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Sonar image registration based on conflict from the theory of belief functions

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Abstract – *This paper presents an application for classified image registration. The idea was developed on a previous paper, and this work presents the results on real data. For seabed characterization, we need to fuse the multiview of sonar images to increase performances. However, before fusion, we have to proceed to an image registration. The proposed approach is based on the use of the conflict due to the combination as a similarity measure in the classified images registration. This allows a good modelization of imperfections and has been employed with success for classifier fusion in image processing.*

Keywords: Sonar, Image registration, Belief Functions, Conflict.

1 Introduction

When talking about underwater imaging, we are always concerned by data acquired by acoustic sensors. Typically, sonars provide remote sensing at ranges far from those offered by optical means, *e.g.* video or laser, and at rates of up to several square kilometers a day. The produced mass of data have led to the development of automatic sonar image registration process.

The difficulty of sonar imaging is that these images are highly noisy. The movement of the sonar can alter the geometry of objects laying on seabed. Moreover, the signal can follow multiple paths, having multiple reflexions on the bottom or on other surfaces, speckle or fauna and flora. These multiple paths lead to interferences on the resultant intensity and results sonar images are noisy, uncertain, and imprecise.

An aspect of sonar image processing is the characterization of seabed. Due to the nature of the images, such characterization is difficult, even for human experts, *e.g.* they might recognize the same sediment, but will not agree on the edges of such an area. Moreover, human experts must deal with a huge amount of data. Fusion techniques can give a response to this problem by merging data from multiple sonars [14]. This characterization gives many landmarks useful for underwater navigation. When an AUV (Autonomous Underwater Vehicle) navigates, it can determine its own position through instruments of navigation (like an inertial measurement unit) which have drifts or inaccuracies. The use of landmarks produced by seabed characterization can help the AUV to calculate its position.

The production of seabed maps is based on registration processes applied to sonar images. Once the transformation needed to align two sonar images is found, the two images are fused to produce a larger one. This image then can be registered with all the sonar images to produce a map. This map can be characterized, and used by an AUV. Sonar image registration process can be improved when using classified images [8, 9], and the final step of the registration process, the generation of the mosaic, can be handled as a fusion problem.

We propose the use of belief functions for fusion and image registration. The belief functions allow us to handle the uncertainty and imprecision of sonar images. With the pixels of the sonar images represented with the theory of belief functions, we can use a dissimilarity criterion based on the conflict generated by combination rule [16]. As this combination is done for the computation of the criterion, it can immediately be used for the fusion given the mosaic.

This paper is organized as follow. First, we present the basic image registration process. Then, we briefly present the theory of belief functions and the way we use it. In section 4 we present our registration process for classified sonar images. Finally, results on some real data will be discussed.

2 Basic Image Registration Process

The aim of an image registration process is to overlay two or more images of the same scene, taken from different sensors, points of view, and/or times. An image registration process must determine the best geometric transformation t from a transform model T to align the images. The figure 2 shows the problem for two images I_1 and I_2. Each image has its own orientation and size, and I_1 is the reference image. We want to register I_2 on I_1. The issue is symmet-

*We want to thanks Hicham for is work and support on the two classifiers used is this paper.

rical so we can *a priori* switch the reference image. The classification of image registration process is a well known discussion [24, 26], and we separate them between two families:

- Geometric methods use features extracted from the images (points, edges, shapes) and try to match them to determine the best transformation.
- Iconic methods use all pixels from the images, and directly compare their intensity, or a function of these intensities.

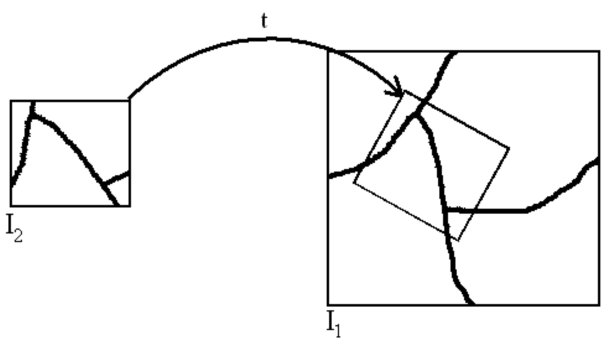

Figure 1: Image registration: image I_1 geometrically aligned on image I_2

Through natural and uncertain background, finding simple geometric shapes we can compare from one image to the other is quite rare. Moreover, the images can be strongly deformed depending on the point of view. Recent works on sonar image registration [9, 2] were based on iconic criterion.

