An alternative technique for Imaging Registration in IVUS images

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Abstract - *Image registration technique has played a major role due to the use of data from different medical imaging modalities in which your main goal is to find anatomical and/or functional matches in two or more images. SIFT algorithm was used to extract a set of descriptors in IVUS images of two different pullbacks and to determine the number of common features between each pair of images. Similarity map was created to establish correspondences between two PCI images. Our method, with saltatory condition, was proved be a good choice in the experiments and in the real case, showing great stability in the establishment of correspondences and reducing overall time used for the diagnosis and/or monitor the development of coronary heart disease.*

Keywords: Image registration, SIFT, DTW, Similarity maps, IVUS.

1 Introduction

Image registration is a technique that uses the overlapping of two or more images of the same scene taken at different times or from different viewpoints and/or from different types of sensors to establish correspondences between pairs of images [1]. The correspondence establishment in images is a problem that has been addressed by different areas of knowledge, such as pattern recognition, image analysis, robotics and computer vision. Moreover, it has been widely used for object tracking [2], image registration [3], 3D reconstruction [4] and object recognition [5].

In medical image processing, the image registration technique has played a major role due to the use of data from different medical imaging modalities in which your main goal is to find anatomical and/or functional matches in two or more images [6]. In addition, the image registration has been employed in key processes such as: characterization of heart abnormalities during the cardiac cycle or the gradual atrophy of the brain with aging, anatomical structures modeling, tissue segmentation by medical atlas, correction artifacts caused by movements in fetal image [7].

Although currently there are software that allows the image registration, much of this task is made by the physician through visual analysis, which makes the process subjective and slow, since an intravascular ultrasound (IVUS) examination may contain up to 1000 images.

According to [8], the image registration algorithms are classified into three categories, depending on the information type used for the record: based on gray levels, based on domain transformations and based on features. The algorithms based on features are the most popular among the methods mentioned. Furthermore, it is more robust to intensity changes and geometric deformation [9].

In the image registration process, key regions and points of interest are often used as features descriptors due to the stability in the detection and description processes [10]. The detecting process of these features descriptors of a region is comprised three steps: i) detecting stable regions, ii) description of these regions and iii) establishing correspondences.

Through points of interest extracted from the images, circular (or elliptical) regions are determined in the vicinity of these points. Such regions may be corners of a flat object or regions of an image. The last one region type is more stable and easier to locate and describe. Color, structure and texture descriptors are widely used, however descriptors with edges guidance information are quite popular because they are more robust to scale, rotation and blurring [10].

Once the local features of an image have been acquired, the correspondence regions between two images are established by comparing the features of an image with the features of the other. This comparison is normally done by a measure of distance or deviation between the features, so that if the distance is less than certain threshold, the images show this features in common.

In a recent paper, we have proposed a method to reconstruct images from IVUS Equipment, independent of the parameters set by the physician during the examination of intravascular ultrasound [11]. The proposal method proved to be robust with regard to fidelity in the reconstruction of structures in comparison with DICOM image.

In this context, we use here the Scale Invariant Features Transform (SIFT) algorithm to extract a set of descriptors in IVUS images of two different pullbacks. Based on these descriptors, SIFT is used again to determine whether there is a relationship between the images descriptors of the first pullback with each one images of the second pullback, determining the number of common features between each pair of images. Using the descriptors of each image and the number of features in common between the pairs of images, a metric is developed to estimate the similarity between each image, thereby creating a similarity map.

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After making the similarity map, we use a dynamic programming technique, known as Dynamic Time Warping (DTW) to establish the correspondences between the images of the first pullback to the images of the second one, establishing a correspondence between images of different pullbacks.

The result of our process is an ordered pair (i, j) where the image i in the first pullback is associated with the image j at the second pullback. This result aims to help the physician in this arduous and time consuming task also eliminating the subjectivity in his analysis.

We first describe the SIFT algorithm we have used. Next, we present our idea of similarity map and the DTW technique for correspondences establishment. So, we applied this technique to three simulated tests to evaluate the performance of our methodology and obtain the better configuration of our technique. After this it was applied to a real study case with 4089 images in the first pullback and 3583 images in the second one to evaluate our methodology with real exams.

2 SIFT, Similarity map and DTW technique

2.1 SIFT– Scale Invariant Features Transform

The act of recognizing someone in a crowd requires the identification of a number of attributes able to distinguish one person from another. Usually, this process is done by us so quickly that we do not give account of the steps involved.

