Non-rigid Registration of Vessel Structures in IVUS Images

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Abstract. We present a registration and retrieval algorithm of medical images. Our algorithm is oriented in a general fashion towards gray level medical images of non-rigid bodies such as coronary vessels, where object shape information provide poor information. We use rich descriptors based on both local and global (contextual) information, and at the same time we use a cooperative-iterative strategy in order to get a good set of correspondences as well as a good final transformation. We focus on a novel application of registration of medical images: registration of IVUS, a promising technique of analyzing the coronary vessels.

1 Introduction

There is a wide range of applications of medical image registration and we refer to books such as [7] for detailed information. We apply registration to IntraVascular UltraSound images (IVUS), a powerful imaging modality for analysis and diagnosis of coronary vessels ([1]). In concrete we present a registration procedure to be used as a first step in a more general retrieval framework. The IVUS technique produces images with quite particularities and noise, difficult to analyze. Thus, creating a retrieval system of IVUS images is of high clinical interest for diagnosis purposes.

Although there is a huge number of works in the area of Registration and Retrieval of Medical Images [2, 7], matching of IVUS images and retrieving cases from an IVUS images database is a new problem to be solved. On the other hand, many works on medical image registration are focused on rigid parts that justifies rigid registration. Medical images of non-rigid bodies such as coronary vessels in IVUS present features quite different as they do not have any characteristic spatial configuration forced by the bony structure. We perform elastic matching with a variational approach for the transformation, given the high variability inter and intra subject of our medical images.

Registration consists on finding structures analog in a pair of images and compute a transformation that align them. We will follow point mapping as a general procedure of registration [5, 1].

* This work is supported by Ministerio de Ciencia y Tecnologia of Spain, grant TIC2000-1635-C04-04.

F.J. Perales et al. (Eds.): IbPRIA 2003, LNCS 2652, pp. 45–52, 2003.

Opposite to many works on medical images such as brain MRIs, which take a grid of characteristic points over all the image, we only extract a small set of characteristic points from the boundaries of the salient regions we want to match. This approach makes the algorithm faster and avoids the necessity of employing a multi-resolution scheme. Given the type of images we deal with, we must choose quite a rich set of descriptors which not only take into account the local statistics near the characteristic point (local descriptors) but also the context of the point (global or contextual descriptors). This gives information of how other structures are located around the point, and at the same time takes account of where the point is located at its own structure. Graphs are the most traditional tool for taking into account the context of some object. However, they are very dependent on an accurate segmentation, and this makes them little robust.

Instead, we make use of the so-called correlograms (see [3]) in order to take account of the context of points, extending the shape-context descriptor of Belongie et al [3] to cope with gray level images. Correlograms in 2-D will allow us to match the couple of images coarsely coping with the spatial distribution of structures, but have the draw-back of including some information about the 2-D shape of the contours not interesting in our case. Thus we extend the contextual information using shape invariant 1-D correlograms after a coarse alignment. The use of these two types of context descriptors as well as local descriptors will make our feature space rich enough.

Yet, the set of correspondences obtained with this set of descriptors is not enough to compute directly the final transformation based on them. We use a cooperative-iterative scheme (see [5]) in searching a good final transformation, which consists on giving feedback from the transformation to compute a new set of correspondences, which at the same time will produce a new transformation and so on, iterating the algorithm. We use a feedback scheme similar to the one used by Rangarajan et al. in [6], but without an annealing framework, as the combination of contextual and local information give us enough information to seek for an accurate transformation in a more straightforward manner.

Summarizing, we extend and combine different important ideas into a single framework: incorporation of contextual information with correlograms modified to cope with gray level images, adding a second type of contextual information, shape invariant 1-D correlograms; a cooperative-iterative scheme similar to the one used by Rangarajan et al. [6] and the use of Thin Plate Splines (TPS) [4], allowing different degrees of regularization-approximation as the correspondences become better and better. The combination of these three factors give our algorithm robustness as well as accuracy.

The article is organized as follows: section 2 explains the description of the registration method, section 3 shows the results obtained and the paper finishes with conclusions and future work.

2 Description of the Method

Coronary vessels present all their structures of interest around the wall of the vessel. We first make an anisotropic diffusion [9] of the IVUS image and let a snake grow from its interior to the wall of the vessel. Then we sample the boundary points in order to take our set of characteristic points and finally we extract the feature vectors associated to each characteristic point.

2.1 Feature Space

We compute local feature vectors associated to each characteristic point and then based on them compute 2-D correlograms and 1-D correlograms. Local feature vectors aim at characterizing the biological structure where the point lies, whereas correlograms will put the points into context. Summarizing, associated to each characteristic point x_i we are going to use three different feature vectors: our local feature vector l_i, a 2-D correlogram v_i, an 1-D correlogram w_i. We will now describe each of them in turn.

