Aggregation Evaluation of a Fusion System Devoted to Image Interpretation

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Abstract – *Information fusion has been studied in various domains of computer science and engineering, and these techniques have been used increasingly. Fusion systems have become, over the time, complex systems integrating information extraction; their representations in an appropriate space, their combinations and their interpretations. The performance evaluation of such systems has become a real problem. The choices of methods and parameter values have a significant impact on the quality of the results. A global evaluation of the fused results do not allow the end-users to adjust the numerous parameters. We propose a local approach to evaluate the mission completeness of the fusion system subparts. In this paper, we focus on the formulation of the mission of fusion subparts and we measure their degree of achievement. The aim is to show to the end-users which subparts do not completely achieve the functionality they were designed for.*

Keywords: Information fusion, complex system, end-users cooperation, subpart mission, local evaluation.

1 Introduction

With the democratization of image acquisition devices, interpretation tasks have increasingly been used by experts to analyze a given phenomenon. Given the large amount of data and the repetitive aspect of such analysis, the experts have appealed to a computer-based system to help them in their work.

In most image analysis applications, the experts look for different kinds of regions simultaneously. The sought-after regions are generally completely different. It is extremely hard to detect these regions using a unique measure based on image processing. Several complementary measurements are needed (texture measurements, structure orientations, form-based measurements, ...) and they must be fused to form the global result. Those systems are called information fusion systems [1]. Their role is to manage a complete information treatment chain starting with information extraction and up to the information interpretation in the expert's working space. The involvement of humans in fusion systems has given rise to cooperative fusion systems [2]. The user is involved in the different stages of information processing by those systems.

Cooperative fusion systems devoted to image interpretation are more and more complex [1]. They are composed of many subparts as illustrated on figure 1.

They also have many parameters and they entail an considerable computation time. Such systems are not easy to use and to adjust to by the end-users who are not specialists in computing. Moreover, an optimized adjustment obtained for given data is not necessarily the best one for other data. This also raises the problem of the evaluation of performance [3] of the information fusion system.

Generally, fusion systems are assessed thanks to the global quality of the output result [4]. This quality is also difficult to be completely obtained because it involves quantitative but also qualitative aspects. Carried out in the output space, it is also not adapted to loop-back on the different subparts of the system. This kind of evaluation does not seem sufficient to improve the interaction with the experts and is not adapted for the management of the fusion systems (for which parameters must be adjusted, and blocks added or removed, . . .).

In this paper we propose to evaluate the performance of the aggregation subpart. The proposed approach is based on a subpart mission achievement evaluation. Its use is illustrated on an industrial application for parameter adjustments. The results show how the approach contributes to giving explicit information [5] on the fusion system.

The paper is organized as follows : in Section 2 the generic fusion system for image interpretation is described, the global result evaluation is dealt with and the limitations of such an evaluation are shown. In Section 3 another point of view is proposed to qualify the fusion process in a better way. Finally, in section 4, an

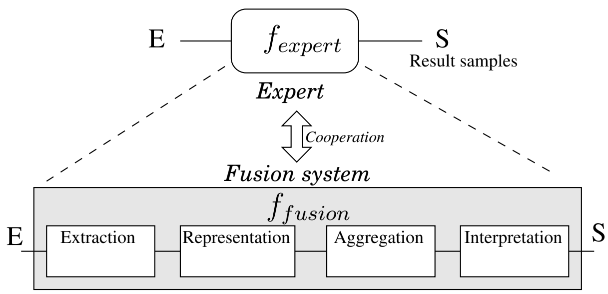

Figure 1: Cooperative fusion system working environment

industrial application of the approach is proposed for the interpretation of 3D tomographic images. In section 5 the paper is concluded and perspectives of this work are given.

2 A Fusion System for 3D Image Interpretation

Fusion systems are mainly designed to help the experts in the analysis of complex phenomena. Their aim is to build a new interesting information from much information (measures, attributes, partial decisions, ...). Applied to image interpretation, these systems are mainly used for typical region detection to facilitate the expert's tasks. Generally, the experts would like to be involved in the process and they have little confidence in automatic systems which look like "*black boxes*". Fusion systems that are able to interact with the end-users are usually called cooperative fusion systems [6].

