SAR IMAGE REGISTRATION USING A NEW APPROACH BASED ON THE GENERALIZED HOUGH TRANSFORM

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Commission VII, WG VII/2

KEY WORDS: Remote Sensing, Vision Sciences, Radar, Analysis, Registration, Algorithms, Matching, Transformation.

ABSTRACT:

Radar Imaging using SAR systems provides specific information that is very useful in the frame of "Digital Earth" applications (i.e. flood supervision, forestry or agriculture watch,). The main interest of such active systems is their capability to gather relevant data whatever the weather and the illumination conditions may be (cloudy, misty, during the night,). In addition, these systems give a useful "distance map" thanks to the wave coherence. Most applications require a follow-up of the situation during weeks or months. Such a follow-up can only be performed if we are able to register images captured at different times. This registration problem is a very classical one and has been widely studied in Remote Sensing, but the proposed solutions are often dedicated to specific contexts (sensors, type of scenes, known relevant elements).Many algorithms have been proposed to register SAR images, and we give, in this paper, a global overview of these methods depending on the chosen approach. They may use filtering or not prior to registration, and they may use landmarks or not; but, in all cases, there will be to take into account the speckle that reduces the efficiency of classical methods for extracting features (e.g. landmarks,) to be paired in both images. During the last years (since 2000), a new set of methods, related to the Hough Transform concept, have been proposed: the algorithm we introduce in this communication can be considered as being in this class of approaches.

1. INTRODUCTION

Using several images related to a given area improves the efficiency of Remote Sensing applications because it enables to integrate into a single model various information on this area. This integration process is directly dependent on the registration one that permits to geometrically superimpose two or more images. In this communication, we focus on a particular case of image registration process for Remote Sensing when images are SAR (Synthetic Aperture Radar) ones captured from a Spatial Platform. Only non-corrected images are studied because the registration process is not required when images have been corrected and thus are geocoded.

When registering images at different times, we may be able to provide a follow up of area specific evolutions. For example, in the field of agriculture, it has been proved that there exits a linear correlation between the pixel values of SAR images and the height of cotton fields in the Ägrâ region (Srivastava et al., 2006), and thus we can use SAR images for controlling the agricultural process. We can also mention the use of SAR images for major risk management as, for example, in the case of flood (Stabel and Löffler, 2003) for disaster areas characterization.

Various physical processes can be used to provide Radar images (Rees 2001) depending on sensor features (wavelength, polarization, viewing angle). This variety of images is interesting because of all the information they carry but it increases the difficulty of the registration process: geometry and radiometry of such images strongly depend on the acquisition process; in addition, all these images are modified by a noise called speckle. Finally, extracting information from such images in order to provide a registration with a subpixel precision, as it is often required (Eastman et al., 2007), is a very hard task to be performed automatically.

This communication is structured as follows. Section 2 is a "State of the Art" on the registration process, especially related to Radar Imaging. In section 3, we introduce a new approach for registering SAR images that is based on the principle of the Hough Transform (Hough, 1962) when images have already been roughly registered. Results on the use of this approach are shown in section 4.

2. STATE OF THE ART

a) Registration

Registration is a process that provides a geometrical correspondence between two images captured from different locations, or at different times, or using different sensors, or through different modalities. Usually, registration algorithms are sequenced as follows (Zitová and Flusser, 2003):

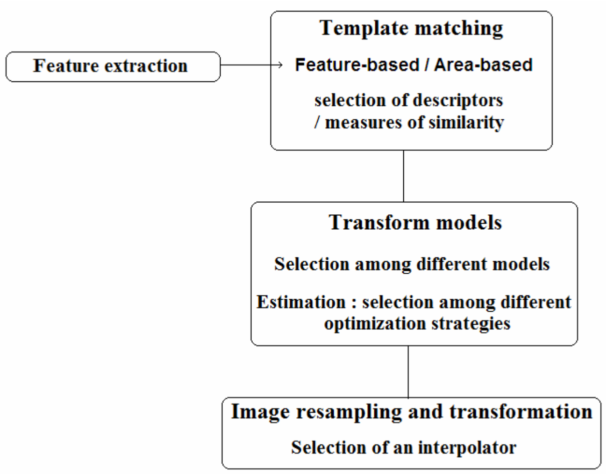

Figure 1. A classical sequence for registration algorithms

Registration algorithms rely on corresponding "control elements" to calculate the parameters of the geometrical transformation that sets the correspondence between all the points of both images. These "control elements" are either landmarks or locations characterized by their neighborhood. Landmarks can be points, contours, line intersections, or regions that have to be extracted from images before: approaches using such landmarks are called "feature-based" ones. Otherwise, when using pixel neighborhood to perform such a matching process, we talk about "area-based" approaches.

