Using the conflict: An application to sonar image registration

Cedric Rominger, Arnaud Martin
E^3I^2-EA3876, ENSIETA
2 rue François Verny, 29806 Brest Cedex 9, France
Email: {cedric.rominger,arnaud.martin}@ensieta.fr

***Abstract*—This paper presents an application of the theory of belief functions for classified images registration and fusion. We extend here some results developed on a previous paper to multi-view images. For seabed characterization, we need to fuse the multi-view of sonar images to increase performances and build a complete mosaic. However, before fusion, we have to proceed to a classification of the data, and to an image registration. The proposed approach is based on the use of the conflict due to the combination as a dissimilarity measure in the classified images registration. The theory of belief functions allows an unique framework to model the imperfections and to fuse the classified images.**

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

I. Introduction

When talking about underwater imaging, we are always concerned about the 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 massive data produced have led to the development of automatic sonar image classification and 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 an answer to this problem by merging data from multiple sonars [11], [23].

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 new image then can be registered with all the sonar images to produce a mosaic. This map can be characterized, and used by an AUV. Sonar image registration process can be improved when using classified images [7], [8], 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 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 IV we present our registration process for classified sonar images. Finally, results on some real data will be discussed.

II. 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 1 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 symmetrical so we can *a priori* switch the reference image. The classification of image registration process is a well known discussion [22], [25], 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.

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

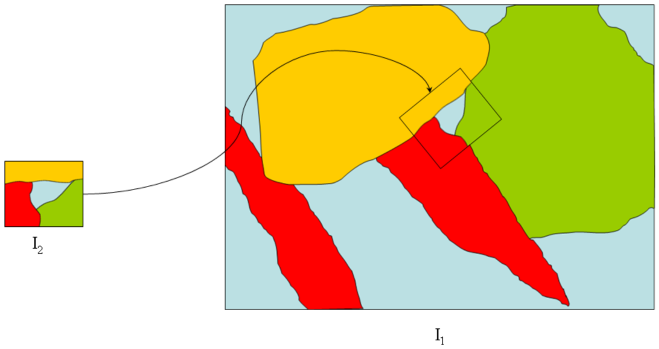

Figure 1. Image registration: image I_2 geometrically aligned on image I_1

depending on the point of view. Recent works on sonar image registration [2], [8] were based on iconic criterion.

A. 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 [10]:

- 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). Projective models suit at most sonar image registration. Curved models are optimal for image registration but need many parameters. In order to reduce this complexity, we can approach a global curved model by a local rigid model.

B. 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 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 [24] and the correlation ratio [14].

Considering the images to register as random variables, it is possible to measure their dependencies with tools like mutual information.

C. 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:

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

or

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

III. Theory of belief functions

The theory of belief functions is based on the works of A. Dempster [3] and G. Shafer [18] under the name of *theory of evidence* or *Dempster-Shafer 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 [21], or in classifier fusion [12]. 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.

A. Basic belief assignment

The theory of belief functions 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 considering the set Θ being exhaustive [18], we place themselves into the closed world (*i.e.* $m(\emptyset) = 0$). As this assumption can be thought natural, it is not necessary and we can accept the world is open [20] (and we will do this) with $m(\emptyset) \geq 0$.

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.

B. Combination rule

Many combination rules have been proposed [17], and the conjunctive rule of Ph. 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 $A \in 2^\Theta$:

$$m_{\text{Conj}}(A) = \sum_{B \cap C = A} m_1(B) m_2(C). \tag{4}$$

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.

C. 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:

$$C = \underset{X \in \Theta}{\operatorname{argmax}}(f(X)) \tag{5}$$

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 are too pessimistic. The most used compromise is the maximum of pignistic probability [19]. The pignistic probability is define for all $X \in \Theta$ with $X \neq \emptyset$ by:

$$betP(X) = \sum_{Y \in 2^\Theta, Y \neq \emptyset} \frac{|X \cap Y|}{|Y|} \frac{m(Y)}{1 - m(\emptyset)} \tag{6}$$

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

IV. Iconic image registration process applied to classified sonar images

In a precedent paper [15], we have proposed a registration process based on conflict, and we will recall here the main aspects of this process, and show the differences. Let us have two images I_1 the reference image and I_2 the one we want to register. As a preparation, we classify both images. Then, we apply an image registration process on these classified images. Once the optimal transformation t_d is found, we can generate a mosaic of our images.