2.1 Transform Model

The purpose of image registration is to determine the best transformation regarding a similarity criterion. This transformation belong to a set of transformations [11]:

- Rigid: Only translations and rotations;
- Affine: Preserve parallelism;
- Projective: Add projections;
- Curved: Any other transformations.

The transform model can be applied to all the images (global model) or only to a part (local model), and the figure 2.1 presents all of these transformations. In order to simplify our problem we restrain our transform model T to the global rigid transform model.

2.2 Similarity Measures for iconic registration

Iconic methods are based on a similarity measure s. This measure shows the link between the intensities of the two

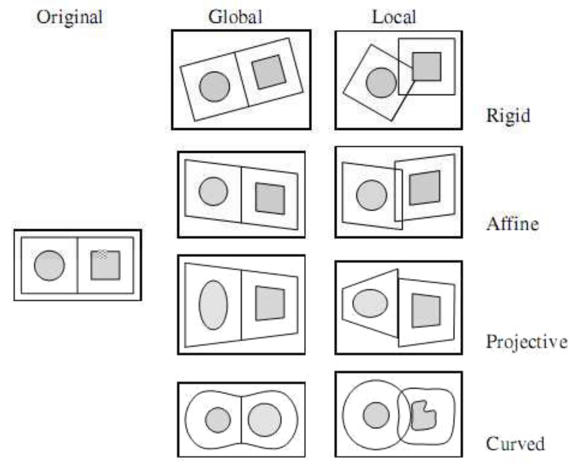

Figure 2: Example of 2D Transformations [11]

images $t(I_2)$, I_1. Depending on the nature of this link, different measures can be used:
We can firstly consider that if the two images represent the same thing (or environment), their intensity on each point will be equals. We can use correlation like measure to evaluate this equality, *e.g.* cross-correlation, sum of absolute differences, standard deviation of intensity, etc. These measures give fast process but fails on aberrant values.
In fact, the intensities depend on the sensors, and they might present different intensities for the same object. We must scale the intensity through an affine relation ($j = \alpha i + \beta$). The affine correlation [6] can handle this relation.
Well designed for monomodal registration problems, the affine relation fails on multimodal problems. The relations between intensities must be extended to a functional relation $j = f(i)$, modeling the idea that any intensity from an image can be associated with an unique intensity from the other image. We found in this category of measures the Woods Criterion [25] and the correlation ration [15].
Considering the images to register as random variables, it is possible to measure their dependencies with tools like mutual information.

2.3 Decision over similarity measures

The registration process determines the transformation t from the set T of considered transformations to be applied to I_2 giving the weakest dissimilarity d (or the strongest similarity s). The best transformation t_d is:

$$t_d = \underset{t \in T}{\operatorname{argmin}}\, d(I_1, t(I_2)) \tag{1}$$

or

$$t_d = \underset{t \in T}{\operatorname{argmax}}\, s(I_1, t(I_2)) \tag{2}$$

3 Theory of belief functions

The theory of belief functions is based on the works of A. Dempster [3] and G. Shafer [17] under the name of *theory of evidence* or *Dempster-Shaffer theory*. They have found their place in image processing in order to take account of uncertainty and imprecision [1]. The theory of belief functions is used in image classification [23], or in classifier fusion [13]. In this last application, we considerer images are already registered [5]. However image registration must also be conducted automatically before fusion. It can be helpful to register the image, and then, fuse them with the same formalism for both processes.