"Feature-based" methods try to identify corresponding landmarks in both images. In fact, this identification is not performed directly on landmarks but on shape descriptor values (descriptions) that represent them. We only consider those shape descriptors that remain invariant through any possible transformation from an image to another. They must also have two important properties that are uniqueness and stability: two different landmarks must be represented by two different descriptions (uniqueness property) but slight changes on a landmark (because of noise, for example) must not change its description (stability property). Finally, landmark descriptions of both images are compared through a similarity measure that helps in finding how to pair landmarks.

"Area-based" methods use a similarity measure to identify two areas that are considered as neighborhoods of corresponding pixels. Then, there is to define a criterion that depends on this similarity measure and whose optimization provides the registration transformation.

Whatever approach we decide to use, we need to make choices (about landmarks, similarity measure,) that take into account the way SAR images are built but also the noise that is a relevant feature of these images. Anyway, the transformation model has to be guided by three considerations that are the geometrical deformation during the acquisition process, the required precision of the registration, and the use of the expected result. Global deformations, local deformations, or both can characterize such transformations.

b) Specificity of Spaceborne platform Radar systems

2.2.1 Finding the position when acquisition is performed from a spatial platform: We need to have a rough approximation of the two images geographic parameters (i.e. location and orientation of the corresponding areas) in order to efficiently initialize the registration process. This information could be derived from sensor position parameters but the orbit and orientation of the platforms that convey these sensors can be modified by several external actions (Arbinger and D'Amico, 2004), as, for example:

- Earth gravity field irregularities, and sun/moon interactions
- Atmospheric friction in the case of satellites whose height is between 300 and 800km
- Photonic pressure

Orbit and orientation parameters are not captured in a continuous way but obtained through estimation from key positions, and this estimation requires quite a long time to be processed: it can take a day to several weeks depending on the precision (Wessel et al., 2007). In addition, even if we had all the metadata for computing such parameters, we would not have enough information on the sensor functioning to exploit efficiently these metadata (Eastman et al., 2007). Finally, we can say that only knowing these external parameters is not sufficient for solving the registration problem between two Radar images. From now, we will suppose that the two images globally represent the same area but are not precisely registered.

2.2.2 Geometrical deformations: A main drawback of SAR systems is to provide image geometrical deformations (Lillesand et at, 2004) that result from the way of sorting points by using their distance to the antenna. The ground position of a point can be slightly (or more) wrong because it has been "seen" as shifted toward the antenna. This kind of error is more significant when the ground height is not uniform: depending on height variations, the target density (a point on the ground is a target for the Radar) can increase and generate artificially clear areas in the image ("highlighting" effect), or it can decrease and create abnormally dark areas in the image ("lowlighting" effect). When height variations are very large, even the target sorting may be wrong ("layover" effect) and some of the targets can disappear because they are masked ("shadowing" effect).

Other deformations have to be taken into account (Richards, 2006): they are related to the earth curvature and to the width of the viewing angle. In such cases, the scanned areas that are far in the nadir direction are widely opened: this situation results in an important non-homogeneity in the pixel distribution, in particular along image boundaries.

2.2.3 Radar image radiometry: Interpreting images from Radar systems is very difficult because of the complexity of the processes involved in their generation (Rees, 2001). Signal intensity for each point – or target – is encoded as a grey level in the resulting image and depends on the way the Radar wave interact with the target. This interaction relies on both sensor features and target features. Sensor features are its wavelength, its polarization and its viewing angle. Target features are its roughness, its dielectric characteristic (it has a high value for metallic elements, and it is correlated to its moisture content), its shape and orientation.

All these parameters mutually interact and thus, it is very difficult to exactly know which are their individual contributions to the returning signal. For example, the target roughness parameter depends on the target itself but also on the incident angle and on the wavelength that has been used for illuminating the target. Several mechanisms related to the reflection and backscattering processes are involved in the image generation: specular reflection, diffusion, corner reflection, and volume diffusion.