A. Classification of sonar images

When preparing the image registration, we need to classify the images. When characterization of seabed is needed, sonar image classifications are based on textures analysis [7], [12]. The aim is to affect each pixel x_i 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 both images.

Let's define $\Theta = \{C_1, \ldots, C_n\}$ 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:

$$\begin{cases} m_{x_i}(C_k) = \alpha_{ik} \quad \text{if} \quad x_i \in C_k \\ m_{x_i}(\Theta) = 1 - \alpha_{ik} \\ m_{x_i}(A) = 0 \quad \text{if} \quad A \in 2^\Theta \setminus \{C_k, \Theta\} \end{cases} \tag{7}$$

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 [13]. 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.

B. Image registration of classified sonar images

Previously our process was using a global rigid transform model. As we want to introduce a more realistic transform model, we have introduced a global curved model into our process.

In order to approximate a global curved model, we can work on a transform model composed of a set of local rigid transformations. This allow us to extract areas of interest I_i^j into the images and work on a more simple registration process based on a global rigid transform model (for each I_i^j). Our process is in fact a series of registration process.

C. Conflict as dissimilarity measure

In our precedent paper [15] we have presented a dissimilarity measure based on the conflict generated by the combination rule from the theory of belief functions. In the theory of belief functions the generated conflict by the combination rule must be reduced in order to increase the results [9]. However, we use here this conflict as information.

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^j with pixels from $t(I_2^j)$, conflict is generated. Using the conjunctive rule (4), 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:

$$m_{(x_1, t(x_2))}(\emptyset) = m_{x_1}(C_{x_1}) m_{x_2}(C_{x_2}), \tag{8}$$

where C_{x_i} is the class of pixel x_i and with $x_1 = t(x_2)$, $x_1 \in I_1^j$, $x_2 \in I_2^j$.

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:

$$m_t(\emptyset) = \sum_{x_1 \in I_1^j} m_{(x_1, t(x_2))}(\emptyset). \tag{9}$$

Using simple support basic belief assignment presents the following interest: all the conflict generated during the combination come only from disagreement of the decision of the classifier on the combined pixels. With more complex basic belief assignments, we must handle the different sources of conflicts, to determine which part come from the disagreement.

D. Fusion of registrated images

At this point, we know the transformation $t \in T$ matching 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:

$$C(x_1, t(x_2)) = \underset{A \in \Theta}{\operatorname{argmax}}\, betP_{(x_1, t(x_2))}(A) \tag{10}$$

for each pixel of the final mosaic.

V. APPLICATION ON CLASSIFIED SONAR IMAGES

The data come from a Klein 5500B and was recorded on “la Grande Vaille” in France by SEMANTIC-TS and by the GESMA (Groupe d’Études Sous-Marines de l’Atlantique) within the DGA/D4S/MRIS contract n° 05.34.011.00.470.75.65 entitled “cartographie de la couverture du fond marin par fusion multi capteurs”.

We work on seven sonar tracks, showing seabed area up to 800 meters long and 130 meters wide, with 10 centimeters resolution. It was acquired in coastal area, around 15 meters deep.

In a precedent paper [15], due to the database we were using two different classifiers in order to simulate a multi-view problem. Here, the database presents several lapping areas, on which we can apply our registration process. The tracks are classified by a *k*-nearest neighbour algorithm based on Dempster-Shafer theory developed by Denoeux [4]. Resulting images contain four classes: sand, ripples, posidonia, and silt.

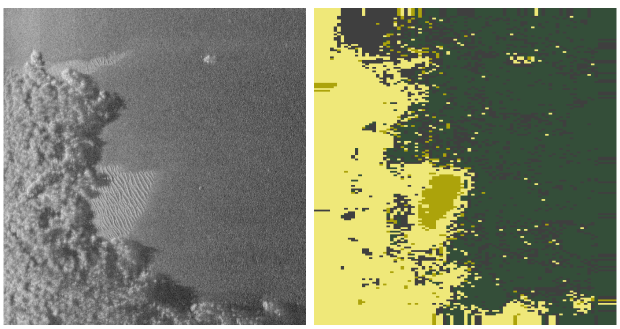

Figure 2. An example of sonar image and its classification (extract)

The classifier was used in previous works, and opposed to human classification, and we have calculated its reliability for each class. This reliability is used to define the basic belief assignment (see equation (7)).