3.1 Basic belief assignment

The theory of belief function is based on a frame of discernment $\Theta = \{C_1, \ldots, C_n\}$ of all the exclusive classes describing the data. The *basic belief assignment* m is defined by mapping the power set 2^Θ (the set of all subsets of Θ) onto $[0, 1]$ with the constraint:

$$\sum_{A \in 2^\Theta} m(A) = 1. \tag{3}$$

The basic belief assignment allows an expert (or a binary classifier) to affect a part of his decision to one or more classes, and/or on a set of classes.
When defining the basic belief assignments, Dempster and Shaffer gave the constraint:

$$m(\emptyset) = 0, \tag{4}$$

considering the set Θ being exhaustive [17]. This assumption is called the closed world. As this assumption can be thought natural, it is not necessary and we can accept:

$$m(\emptyset) \geq 0, \tag{5}$$

and the world is open [20].
We can define a basic belief assignment for each expert (or classifier) and then combine them. This operation allows us to preserve a maximum of information and to take a decision on an unique basic belief assignment.

3.2 Combination rule

Many combination rules have been proposed [21], and the conjunctive rule of P Smets [19] allows us to stay in open world. Defined for two experts (or classifiers) S_1 and S_2 giving two basic belief assignments m_1 and m_2 for each $A \in 2^\Theta$:

$$m_{\mathrm{Conj}}(A) = \sum_{B \cap C = A} m_1(B) m_2(C). \tag{6}$$

This rule is associative and commutative but not idempotent. The assigned belief to the empty set $\emptyset$ is usually considered as conflict. Despite part of this conflict comes from the non-indempotence, it is generally considered as a lack of sufficiency in the frame of discernment, or the sensor unreliability, or because the data does not represent the same scene.

3.3 Decision into theory of belief functions

The last step of a classifier fusion problem is the decision of the class C_k over the image or the part of the image observed. The decision of the class $C \in \Theta$ is given by:

$$C = \underset{X \in \Theta}{\operatorname{argmax}}(f(X))$$

where f can be a basic belief assignment. The theory of belief functions provides many other belief functions than the basic belief assignment. We can use plausibility function or credibility function, but the decisions taken on maximum of plausibility are often too optimistic, on the contrary decisions on maximum of credibility that are too pessimistic. The most used compromise is the maximum of pignistic probability [18]. The pignistic probability is define for all $X \in \Theta$ with $X \neq \emptyset$ by:

$$betP(X) = \sum_{Y \in 2^\Theta, Y \neq \emptyset} \frac{|X \cap Y|}{|Y|} \frac{m(Y)}{1 - m(\emptyset)} \tag{7}$$

where $|X|$ is the cardinal of X.

4 Iconic image registration process applied to classified sonar images

We present here the proposed registration process. It is decomposed in two steps. Let us have two images I_1 the reference image and I_2 the one we want to register. As a preparation, we classify the two images. Then we apply an image registration process on these two classified images.

4.1 Classification of sonar images

In order to prepare the image registration, we need to classify the images. When characterization of seabed is needed, sonar image classifications are based on textures analysis [8, 13]. The aim is to affect each pixel $x_{i,j}$ of each image I_i to a class C_k of seabed sediment like sand, rock, ripples or silt. Each image I_i is classified by a classifier S_i which can be identical for the two images.

4.2 Image registration of classified sonar images

Our image registration process is in fact two image registration processes in one. Facing the computation cost of image registration processes, it has been shown that a coarse registration before a precise registration can handle these costs [8, 22], and reduce them. Moreover the images we are using might be huge (500×1000 pixels) with large uniform areas. We extract a test image from I_2 which presents several areas, *i.e.* the less uniform as possible.
The first registration process applied is a coarse registration process. We scan reference image I_1 with a step of approximatively 40 pixels. This will generate a thousand candidates to match with the test image. Therefore we register each of these candidates with the test image. The transform model is only the set of rotations from 0 to 360 degrees by steps of 10 degrees. The candidate that matches the test image

through the similarity criterion is kept for the second step of our registration process.
The second step is a fine registration process. We extract a new candidate taking account an area larger than the candidate from the first step. Then we apply a basic registration process with a rigid model transform T.