This process starts with the identification of attributes belonging to each individual as eye color, hair color, skin color, height, age, etc. Once identified these attributes, they are used to identify a particular person in the crowd. Just as people, images also have features that distinguish them from each other and recognize these features in two images, different in a first moment, allows us to conclude that it is the same image or different images.

The SIFT method is a technique that allows the descriptors extraction of local features invariant to scale, translation and rotation, and partially invariant to illumination changes. Furthermore, this method enables a robust object recognition, even partially occluded images.

For the descriptor extraction, the SIFT method transform an image into a vectors collection of local features, each one invariant to scale, translation and rotation. During the features vectors extraction, the SIFT algorithm performs a filtering approach divide into 4 stages:

1. scale space extrema detection, through a cascaded filter approach;
2. location of interest points;
3. orientation assignment based on local image gradients; and
4. obtaining the descriptors of interest points.

The end result of this process consists of a vector containing 128 components, called SIFT descriptor.

The complete and detailed description of the descriptor construction process of the SIFT method is found in the article of David Lowe [12].

2.2 Similarity map and Correspondence establishment

The Similarity Map for Image Registration (SMIR) consists in building a cost matrix from the features extracted by the SIFT method.

The similarity map permits the establishment of correspondences between images of the same patient examinations performed at different times (pre and postoperative periods, for example), in order to identify, in a semiautomatic way, the correlation between the images of the two exams.

Once obtained the similarity map, a dynamic search process is employed for the connections establishment between the exams images. With this, it is expected to reduce the time to identify the images of the same region, in separate exams, thereby assisting in monitoring the development of coronary heart disease.

Our process starts extracting the SIFT descriptors from each images of each one of the pullbacks.

After this, the SIFT algorithm is employed again in the comparison images pairs. The purpose of this step is to extract two pieces of information: the descriptors numbers in common that images have and the location of these descriptors.

With the descriptors, descriptors number and the location of descriptors, it is established an empirical metric defined by equation

$$S = 1 - \frac{P_1 A + P_2(1 - B)}{P_1 + P_2} \quad (1)$$

in order to evaluate the cost or the similarity between each pair (i, j) images, thereby bulding the cost matrix.

In equation (1), the term A is the number of common descriptors and the maximum number of descriptors ratio that the image pair (i, j) can have in common. The term B uses the Euclidean metric to measure the distance or deviation between the common descriptors for the pair of images (i, j). This value is weighted by the maximum number of common descriptors that images can presents. Both components, A and B in equation (1) have values between 0 and 1 because each SIFT descriptors for each image also represent values in that range.

The similarity equation is also weighted by weights P_1 and P_2 empirically obtained such that each element in the similarity matrix is also a value in the range 0 and 1. Thus, each element (i, j) in the matrix similarity or cost matrix represents the similarity between the image i from the first exam and image j extracted from the second exam, wherein, closer this value is to zero, greater is the images similarity.

In the classical algorithm of DTW, the optimal way for the correspondence between the elements in the accumulated cost matrix assumes the last element of the matrix, (n, m) position, is the first match. From it, the next matching elements are determined by the choice of the smallest value in the cost matrix among three directions: to above $(n-1, m)$, to the diagonal northwest $(n-1, m-1)$ and to the left $(n, m-1)$, respectively, 90° , 45° and 0°, a condition known as pitch . However this rigid approach to classic DTW does not include the medical image registration problem, since this type of examination there is no guarantee that the latest images on separate examinations are equal.

To overcome this adversity, we used a semi-automatic approach, in which the first match was provided by the user, and from it, the search algorithm for optimal path is in charge of finding the other matches.

In the traditional implementation for step condition, we proposed a variation on this condition allows to observe non-adjacent neighbors in order to obtain the optimum path. This implementation allows “jumps” in establishing correspondences when referencing the way the search in directions 23º $(n-1, m-2)$, 45º $(n-1, m-1)$ and 67º $(n-2, m-1)$. The results of both implementations are illustrated and discussed in the next section.

3 Results and discussions

3.1 Simulated Tests

To validate our methodology was developed 3 experiments. Each experiment is composed by two pullbacks. One pullback contains 600 real IVUS images from one patient and the other contains 500 real IVUS images exactly the same as the first.

In all of the experiments, one pullback remains unchanged (pullback with 500 images) while the other was modified to simulate blurring, rotation and mixing of images.

In the first experiment the images was blurred with a Gaussian noise and compared with the original images in the other pullback. The second the images was blurred and rotated 135º counterclockwise. And the third one, an image was interspersed once every two other, remaining with 900 images. Beyond this, each experiment was submitted to the classical implementation with semi-automatic approach, in which the first match was provided by the user and the optimal path was obtained using the traditional step condition and the saltatory condition.