During the record of data (unlike previous database), the boat towing the sonar was able to determine its own geographic position through a GPS (Global Positioning System). This information is more precise than one given by an inertial measurement unit from an AUV, because of the derive observed with this device.

Therefore, we can generate an image of the projection of our classification, following the geographic position of the boat (as in figure 3). But this information does not handle the movement of the sonar itself. Hence, we register two images, but it will remain some errors we will want to correct.

On this registration, we can merge the two images. This fusion, through the combination rule provides some conflict. The points were the conflict is the highest will show us where are the mistakes done through the geographic registration. Around these points, we can determine areas of interest, and use them in the registration process.

Due to the movements of the sonar itself, imprecision is over different parameters (like the length of the cable), we know this first registration leads us to admit an error up to ten meters. We randomly decide which track will be the reference. In the areas of interest, we extract square images of 300 pixels wide (*i.e.* 30 m), that called the reference images. In the unregistered image, we extract (also in the areas of interest) images 100 pixels wide. This allows us to compute the dissimilarity measure over an area of 100 m^2 and apply our registration process to correct the 10 m error admitted on the geographic registration.

We have applied our registration process to the previously presented images. The figure 5 presents the areas of interest for our registration process.

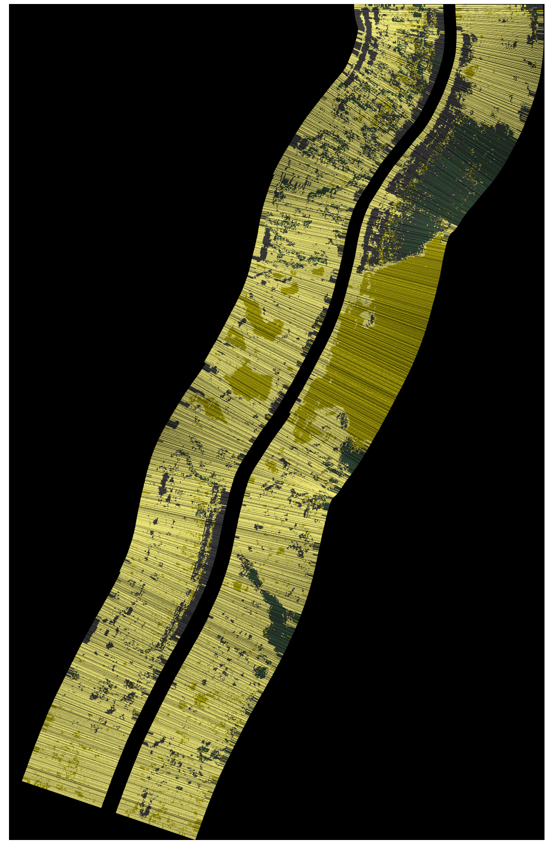

Figure 3. Sonar track following GPS informations

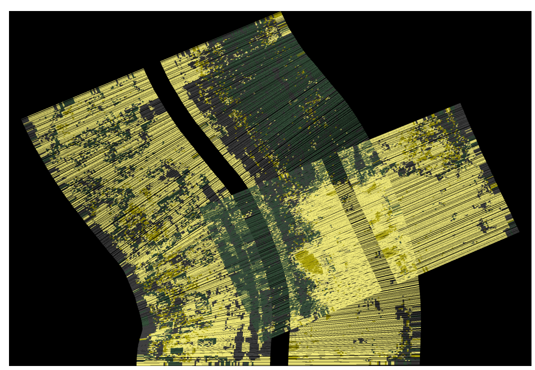

Figure 4. Two parts of sonar track registrated with GPS datas, and merged.

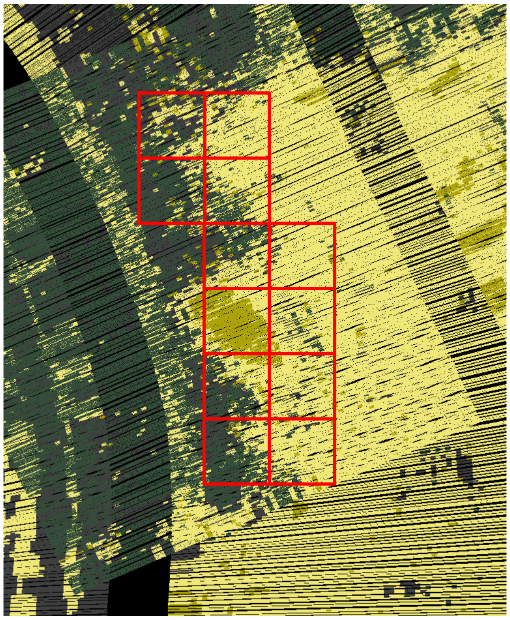

Figure 5. Areas of interest.