4.3 Conflict as dissimilarity measure

In a precedent paper [16] we have presented a dissimilarity measure based on the conflict generated by the combination rule from the theory of belief function. In the theory of belief functions the generated conflict by the combination rule must be reduced in order to increase the results [10]. However we use here this conflict as an information.
Let's define $\Theta = \{C_1, \dots, C_n\}$ the set of classes found by the classifiers S_1 and S_2. It is the frame of discernment of our images. We know each pixel x_i belongs to a class C_k, and we can define a basic belief assignment:

$$\begin{cases} m_{x_i}(C_k) = \alpha_{ik} \ \text{ if } \ x_i \in C_k \\ m_{x_i}(\Theta) = 1 - \alpha_{ik} \\ m_{x_i}(A) = 0 \ \text{ if } \ A \in 2^\Theta \setminus \{C_k, \Theta\} \end{cases} \tag{8}$$

where α_{ik} is the reliability of the classifier S_i used to produce the image I_i for the class C_k. It can be defined from the error rate of the classifier [12]. When this rate is quite the same for all classes, we can use an unique reliability α_i based on the global error rate of the classifier.
We want to measure the dissimilarity on images matched by the transformation $t \in T$. When combining basic belief assignment of pixels from I_1 with pixels from $t(I_2)$, conflict is generated. Using the conjunctive rule (6), this conflict is found on $m_{\text{Conj}}(\emptyset)$. As we use simple support basic belief assignment, the computation of conflict can be simplified to:

$$m_{(x_1,t(x_2))}(\emptyset) = m_{x_1}(C_{x_1}) m_{x_2}(C_{x_2}), \tag{9}$$

where C_{x_i} is the class of pixel x_i and with $x_1 = t(x_2)$, $x_1 \in I_1$, $x_2 \in I_2$.
When combining pixels from different classes, the conflict will raise. On the contrary, when combining pixels from the same class, conflict will be low. Applied to each pixel of the images, this conflict is a good measure of dissimilarity and we define this measure as:

$$m_t(\emptyset) = \sum_{x_1 \in I_1} m_{(x_1,t(x_2))}(\emptyset). \tag{10}$$

This dissimilarity measure is used in both images registration of our algorithm.

4.4 Fusion of registrated images

At this point, we know the transformation $t \in T$ that match I_2 with I_1. We also know the combined basic belief assignment $m_{(x_1,t(x_2))}$ for all pixel $x_1 = t(x_2)$, $x_1 \in I_1$, $x_2 \in I_2$. We can compute the pignistic probability $betP_{(x_1,t(x_2))}$ and decide:

$$C(x_1, t(x_2)) = \underset{A \in \Theta}{\operatorname{argmax}} \, betP_{(x_1,t(x_2))}(A) \tag{11}$$

4.5 Evaluation of registration

In order to evaluate the quality of our registration process, we introduce a measure of derive md. Considering we know the expected transform t_0 composed by a rotation of an angle θ_0 and a translation (x_0, y_0), and the found transform $t_d = (\theta_d, x_d, y_d)$ we can measure the longest distance between the position found for a pixel and its expected position. If we consider only the translations, the distance is given by an euclidean distance between the parameters of the translation: $d_t = \sqrt{(x_0 - x_d)^2 + (y_0 - y_d)^2}$
The rotations are applied from the center of the images, so the most important errors are made on the pixels from the corners of the images. Let $\theta = |\theta_0 - \theta_d|$ be the angular error and $\frac{l_2}{2}$ the distance from the center of the unregistered image I_2 to one of its corner (half of the diagonal). The distance between the found position of corner, and is expected position can be found through a simple geometric problem:

$$d_\theta = l_2 \times sin\left(\frac{|\theta_0 - \theta_d|}{2}\right)$$

In the worst case, these two errors can be added. The longest error is made when the expected position of a pixel is in a corner of the reference image I_1 and his found position is on the opposite corner. This distance is the length l_1 of the diagonal of the reference image I_1. Our measure is defined by:

$$md = \frac{l_2 \times sin\left(\frac{|\theta_0 - \theta_d|}{2}\right) + \sqrt{(x_0 - x_d)^2 + (y_0 - y_d)^2}}{l_1} \tag{12}$$

An important threshold of md is $\frac{l_2}{l_1}$. If a found transformation is measured above this threshold, it means that the found parameters are too far from the expected transformation (the translation throw the unregistered image above the target area, or the angular error is too important).