In IVUS images regions such as calcium plaque are characterized by the gray level they have inside them and the gray level they cause outside them because of their echogenic impedance. Thus a good descriptor of the structure the point is at, is the gray level profile along the line perpendicular to the wall from the point towards the outside part of the vessel. We measure a set of statistics over this profile and its first derivative which conform our local feature vector [1].

Correlograms consist of partitioning the image in cells distributed radially around its origin, which is the current point we are describing. In fig. 1 we can see a correlogram, a partition of the image in sectors or cells, each one accounting for some part of the image at a specified range of angles and radius, taking as origin a characteristic point x_i. The radial length of the cells grows with logarithmical rate from the origin towards outside, giving more importance to the near context of the point.

In every cell of the correlogram we compute a statistic such as the mean over the local feature vectors of the points that lie inside the cell. Let v_i be the 2-D correlogram associated to x_i. Let $\{x_{u_1}, x_{u_2}, \ldots, x_{u_t}\}$ be the characteristic points which lie in the u cell of v_i. We take the local feature vectors associated to these characteristic points: $\{l_{u_1}, l_{u_2}, \ldots, l_{u_t}\}$ and compute a mean over each of their characteristics. Let every local feature vector l_k have d characteristics: $l_k = (l_{k1}, l_{k2}, \ldots, l_{kd})\ \forall k$. Let $c_{uj} = mean(\{l_{u_1 j}, l_{u_2 j}, \ldots, l_{u_t j}\})$, the mean over the j characteristic of the local feature vectors $\{l_{u_1}, l_{u_2}, \ldots, l_{u_t}\}$. If we have r cells for every correlogram, we can express the 2-D correlogram associated to the characteristic point x_i as $v_i = (c_{11}, c_{12}, \ldots, c_{1d}, c_{21}, c_{22}, \ldots, c_{2d}, \ldots, c_{r1}, c_{r2}, \ldots, c_{rd})$.

The 1-D correlogram is a division in cells but now of the contour curve where we have our characteristic points. Let w_i be the 1-D correlogram for the characteristic point x_i. We can express the contour curve as a function $\varphi : [0,1) \to \mathbb{R}^2$ depending on an intern parameter $s \in [0,1)$: $\varphi(s) = (x, y)$. We take as intern parameter s an approximation to the arc-length of the curve, and such that $\varphi(0) = x_i$. Then we take as cells of the 1-D correlogram a set of

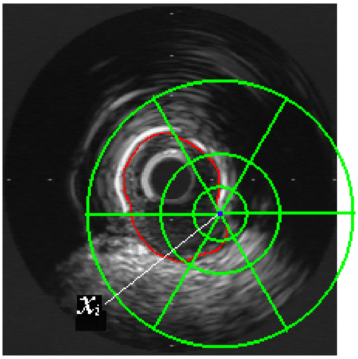


Fig. 1. Correlogram with 12 intervals of angles and 5 intervals of radius

intervals $I_u \subset [0,1) \forall u, \bigcup I_u = [0,1), I_u \bigcap I_v = \emptyset \leftrightarrow u \neq v$. This correlogram is not based on the local feature vectors directly but on a classification result of the characteristic points using these local feature vectors. For all the points that fall inside one cell of a correlogram w_i we count how many of these points belong to the same type of structure and this is the value associated to this cell.

The 1-D correlogram does not take into account the particular shape peculiarities of two structures to be aligned. Once we have put the structures close by using the 2-D correlogram, which take account of the 2-D distribution of structures, we finish an accurate matching of points from two analog structures by using the 1-D correlogram. This descriptor accounts mainly for the position of the point along the boundary of the structure it belongs to, saying intuitively if this point is at one extremum (and in which extremum it is) or if it is near the center of the structure. Thus extremum points from both structures are matched together, central points together, and so on.

2.2 Iterative Scheme and Final Algorithm

Once extracted a set of characteristic points, we apply a coarse alignment using as feature vectors only the 2-D correlograms, which accounts for the 2-D distribution of structures and put analog structures close enough.

After this coarse alignment, we perform a classification of the points. Let I_1 be the query image and I_2 be the complementary. For any pair $x_i \in I_1$, $y_j \in I_2$, the distance between them is computed as $d_{class} + d(w_i, w_j)$, where the distance $d(w_i, w_j)$ is the χ^2 distance (see [3]) between the 1-D correlograms of both points, and d_{class} is infinite if both points do not belong to the same type of structure (class), and 0 if they do. By adding d_{class} we are restricting the correspondences to match always points belonging to the same structure. Furthermore, we restrict the region where the matching point lies to be near the mapped characteristic point, $f(x_i)$, where f is the coarse transformation obtained in the first step. With these measures of distance between every couple of points we compute the final set of correspondences and based on them the final transformation. The computation of the transformations is done by adjusting a TPS to the set of correspondences obtained at each step.

