldsymbol{p})$ is pointing in a direction that forms an angle with $\boldsymbol{d}$ that is minor than $\pi/2$. We call this the *directional constraint*. It is easy to understand that the gradients forming the outer boundary of the vessel can not respect this constraint. Using the update equations (1) and (2) only if $\boldsymbol{p}$ respects the *directional constraint* improves the detection of the vessel center and radius avoiding "false symmetries" introduced by the outer vessel boundary.

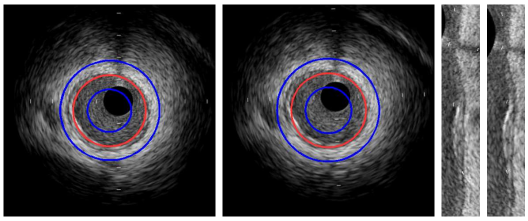
Implementing sub-pixel precision Instead of searching for the maxima in $S(\boldsymbol{p})$, we compute the center of mass of the values in $S(\boldsymbol{p})$. This gives sub-pixel precision in the detection of the center. To obtain sub-pixel precision for the radius, we perform a weighted average between different "layers" $L_r(\boldsymbol{p})$. Being $\boldsymbol{k}$ the estimated center of the vessel, then the sub-pixel precision radius is obtained by the following formula:

$$R(\boldsymbol{k}) = \frac{1}{\sum_{r \in \Omega} L_r(\boldsymbol{k})} \sum_{r \in \Omega} r L_r(\boldsymbol{k}) \tag{4}$$

This averaging process is more prone to outliers, however we heavily reduced the outliers numbers using the *directional constraint* and the outliers strength using an $\alpha > 1$ parameter in equation (3). Applying the Modified FRST over all the T frames of the pullback, we obtain a sequence of estimated center and radius of vessel. We denote these quantities as following: $\{(x_1, y_1, r_1), \ldots, (x_T, y_T, r_T)\}$.

2.4 Rotation estimation focused on vessel boundary

As discussed before, to estimate the rotation between subsequent frames we use the algorithm proposed in [6]. The authors estimate the rotation between two subsequent images (represented in polar coordinates with the origin that lies in the previously estimated center) by spectral correlation analysis [10] but improving the algorithm's robustness (see [6] for details). In our implementation we take advantage of the estimation of the vessel's radius and thus we perform the rotation estimation only on a portion of the image that represents the vessel boundary. Stabilizing the vessel boundary directly implies that the plaque and calcium structures, linked to it, will be stabilized too. This is a very important aspect of the proposed method. Actually, if r_i and r_{i+1} are the estimated radii of two subsequent frames, we sample the first image in the range of radii $r_i \pm \Delta R$ and the second one in the range $r_{i+1} \pm \Delta R$, where ΔR is an algorithm parameter (see figure 2). In this way, the rotation estimation is focused on the vessel boundaries and moreover, if a dilation or a contraction is present between subsequent frames, this procedure acts as a scale normalization procedure. Regarding robustness, if the parameter ΔR is not too small, the sampling catches the sufficient information to estimate the rotation. We empirically set $\Delta R = 0.64\ mm$ for all the results presented in the paper.



(a) (b) (c) (d)

Fig. 2. (a) and (b) are two subsequent frames. The red circle is the detection of center and radius obtained with the modified FRST. The blues circles show the area that has been sampled to obtain the respective polar images (c) and (d). The rotation estimation is applied on the images (c) and (d), thus focusing mainly on vessel boundaries.

2.5 Computational issues

First, we estimate the vessel center and second, we estimate the relative rotation between vessel structures as in [6]. The first part has computational cost $\mathcal{O}(KN)$ where N is the image pixels and K is the number of radii involved in the computation of the fast radial symmetry (referring to formula (3), $K = |\Omega|$). The second part has a computational cost $\mathcal{O}(\tilde{N} \log \tilde{N})$ since it involves a convolution, where $\tilde{N}$ is the number of pixels of the polar image. Since creating the polar image requires a re-sampling, in general $\tilde{N} \neq N$. However, once $\tilde{N}$ is fixed, we can reduce the computational cost by transforming just a part of the polar image as discussed in the previous subsection. Summarizing, our method is K times slower than the one in [6] with regard to center estimation but it is much faster regarding the rotation estimation. Keeping K low is important to obtain a fast algorithm. To tackle this, we assume that the vessel radius changes slowly during the pullback. Thus, we perform the center estimation of first frame with a large K_{init} and, for next frames, we progressively reduce it until it reaches a smaller predefined value K_{min}. While doing this, the center of the set Ω at frame i, $r_{(\Omega,i)}$ is set to be the previously estimated radius r_{i-1}. In this way, we perform a tracking of useful radii for the FRST computation.

3 Results

We tested our algorithm on a set of 9 pullbacks from 7 patients, each containing 1000 frames. Pullbacks can present metallic stents, soft and hard plaque and one or more bifurcations. Some pullbacks present a vessel shape that is seriously far from being circular. After a preliminary empirical evaluation we found that a good setting of parameters is: $K_{init} = 100$, $r_{(\Omega,1)} = 2mm$ and $K_{min} = 10$, such that the first FRST spans 100 radii from $1mm$ to $3mm$ and after some frames the minimum number of spanned radii is 10, covering $0.2mm$ thus implicitly assuming that the maximum radius change between two subsequent frames does not overcome $0.1mm$. Regarding the radial strictness parameter, we set $\alpha = 2$ as suggested in [8]. During preliminary testing we noticed that, while varying α does not influence heavily the algorithm performance, the setting of K_{min} needs further investigation.