5 Application on real data

5.1 Database

The database is composed of 13 sonar images provided by the GESMA (Groupe d'Études Sous-Marines de l'Atlantique). The images were obtained with a Klein 4500 sonar. The figure 3 presents one of these sonar images.

5.2 Classification

Our database contains only one image per scene. In order to simulate a multiview problem like an AUV registrating his own sonar image on a map, we use two different classifiers of the same image. The first one is a neural network , and the second one is a k-nearest neighbor (KNN) based on the theory of belief function [4]. The neural network generates the image I_1, used as reference image.
We define a transformation t_0 that will be used as the reference transformation. This transformation is defined as a rotation of angle θ_0 and a translation (x_0, y_0). First, we apply a rotation of angle $-\theta_0$ and extract a sub-image from

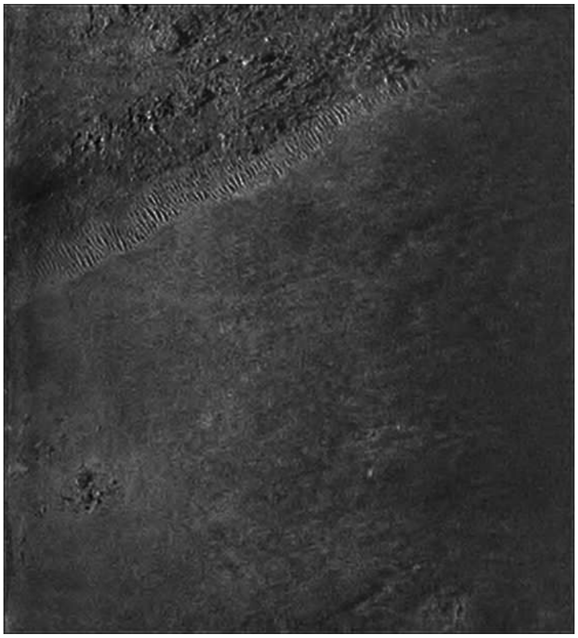

Figure 3: Example of sonar image

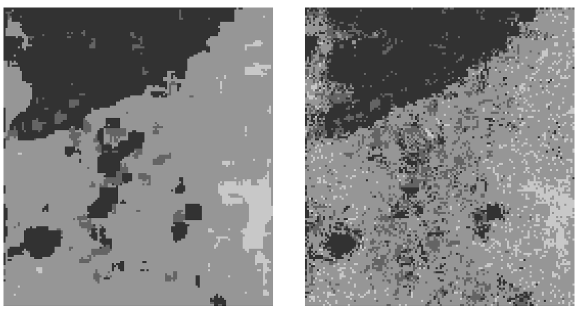

Figure 4: Example of classified images (by Neural network on left, and by K-nearest neighbor on right)

the image generated by the KNN, starting at (x_0, y_0), and with a height and weight equal half the original image. This sub-image will be considered as the unregistered image I_2. Example of these images are presented in figure 4. The images are classified with four different classes representing sand, rocks, ripples, and others sediments.

5.3 Results

Here we observe the registration with a transform model composed of translations (a rigid transform T model limited to transformations $t \in T, t = (0, x, y)$), knowing the expected transformation $t_0 = (0, x_0, y_0)$. Through each step of our registration process, we use our dissimilarity criterion $m_t(\emptyset)$ (equation 10).
We have applied our algorithm to the images of the database and we compared the results of our registration with the same registration but using another criterion. This criterion used by I. Leblond [9] is based on the sum of absolute differences (SAD) of binary images generated by the two main classes of the two images. The table 1 presents the evaluation of the registrations based on each criterion. For all the images, the threshold is 0.25. Over this trigger, the error made on the found transformation is more important that the length of the diagonal of the test image.
The figure 5 presents the behavior of our criterion through the coarse image registration of the image. This figure presents the values for each candidate extracted from I_1, showing our criterion reach a minimum for the nearest candidate from the transformation t_0. The same behavior can be observed during the fine registration (figure 6).