The results are shown in the figures 3.1 to 3.6 and the black line represents the match obtained by our methodology and the gray line shows the ground truth.

The figures 3.1 to 3.4 shown the results of the experiments blurred and blurred and rotated. In this figures, the algorithm’s path and the ground truth appear as two lines overlap. These figures shown that the methodology proposed is robust in respect to blurring and rotation.

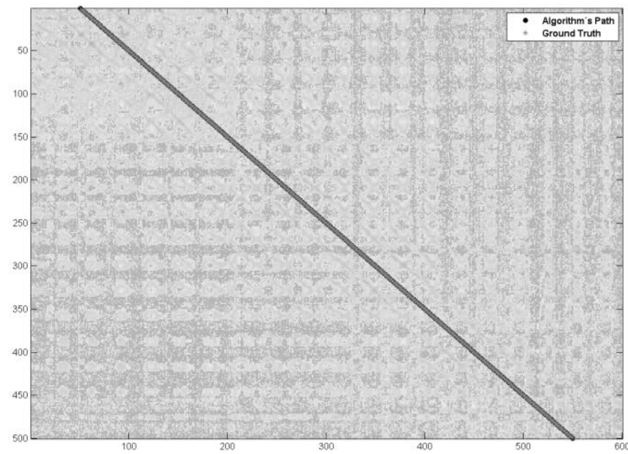

Figure 3.1: Similarity Map with classical path. Blurred images.

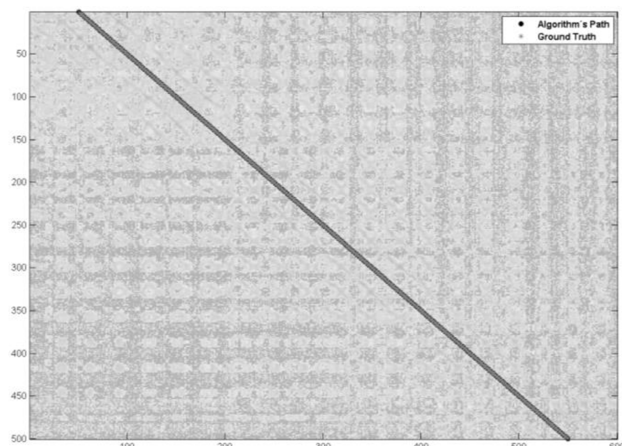

Figure 3.2: Similarity Map with saltatory condition. Blurred images.

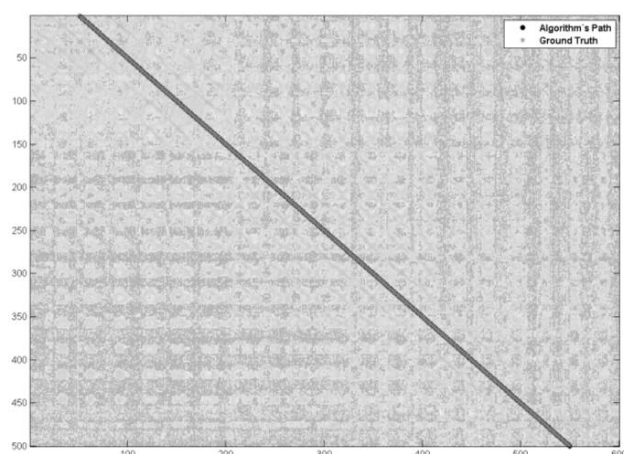

Figure 3.3: Similarity Map with classical path. Blurred and rotated images.

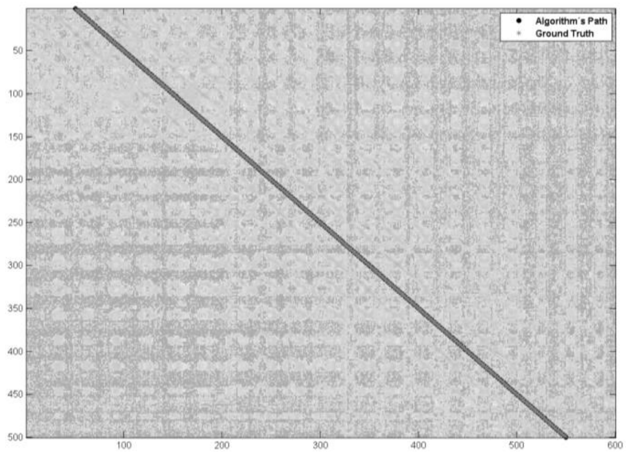

Figure 3.4: Similarity Map with saltatory condition. Blurred and rotated images.