For both steps we also use an iterative step that aims at doing cooperation between neighbor points in the computation of a reliable set of correspondences. The idea of cooperation is based on the fact that if one point x_i is matched with y_i, a neighbor point x_{i+1} of x_i should not be matched with a point y_j too far away from y_i. Let a couple of points $x_i \in I_1$ and $y_j \in I_2$, and let its distance in the feature space be d_{ij}. We have such a distance for every possible couple of points. After obtaining an initial set of correspondences based on these distances, we make a transformation by TPS. Let $f(x_i)$ be the mapping of x_i by the TPS. We recompute the distance between every couple of points $(x_i \in I_1, y_j \in I_2)$ as $d_{ij} + \alpha\|f(x_i) - y_j\|$. With these new distances we compute a new set of correspondences that produce a new transformation and this is iterated several steps. The TPS do not allow two neighbor points x_{i+1} of x_i to be mapped far away from each other. Thus, by adding the term $\alpha\|f(x_i) - y_j\|$ for the point x_i and $\alpha\|f(x_{i+1}) - y_j\|$ for the point x_{i+1} to the set of distances, we are biasing both points towards the same region of I_2. The parameter α indicates how much we rely on the last transformation. If the last transformation is very accurate, we take as α a high value, restricting the corresponding points $y_j \in I_2$ to be near the mapped points $f(x_i)$. Thus, as the process makes the transformations better, we must increase this parameter through the successive iterations, beginning with a small value. Also the regularization degree of the TPS becomes smaller as the set of correspondences is better, as a high regularization is only needed to approximate coarsely noisy correspondences. Thus we decrease the regularization through the successive iterations.

Both types of correlograms depend on the spatial distribution of the characteristic points. As the spatial distribution of the points become modified by the successive mappings, we must recompute these correlograms through successive iterations of the algorithm.

3 Results

We would like to show first the necessity of using contextual as well as local information, and the necessity of using as contextual information not only the 2-D correlograms but also 1-D correlograms. For an explanation of the parameters used see [1].

In fig. 2 we can see a first couple of IVUS images with two calcium plaques, one on the left and the other one on the right. The IVUS image of 2-(a) corresponds to the query image, and the IVUS image of 2-(b) to its complementary image. In fig. 2-(c) we show the anisotropic diffusion of the query image and superposed in red the boundary of the vessel from which we extract the characteristic points. In fig. 2-(d) we show the anisotropic diffusion of the complementary image and superposed in red the boundary of the vessel from which we extract the characteristic points. In fig. 6 we see the final set of correspondences.

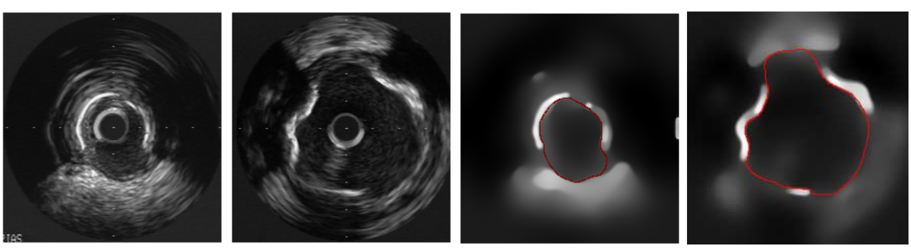
In fig. 3 we compare the result of the first coarse transformation using contextual information (2-D correlograms) and using only local information (our local feature vectors). We show transformation results on the anisotropic diffusion of the images because it is visually more clear. In 3-(a) we show the anisotropic diffusion of the query transformed by the coarse mapping. In 3-(b) we show the complementary image with the edges of the transformed query image superposed in red. We can see how both calcium plaques are mapped close, as well as the adventitia tissue. In 3-(c) and 3-(d) we show the same coarse transformation using only local feature vectors. We can see that one of the calcium plaques has not been mapped closed to any of the calcium plaques of the complementary image.

In fig. 4 we see how the set of correspondences using only a 2-D correlogram is more noisy than using a combination of 1-D correlogram and local feature vectors.

If fig. 5 we compare the result of the transformation obtained in the second step using 1-D correlograms and including the classification information by the distance d_{class} (see previous section), with a transformation obtained by the same algorithm but using 2-D correlograms and including also the classification information. As can be seen the transformation using 2-D correlograms is more inaccurate and produce an irregular warping with the noise seen in the images. The irregular warping is due to be using a slow regularization degree of the TPS based on a too noisy a set of correspondences for such a small degree of regularization. Finally we see results for another couple in fig. 7.