Different quantitative evaluation methods for IVUS pullbacks rigid alignment have been proposed: among others, [6] proposes the use of normalized cross-correlation on plaque areas to measure the oscillation due to the heart beating, and thus an eventual decrease in the oscillation due to the alignment algorithm. In our opinion, even if this method could be reliable, it is restricted to the analysis on plaque areas and thus it is not general enough. In [11] authors propose the Cardiac Alignment Rate (CAR) as a measure of how much the motion artifacts have been suppressed by an alignment algorithm. The CAR is defined as:

$$\mathrm{CAR} = 1 - \frac{|\mathcal{F}(q_{out}(t))(f_c)|}{|\mathcal{F}(q_{in}(t))(f_c)|} \tag{5}$$

where $q_{out}(t)$ and $q_{in}(t)$ are two quantitative measurements respective to the aligned sequence and input sequences, $\mathcal{F}$ is the Fourier transform and f_c is the fundamental frequency of oscillation due to the heart beating. In [11] authors propose as a measure for computing $q(t)$ the image local density of mass (given by the local mean) in order to minimize the impact of texture variability and speckle. Even though this could be a practical solution, this can underestimate the oscillation, due to the averaging process and moreover it is not focused on the vessel boundaries. Starting from this approach, we add two important modifications. First, since the oscillation is rarely perfectly sinusoidal we restate the CAR measure involving the values of the first 4 main harmonics of the base frequency f_c, i.e:

$$\mathrm{hCAR} = 1 - \frac{\sum_{n=1}^{4} |\mathcal{F}(q_{out}(t))(nf_c)|}{\sum_{n=1}^{4} |\mathcal{F}(q_{in}(t))(nf_c)|}. \tag{6}$$

In the case of a triangular oscillation the Fourier series decreases as $1/n^2$, thus the fifth harmonic has an amplitude that is $1/25$ of the main harmonic ($n = 1$) and consequently, stopping the summation at $n = 4$ seems sufficient to our measurement. Secondly, we restrict the analysis to the area of vessel boundaries but without averaging on a local neighborhood, since we expect that texture variability and speckle noise will not influence the Fourier amplitudes involved in equation (6) but will be distributed almost randomly on other frequencies. Moreover, for visual inspection and automatic or manual segmentation in longitudinal cuts, the alignment of the vessel boundaries is far more important than the alignment of other structures of the short axis image. The Conservation of

Density Rate suggested in [11] cannot assure that the vessel structures are actually influencing the overall evaluation of the alignment algorithm. Following these guidelines, we compared the proposed algorithm to the one in [6], obtaining the table 1. The proposed algorithm outperform the one in [6] in all cases (200% better on average). Figure 3 shows different longitudinal cuts: row (a) shows the input sequence, row (b) shows the aligned sequence using the algorithm in [6] and row shows (c) our results. It can be noticed that our algorithm performs a registration that aligns important vessel's structures improving the visual inspection of e.g. the hard plaque length and the adventitia border. Moreover, in our results the lumen appears horizontal, thus showing that the algorithm removed great part of the catheter translation. It is worth to remind that different longitudinal cuts can show different features since the relative rotation between subsequent frames can be different for different algorithms.

Seq. ♯	1	2	3	4	5	6	7	8	9
Osc. Amp.	216.14	322.64	224.02	186.94	203.42	336.36	194.75	263.90	264.93
hCAR-[6]	0.12	0.14	-0.036	0.011	0.038	0.29	0.12	0.15	0.056
hCAR-our	0.18	0.33	0.096	0.072	0.19	0.4	0.2	0.21	0.084

Table 1. The table presents, for each sequence, the input oscillation (actually the denominator in equation (6)) and the hCAR for both algorithms. Higher values mean better performance in reducing oscillation artifacts.

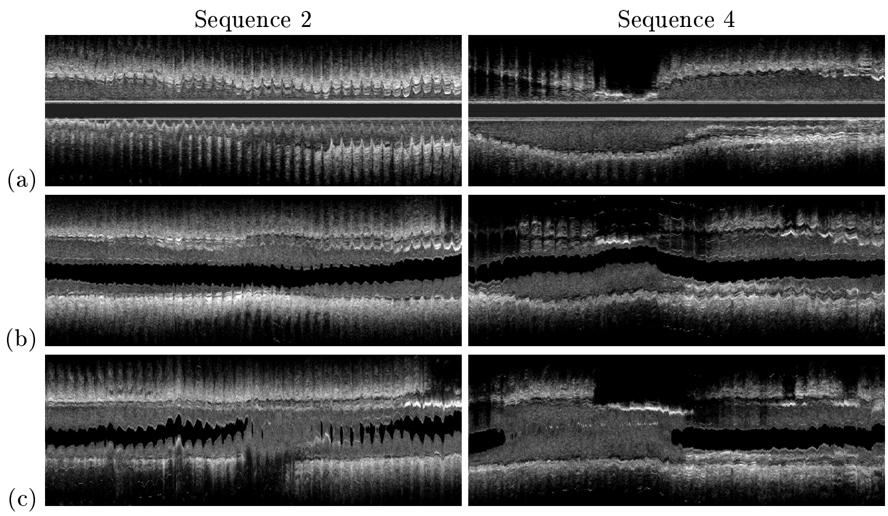


Fig. 3. Longitudinal cuts showing algorithms performance (see text for details).

4 Conclusion

The registration can be a precious tool for simplifying the visual inspection and manual measurements in longitudinal cuts. Moreover, it can be a pre-processing step for automatic segmentation of sequences and volumetric estimation. In this paper we presented a new algorithm for vessel's structures registration based on the Fast Radial Symmetry Transform. Experimental results show that the algorithm outperforms a previous approach with comparable computational cost. As a future direction, the method can be extended to fit a vessel elliptic model and also to fit different structures at a time thus detecting the lumen, the adventitia border and metallic stents.

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