The Figures 3.5 and 3.6 shown the results for the pullback with an image interspersed once every two other.

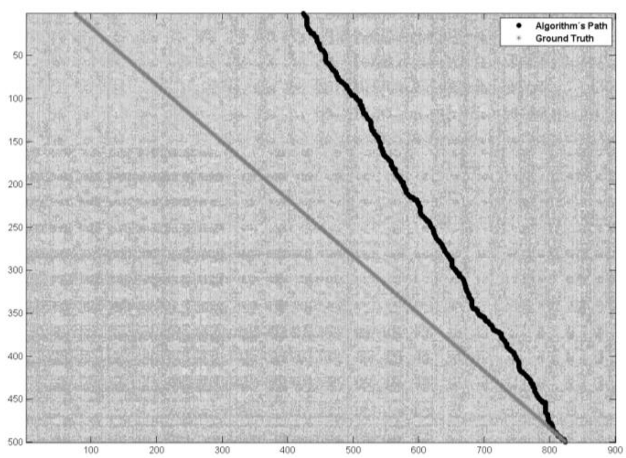

Figure 3.5: Similarity Map with classical path. Blurred, rotated and interspersed images.

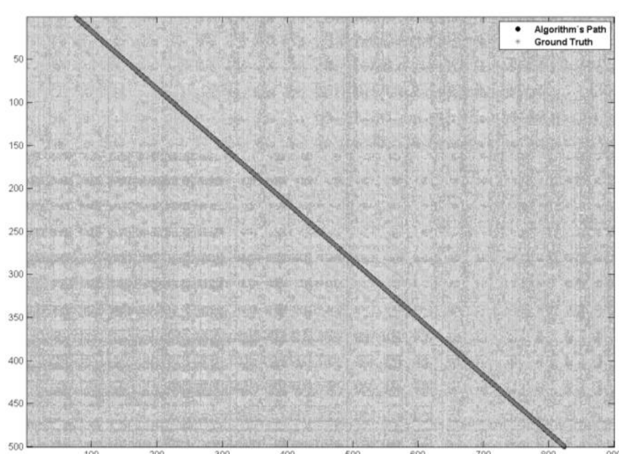

Figure 3.6: Similarity Map with saltatory condition. Blurred, rotated and interspersed images.

In the case of classical path, the dynamic search diverges in the beginning of the path. However the saltatory condition overcome this limitation and finds the exact path.

3.2 Case Study

After validation of our methodology in section 3.1, it has been applied to a case study, consisting of two pullbacks exams, pre and post-percutaneous coronary intervention, obtained in the Bellvitge University Hospital. This exams contains 4089 and 3583 images pre and post-operatory, respectively, and then anonymized to avoid the identification of the patient and used only for research purpose.

In this case study was used the Similarity Map with a saltatory condition that shown better results in the simulated tests.

The result of similarity map is shown in the Figure 3.7, where the white line is the ground truth performed by the physician and the black line is the match obtained by our algorithm.

As can be seen in the Figure 3.7, the ground truth and the match obtained by our algorithm are almost two lines overlapped, that shows a very good agreement between our methodology and the ground truth performed by the physician.

Beyond this, the Similarity Map of the case study is 48 times greater than Similarity Map used in the simulated tests. The results show that our methodology, to establish the correspondence between two pullbacks exams, is robust with respect to number of images in each exam.

4 Concluding remarks

In an IVUS examination the catheter is subject to rotation, blurring and artifacts from heart movement, as a discontinuity in images, like the third experiment.

Beyond this, due to the large amount of images in the examinations, the medical specialist does not perform reading and therefore the comparison of all the images from the first pulbacks with the images from the second one. The analysis pattern is to consider 1 every 6 images reconstructed by the equipment. The consequence of this is, when considering all images of pullback, that not always a corresponding image will have to ground truth.

This characteristic to establish the ground truth makes it difficult to estimate a metric to evaluate the difference between the correspondence determined by the algorithm and the ground truth set by the specialist. Thus, it is only possible to make a comprehensive analysis of the similarity maps by visual comparison of matches determined by the algorithm and the specialist.

In the classical implementation of the DTW, the optimal path obtained by our method has a greater proximity to the ground truth only in the cases without a discontinuity of the images (see Figures 3.1 to 3.4).