Finally, the information variability from an image to another is a very tricky problem for comparing their content: same objects can produce very different signals depending on capture parameters and external conditions. For example, different wavelengths or polarizations provide different results but it is also the case when using the same Radar parameters and when external conditions are not the same (after raining, the dielectric constant of the ground changes and produces a different response).

Another main difficulty with Radar image interpretation concerns the speckle, which is a noise that gives the images a grainy appearance (Rees, 2001). The speckle is a direct consequence of the wave coherence: the interaction with the target may shift the wave phase because of the target height variations and/or physical properties. The result of this interaction is a multiplicative noise. This effect has been modeled through a statistical approach (Chitroub et al., 2002) although it is deterministic.

Many algorithms have been proposed to reduce this noise, especially through the creation of filters (Touzi, 2002) that are supposed to widely eliminate the speckle effect while preserving most of the information being in the images (radiometry, contours, texture,) and not generating any artifact.

Specific algorithms have to be designed for extracting primitives (or landmarks) from images because of speckle. For example, when using classical tools such as gradient or Laplacian filters, we obtain a variable rate of false alarms (it increases in areas where the signal is very intense). Thus, the main objective when designing a new algorithm for extracting primitives from Radar images is to create a filter that produces a constant rate of false alarms; these filters are called CFAR detectors, CFAR meaning "Constant False Alarm Rate" (Touzi et al., 1988).

2.2.4 Conclusion on Spaceborne platform Radar images: Automatic registration of Spaceborne platform Radar images is still a challenge because of some key difficulties:

- We do not have any accurate information on the image relative positions
- These images went through various geometrical deformations
- Radiometry may be modified by speckle but also by several physical phenomena related to the backscattered signal.

Concerning this last point (i.e. radiometry modifications):

- Speckle: this noise changes the value of the similarity measure and thus, it reduces the efficiency of landmark extraction
- Physical phenomena: a main question when the two images come from very different acquisition conditions is to determine if there is enough common information to provide an automatic registration.

c) Spaceborne platform Radar image registration

As we discussed in the previous section, registering such Radar images is still a challenge and thus, many research groups focus their work on this topic (Wessel et al., 2007). In this section, we mainly discuss on the matching process itself and on the way the Radar image generation has an effect on this process.

We remind that we can use either an "area-based" approach or a "feature-based" approach, the first one using statistical properties of the pixel neighborhood, and the second one using primitives extracted from images as landmarks to be paired. Now, let us see how the Radar imaging specificity makes difficult such processes.

Neighborhood statistical properties are characteristic of what is called texture, and thus, "area-based" approaches can be seen as texture pairing methods. In fact, two textures are superimposed in Radar images: the texture that is characteristic of the area (we call it the "scene" texture) and the speckle texture. The main difficulty is then to find algorithms that describe correlations between the "scene" textures of the two images without having any interaction with the speckle texture although these two textures ("scene" and speckle) are mixed in the image.

Primitive extraction from SAR images is also dependent on speckle, but in a different way than for "area-based" approaches. As we have seen before, the SNR (Signal to Noise Ratio) is not very high and thus there are a lot of false alarms (with a variable rate): these false alarms result in small variations of the primitives used as landmarks, which produces a slight instability or a loss of accuracy.

A question arising when registering two SAR images acquired with different conditions during data acquisition or with different sensor features, is the nature of the information they provide. As already mentioned before, information strongly depends on these factors; two SAR images gather a common part of information, while at the same time they carry another part of unique information due to specific internal and/or external parameters of acquisition. Matching step in a registration algorithm is thus a difficult problem in SAR imagery, as methods should be able to rely on common information only. Scene texture is dependent on acquisition parameters in a very sensitive way, so that area-based methods may be particularly affected. Feature-based are concerned too: landmarks may simply not occur simultaneously in two SAR images for example

Finally, local geometrical distortions provide an additional level of difficulty in the registration problem. These distortions result in data distribution variations, which has a disturbing effect when the viewing geometry on a given area is very different from one image to the other one.

As a conclusion, we can say that classical registration approaches, whatever they are (area or feature based) have to face to very tricky problems in SAR imaging because of noise, distortion and complementary information.

In the next section, we introduce an alternative solution to the SAR image registration problem that uses the Hough Transform. Although it is not classically used for solving such kind of problems, the Hough Transform brings a help to automatically discriminate the common information from the complementary one, and thus to have a common support for registering SAR images that have been acquired using different parameters.