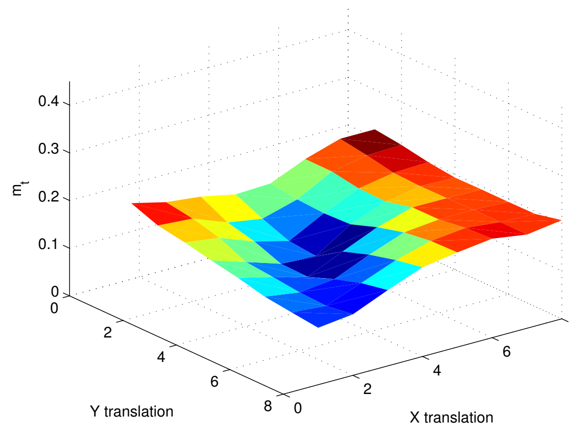

Figure 5: Behavior of conflict criterion through coarse registration

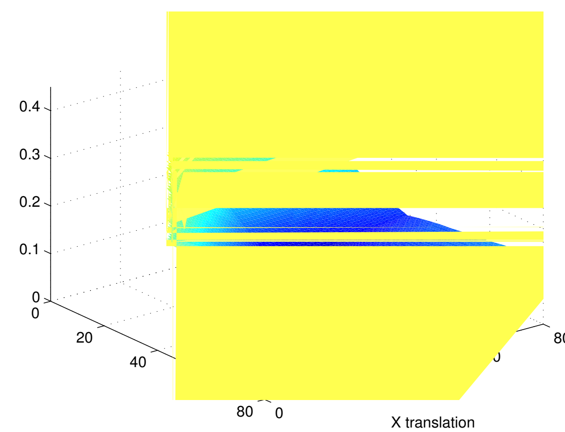

Image	SAD	Conflict
1	0.00508	0.00127
2	0.04124	0.01641
3	0.006698	0.008049
4	0.03293	0.030122
5	0.2922	0.3100
6	0.00575	0.00575
7	0.001224	0.001224
8	0.09501	0.0002378
9	0.5244	0.000282
10	0.09266	0.2877
11	0.001567	0.001567
12	0.005926	0.01911
13	0.3734	0.04255

Table 1: Values of derive md (equation 12) for the images of the database

flict criterion $m_t(\emptyset)$ is 1.5 slower than the SAD registration. Indeed we must compute the combination rule between the basic belief assignments, and as our implementation is based on the use of code developed by P. Smets, using the Moebius transformation [7], this operation is combinatorial explosive.
Through simple images like image 1 or 6, our criterion provides registration equivalent or a bit more precise. The value of derive md shows an error under a few pixels. A value of md over 0.009 shows an error of more a hundred of pixels

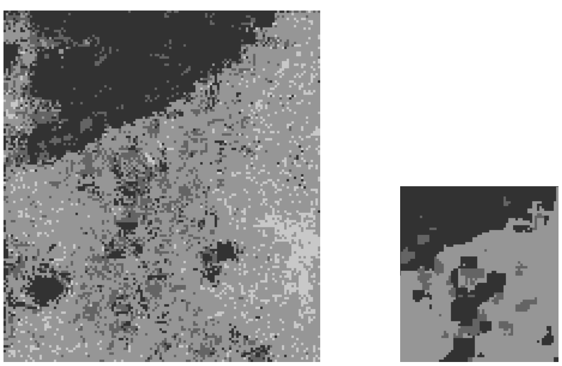

Figure 7: Reference image I_1 and unregistered image I_2 from image *1*

The fails on image 4, 5, and 10 depend on the fact that the extracted image contains one class that cover over 80% of the image. In such uniform areas, we are missing enough usefull landmarks (like a group of pixels of another class, or a long border) for the registration process. Except for image 9, which provides enough landmarks for a conflict based registration, but not for a SAD registration.
For the last step of our application, we fuse the transformed image with the reference image. Figures 7 and 8 presents the reference image 1 and the test image 1, and then the reference image fused with the test image.