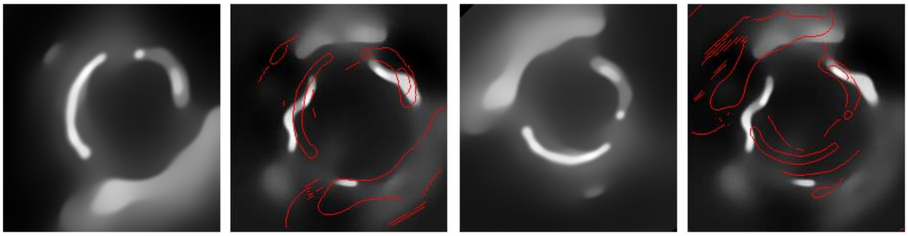
4 Conclusions and Future Work

We apply a registration technique to a novel type of medical images, IVUS images of highly elastic bodies and quite difficult to analyze. These types of images need a rich feature space, using not only local information around the point but also providing context or global information relative to this point. We extend the work of Belongie et al. [3] using a modification of their correlograms in order to cope with gray level images, and adding a second contextual information, shape



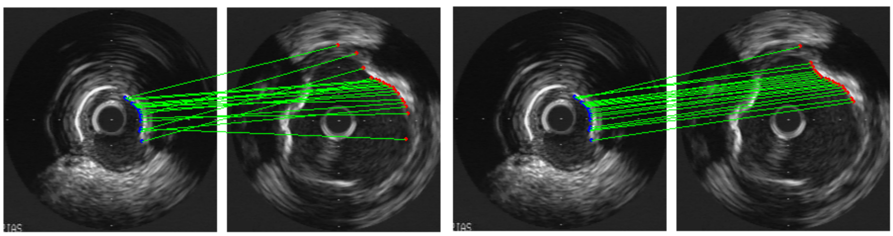
a b c d

Fig. 2. Query and its complementary IVUS (a)-(b). Their anisotropic diffusion results (c)-(d)



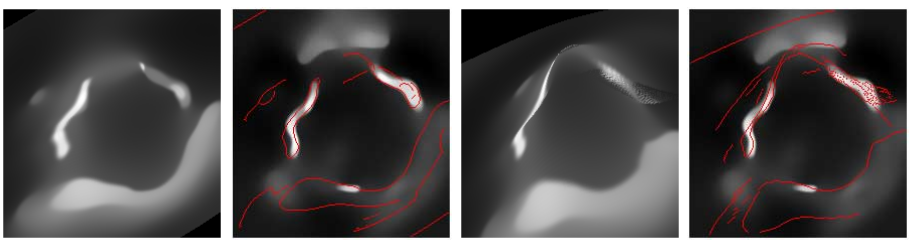
a b c d

Fig. 3. Coarse alignment (first step of the algorithm) using first contextual information (a)-(b), and then only local information (c)-(d)



a b

Fig. 4. Correspondences with only 2-D correlograms (a) and correspondences with 1-D correlograms and local feature vectors (b)



a b c d

Fig. 5. Second transformation using first in 1-D correlograms (a)-(b), and then 2-D correlograms (c)-(d)

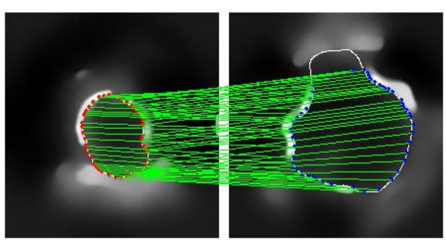
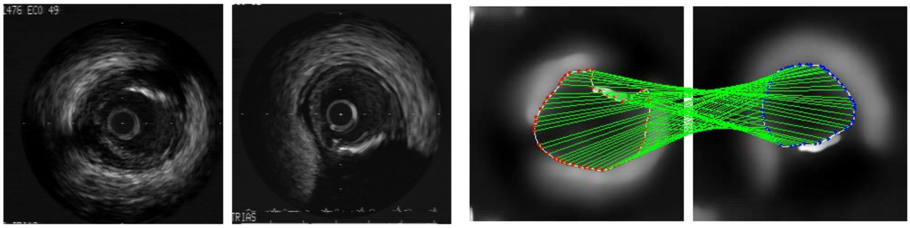


Fig. 6. Final set of correspondences of the first pair of images



a b c

Fig. 7. Query (a), complementary (b), and final set of correspondences on their anisotropic diffusions (c)

invariant 1-D correlograms. We incorporate this rich set of descriptors into a cooperative-iterative scheme similar to the one used by Rangarajan et al. [6], but without the deterministic annealing framework they use, as the combination of contextual and local information gives us enough information to seek for an accurate transformation in a more straightforward manner. The combination of rich descriptors, TPS, and the use of an iterative-cooperative scheme gives our algorithm robustness as well as accuracy, the result not depending on accurate classifications of all the points. Currently, we extend the IVUS registration including textural information.

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