2.4 The Hough Transform

P. Hough introduced his transformation in the early 60s (in 1959) and then, as a US patent, in 1962 (Hough, 1962); in 1972, R. Duda and P. Hart (Duda and Hart, 1972) showed this transformation being efficient for the detection of lines and curves in pictures; then, the Hough Transform has been generalized to provide the detection of parameterized models such as transformations, and not only geometrical primitives.

For a long time, the Hough Transform has only been used in Remote Sensing for detecting patterns as specific landmarks (such as lines or circles) in the images; since a few years, it has been used to characterize the parameters of the geometrical transformation that provides the correspondence between two images.

To some extent, we can say that using such a kind of approaches replaces the problem of finding a few reliable landmarks (and reliable pairings) by finding many possible landmarks in both images and studying the statistical distribution of their possible pairings. The robustness to noise of this approach makes it interesting for SAR image registration because, as we discussed before, such images are not always easy to interpret and the speckle makes the landmark detection difficult.

Many questions have to be answered to develop a Hough Transform approach, one of them being the characterization of the representation space (the Hough Space) that provides the expression of the model items (in our case, all the transformations) and must be as homogeneous as possible. Another question is the definition of the elements that will be used to produce the model items.

Although the idea of using the Hough Transform for solving such a registration problem has been published for the first time in 1982 (Stockman et al., 1982), it is only at the beginning of the 2000's it has really been studied and developed.

Most authors provide the registration by pairing a set of points on the base of a rigid transformation that is a similarity. But in this case, the main problem is the algorithmic complexity because of the number of points to be paired. Filtering the data sets through geometrical invariants enables to reduce this complexity (Seedhamed and Martucci, 2002).

The complexity is not the only problem with the Hough Transform: the parameter representation – i.e. the Hough Space characterization (dimension, homogeneity,) – is even the most important question to be answered in such a case. Especially, any additional dimension of the Hough Space increases a lot the problem complexity.

The "Modified Iterative Hough Transform" (MIHT) has been proposed as a solution to this problem (Habib and Alruzouk, 2004): all the parameters are evaluated sequentially, which transforms the problem of finding a point in a d-dimension space (this point being the transformation) into finding sequentially d parameters, each of them in a one-dimension space (these parameters being those of the transformation). This is only valid if all the transformation parameters are independent, which is "almost the case" when images are "almost registered". Such an initial condition can be obtained by using an approximate registration on degraded versions of the images (Li and Zhang, 2005).

In fact, when using the "Modified Iterative Hough Transform", we do not evaluate all the parameters independently one from another but we converge toward the solution iteratively in each dimension as we could do for an optimization problem. Interesting research works have been published a few years before (Shekhar et al., 1999) to propose a different solution to this problem: they formalize the "parameter observability" and "parameter separability" concepts by using a method they call "feature consensus". This method builds a set of one-dimensional parameter spaces that are not correlated one from another. It has been used successfully, with a few improvements, for a "Radar Image" to "Map" registration problem using an affine transformation (Borghys et al., 2001).

The "Hough-like" approaches seems to be the most efficient ones because they provide an automatic selection among the information to discriminate on one side the common information, that comes out in the Hough Space, and, on the other side, the complementary information and the noise. But, as we discussed in the last paragraphs, there still are some problems to solve for using them. In the next section, we propose new solutions for that in the frame of Radar imaging.

3. IMPROVEMENTS IN RADAR IMAGE REGISTRATION USING THE HOUGH TRANSFORM

In this section, we introduce our contribution to Radar image registration using the Hough Transform. We precisely describe our global methodology and our choices about preprocessing, deformation models and primitives. Our strategy is based on two hypotheses that are practically always verified. The first one is that we can extract arcs of curves in both images, part of them corresponding to the same scene elements. The second hypothesis is that image positions are not so far one from the other: in other words, images are coarsely registered, which is often the case, and we want to obtain a very fine registration

3.1 Preprocessing: filtering and landmark extraction

Landmark extraction requires algorithms dedicated to SAR images analysis. We consider the Touzi edge detector as being the most suitable one because of the constant rate of false alarms it generates. It provides a binary image that contains arcs of curves, i.e. one-dimensional structures. These structures enable the production of primitives that contain local variational properties, as we will discuss in 3.3.