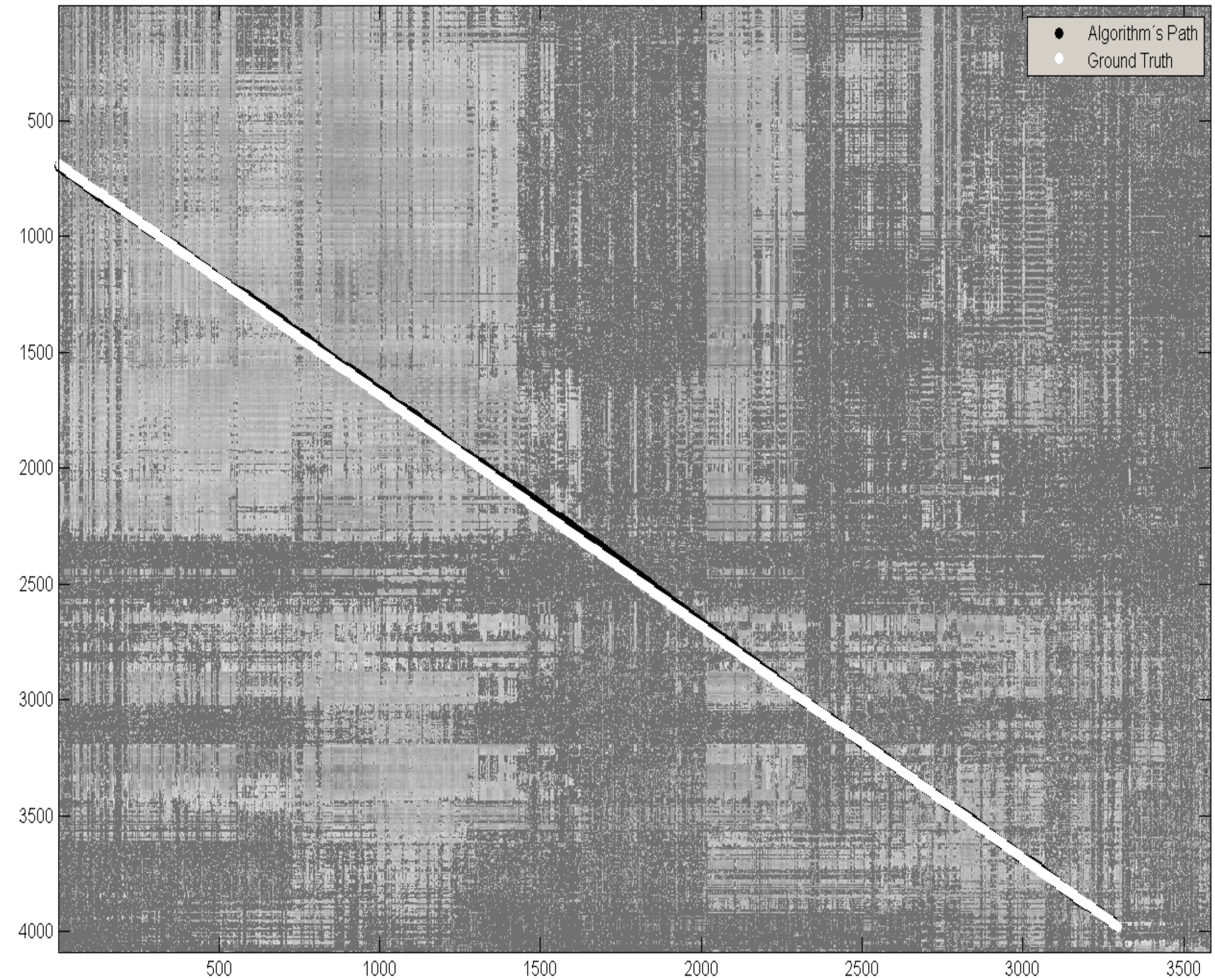

Figure 3.7: Similarity Map with saltatory condition. Case study.

In cases with a discontinuity, the saltatory condition was proved be a good choice, showing great stability in the establishment of correspondences, Figures 3.5 and 3.6.

This results show that the saltatory condition provides better results than classical path as can be seen in the comparison between figures 3.1 to 3.6.

Appling the saltatory condition to a case study, we obtained the Figure 3.7. This figure shows this condition provides a very good agreement with a real case.

Although, it is not possible to establish a metric for assessing the correspondence between the ground truth and the optimal path, the results obtained by saltatory implementation allow, from a single correspondence initially obtained, it is possible to reduce the range of images to be considered in establishing the real ground truth, reducing overall time used for the diagnosis and/or monitor the development of coronary heart disease.

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