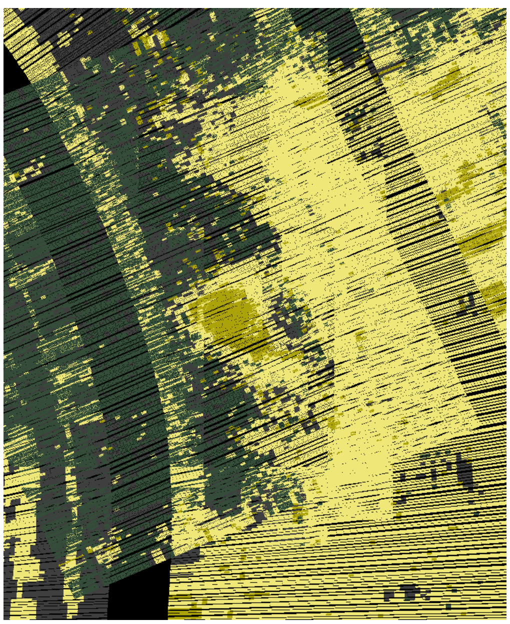

Figure 6. Mosaic after registration

The figure 6 presents the mosaic generated at the end of our registration process. All the determined local rigid transformations follows the same orientation (to the right), and the same length (some meters). Theses transformations are consistent with the data, because the reference track was classified with posidonia whereas the other track was classified with sand. Our process has determined transformation that lead unregistered images to the sand area of the reference track.

Our tracks was classified by a human expert. As our process can be used to improve the seabed classification, we have computed confusion matrix to evaluate the evolution of the classification. The tables I and II shows the evolution the confusion made by the classifier before and after the registration process.

	posidonia	ripples	sand	silt
posidonia	0.325	0.055	0.320	0.298
ripples	0.046	0.320	0.545	0.087
sand	0.049	0.033	0.826	0.091
silt	0	0	0	0

Table I
CONFUSION MATRIX BEFORE REGISTRATION

	posidonia	ripples	sand	silt
posidonia	0.339	0.055	0.317	0.288
ripples	0.050	0.300	0.483	0.165
sand	0.052	0.034	0.817	0.094
silt	0	0	0	0

Table II
CONFUSION MATRIX AFTER REGISTRATION

Obviously, the classification is not really improved. Two reasons can be evoked to explain this stability. The first one is the great entropy in the classification. The table I present a great disparity of decisions (the rate of good classification for posidonia and ripples are only a bit above 0.3), and any transformation that will correct the firsts mistakes might lead to other mistakes. Our process have lead areas of sand that was lapping area of posidonia to move away, improving classification rate of posidonia, but generating mistakes on the area of sand by introducing pixels of ripples and posidonia.

The second one is the shape of the data. When projecting the tracks along theirs GPS informations, holes appear within the tracks. Non classified pixels are ignored during the registration process, and can interfere in the computation of the dissimilarity criterion. This ignorance generate less conflict (in fact zero conflict) and might lead the registration process to decide inaccurate transformations.

There is two way to handle this inaccuracy. One is to close the holes with image processing techniques. The other one is to define particular basic belief assignments for the holes

VI. CONCLUSION

We present in this paper an image registration process applied to classified sonar images. In order to handle the classification imperfections of sonar images, we use the theory of belief functions. The next step to the registration is the fusion of images, and the theory of belief functions is fully developed for this type of application. With the same framework, we perform two different processes.

We use here the conflict generated by the combination of basic belief assignments as dissimilarity criteria to find the best transformation in a registration process. Moreover with this combined basic belief assignment, we compute the fusion of the two registered images. We have shown the result of our process extended with a curved transform model, and applied to real multi-view data.

This work can be extended by more complex model of basic belief assignment, but this will lead us to discuss the nature of the conflict generated by the combination, and how to handle the part of conflict that does not come from disagreement of the sources.

Fusion in theory of belief functions 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.

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