Most approaches use a filtering process before extracting landmarks, in order to facilitate this extraction process. We do not provide such a filtering because the Hough Transform automatically eliminates all the inconsistent schemes.

3.2 Choosing a deformation model

Image registration requires a deformation model. The second hypothesis (i.e. images are already coarsely registered) enables us to reduce the deformation (from one image to the other) to a 2D rigid transformation, i.e. a combination of a translation and a rotation, as it has been mentioned in (De Bonet et al, 1998).

3.3 Primitive type and Hough Space characterization

The simplest type of primitive is the point. But pairing points without any additional constraint provides too many elements in the Hough Space: the noise generated in such a way makes the analysis of this space very difficult. Thus, for a better pairing, it should be interesting that primitives not only carry location information. We propose to enrich the primitive type by adding an orientation attribute. This choice is the result of a previous remark that is related to the one-dimensional feature of the extracted structures: a tangent orientation can be assigned to each point of such structures. From now, we will consider that a primitive is a triplet defined as a point location (x and y) and a tangent orientation ( ).

3.4 Hough Space Characterization

The Hough Space is a 3D space whose dimensions are a, b and – (a,b) being the translation and being the rotation angle (rotation center being the image center). We will not focus a lot on the Hough Space representation because the data associated with each dimension is represented homogeneously, and thus we only have to use a classical scheme for representing this data (i.e. cells in which we capitalize votes,).

An item (a,b,) of the Hough Space is calculated as the transformation that makes a primitive (x1,y1, 1) of Image1 matching with a primitive (x2,y2, 2) of Image2. It provides a classical non-linear system of three equations with three unknown variables (a, b and), whose solution is classical.

Once we obtain all these items – i.e. (ai,bi, i) points in the Hough Space – we have to classified them in order to find the densest area that is characteristic from the expected transformation. This process is also very classical because of the Hough Space homogeneity.

The only difficulty, and it is an important one, is to find primitives in both images and to pair them efficiently.

3.5 Primitive detection and matching

In this section, we introduce our contribution in finding and pairing primitives, and we describe precisely the algorithm we have designed for that. Then, in the next section, we show some results we obtained using this algorithm.

Let us consider two images Im1 and Im2 to be registered.

We first compute two corresponding binary images ImB1 and ImB2 by applying a Touzi filter and morphological transformations as opening and thinning. Thus, ImB1 and ImB2 only (or mainly) contain one-dimensional structures (i.e. based on arcs of curve). Most of these arcs of curve appear in both images (ImB1 and ImB2) but some of them only appear in one image (ImB1 or ImB2) and not in the other one.

We assign an orientation to each point of ImB1 (from now, when writing “a point” – in a binary image – we mean a point whose value is 1). This orientation is obtained by using a simple but efficient algorithm: we define a (small) neighborhood and we consider all the possible “discrete thick lines” centered on this point; then, we keep the direction of such a line that covers most points of ImB1 within this point neighborhood (this number of points is the “score” s that characterizes the relevance of the selected orientation). Finally, we represent each point of ImB1 by four values ((x,y,),s) and we provide a selection on this set of points in order to obtain the set S1 of primitives P1,i of ImB1 (and we proceed in the same way for ImB2). Let us see now how we provide this selection.

We only keep the points whose orientation is relevant enough and we impose a constraint that is formulated as follows: “the distance between two primitives must not be lower than a given value dmin”. For ImB1 (and then for ImB2), our algorithm consists in:

1. eliminating all the points whose score is below a given threshold
2. sorting all the remaining points by decreasing values of s
3. selecting the first point of the list (i.e. whose score is maximum) and then, sequentially, doing the same for all the other points under the condition they are not at a distance below dmin of any other point selected previously

We obtain two sets of primitives S1 = {(xi,yi, i), i ∈1..n1} (in ImB1) and S2 = {(xj,yj, j), j ∈1..n2} (in ImB2) to be paired.

A primitive P1,i of S1 is paired with a primitive P2,j of S2 when they satisfy a proximity constraint that is “the distance between points is below dmax” and “the difference of their orientations is below max”). Then, we can compute Tij – represented by (aij,bij, ij) – that transforms P2,j into P1,i. The transformation Tij is a “point” (or item) of the Hough Space.

The key point of this algorithm is that we replace a set of possible landmarks (the one-dimensional structures) whose size, distribution, complexity and reliability is variable, by a larger set of primitives that all have the same complexity and reliability, and that are more uniformly distributed.