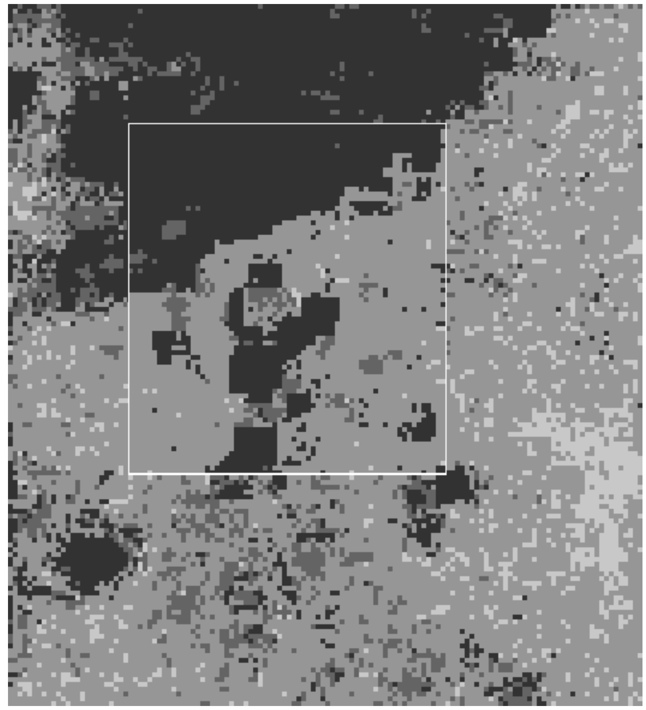

Figure 8: Image *1* after registration and fusion of I_2 and I_1

Observing the specific area concerned by the fusion (figure 9), we observe a global reduction of entropy, and generation of more uniform areas. The interest of fusions techniques is here shown. The fusion reduce imperfections of classification.

6 Conclusion

We propose in this paper an image registration process applied to classified sonar images. In order to handle the imperfections of classifications of sonar images, we use the theory of belief functions. The step next to the registration is the fusion of images, and the theory of belief function is fully developed for this type of application. Were are able with one theory to compute two different processes.
Here we use the conflict generated by the combination of basic belief assignments as dissimilarity criterion to find the best transformation in a registration. Moreover with this combined basic belief assignment, we are able to compute the fusion of the two registered images. The presented results in this paper show the possibilities of this approach applied to real sonar images.
This work can be extended by more complex model of basic belief assignment, and with a transform model extended to non-rigid transformations. The cost of computation due to the use of basic belief assignment might be reduced by adapting the code to simple support basic belief assignments.
Fusion in theory of belief function is not limited to two sources, so we could extend the registration and fusion process to work three or more images at the same time.

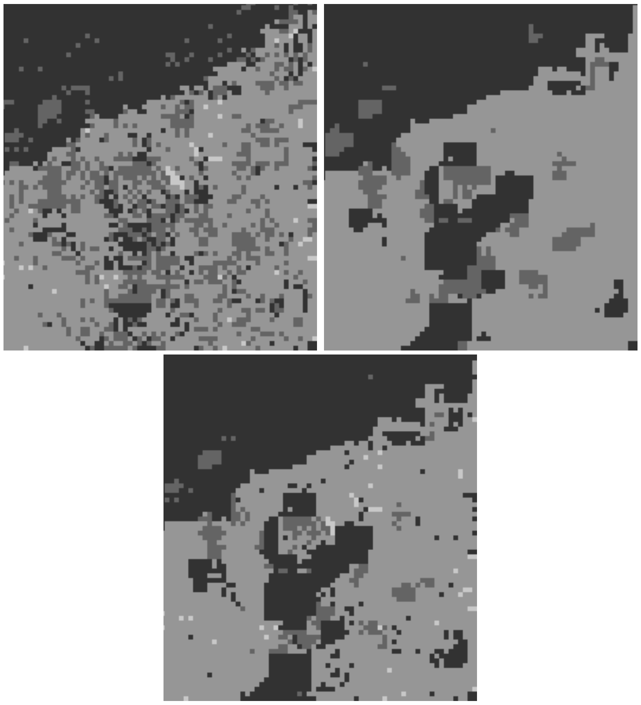

Figure 9: Detail of the registration area on reference image I_1 before fusion(upper left), test image I_2 (upper right) and registration area after fusion (down)

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