4. RESULTS

We experienced our approach on actual data in order to illustrate its feasibility. We used the Tsunami Dataset Package provided by ESA, and we chose two pre-tsunami images from ENVISAT/ASAR (*).

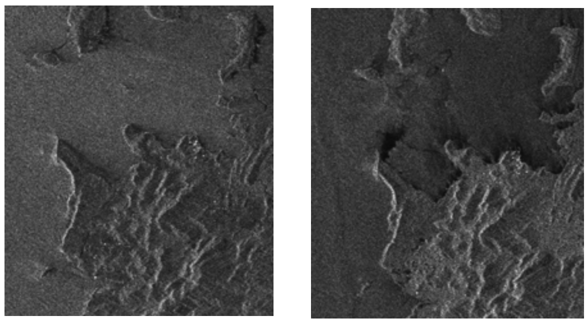

Figure 2. ENVISAT/ASAR images.

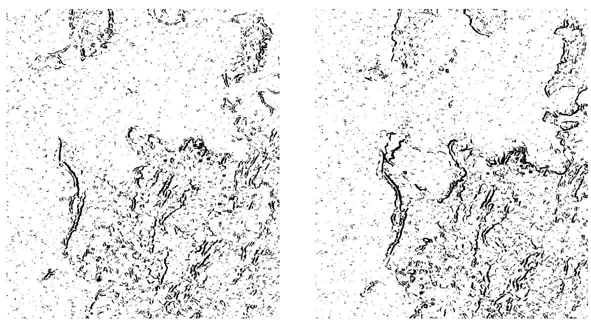

Figure 3. Binary images obtained by using the Touzi algorithm.

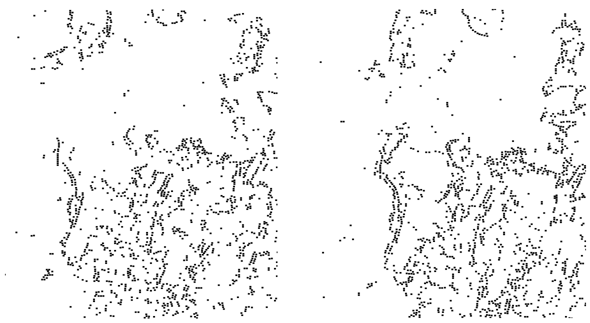

Figure 4. Selected primitives (represented as dots).

The Touzi edge detector provides the binary images shown in figure 3. We then select primitives using the proposed algorithm with the following parameter values: n=15 (neighborhood size), st=0.5 (score threshold) and dmin=10 (minimal distance between two primitives). The number of primitives is approximately 2.5% of the initial number of points in binary images (figure 4).

An interesting property of the Hough Transform for characterizing the transformation is that it focuses automatically on the common information (i.e. primitives that are similar in both images, as shown in figure 5) and it eliminates all information that is specific to only one of the images: figure 6 shows primitives that belongs to one image and not to the other one.

Finally, we also checked the accuracy of the method we propose. We did it by registering manually these two images (using an interactive landmark selection procedure), which

shows, on this example, that our automatic registration process has a subpixel precision.

Figure 5. Landmarks that belong to both images.

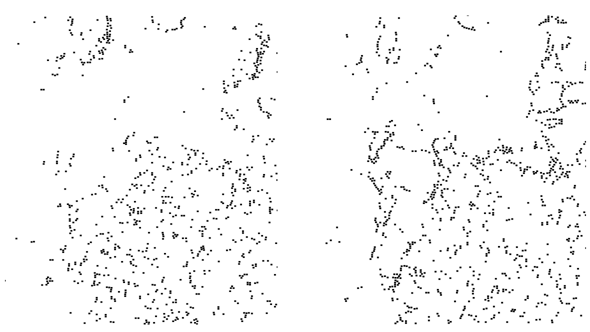

Figure 6. Landmarks that belong to only one image.

5. CONCLUSION

In this communication, we have introduced a new algorithm that registers accurately SAR images when these images are already coarsely registered. This algorithm takes advantage of the Hough Transform properties to find the rigid transformation that provides the best matching between the images. This algorithm can be improved, especially through the research of more suitable sets of primitives, or eventually by using other primitives. It also should be interesting to estimate the accuracy of the process as depending from the number of relevant features in the images, or from their relative initial position.

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