2.1 Working Environment of a Cooperative Fusion System

To evaluate a fusion system, it is first important to precise the environment in which the system evolved. Figure 1 shows that the working environment of the fusion system is the same as the experts. Input information of the fusion system, noted E, is the same set of data analyzed by the experts. This set is generally "*imposed*", by the context of the application (tomography images in medical application, video in surveillance application, ...), to the fusion system. Output information, noted S, generally corresponds to objects the experts are interested in. This set is also imposed to the fusion system and it corresponds to an understandable space for the end-users (cartography of segmented images, regions of interest in medical images, ...). Moreover, the experts are able to give some result examples which means that they have their own transfer function noted f_{expert}. The result samples given by the experts are generally used as references to evaluate the final output of the information fusion systems.

The design of an information fusion system consists in finding a computer-science-based system able to model the expert's behavior. The fusion system can be divided in four main subparts (illustrated on figure 1) that generally come from the way the experts analyze the input data E: they look at the data and search for typical characteristics (*extraction steps*), then they have some rules (*representation and fusion steps*) based on their experience in order to detect a possible occurring situation. Finally, they decide between the set of possible relevant cases (*interpretation step*).

Conception of a fusion system consists in making several choices for each subpart in order to approach the expert's behavior (as soon as possible). Automatic minimization of $f_{expert} - f_{fusion}$ is obviously not possible for two reasons: the analytic expression of f_{expert} is unknown and f_{fusion} is generally complex (composition of non-linear and non-continuous functions). This specific working environment will influence the performance evaluation of a fusion system.

2.2 The Studied Cooperative Fusion System

The cooperative fusion system studied in this paper, was designed for 3D gray level image interpretation. In the concerned application, the experts introduce their knowledge by pointing out regions of reference directly on the input image (i.e. the input space E). The designed system is presented on figure 2. Its efficiency was demonstrated in [6].

First, different image characteristic measurements based on image processing techniques have been implemented to acquire pertinent information on the sought-after regions. The main family measures are based on:

- *local organization measure*: based on voxel intensity gradient analysis.
- *coocurrence matrix evaluation*: useful for texture characterization
- *morphological measurement*: the specific form of the object in the images is taken into account.

The representation step consists in building similarity maps for each attribute A_i and for each region R_j. All the information is thus expressed in a common and commensurable space (Fig.2). Then, Choquet integrals are applied to compute for each voxel a belonging degree to the sought-after regions. The main advantage of this aggregation tool is its capacity to take into account the interaction between attributes. An interpretation stage is then necessary to build the complete mapping of the 3D image.

2.3 Classical Image Analysis System Evaluation

Existing image quality evaluation methods can be divided into subjective and objective evaluations.

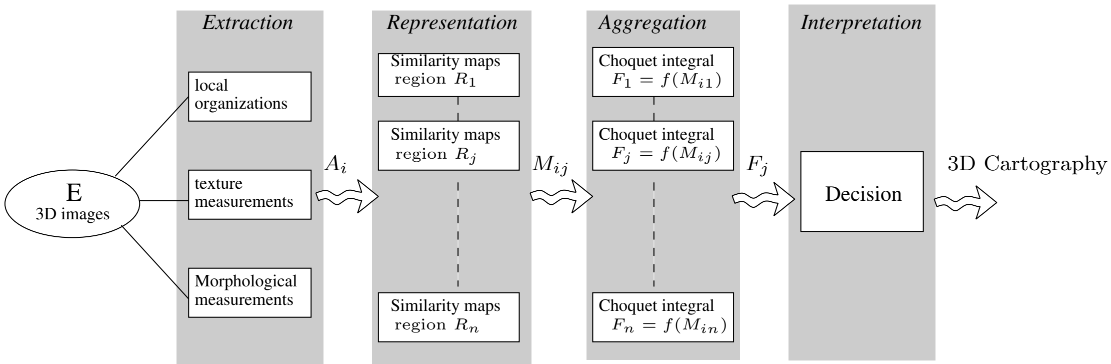

Figure 2: Fusion system designed for 3D image analysis

- **Subjective evaluation:** subjective or perceptual evaluation methods have been established as a reliable method for general image and video quality assessment with well-established experimental procedures and practice. These methods are classified as **full reference (FR)** methods. However, subjective evaluations are inconvenient, time consuming, expensive, and the conditions cannot be guaranteed to be exactly the same. Although widely accepted for their credibility and robustness in evaluating image fusion performance, subjective tests are not practical in many cases due to heavy organizational and equipment requirements and strict test conditions that have to be observed [7].

- **Objective evaluation:** many image quality evaluations in the literature use an ideal fused image as a reference for comparison with the image fusion results. However, ideal fusion images are not available to most real world applications. Therefore, objective quality evaluation methods have been developed that do not need a reference image. A mutual information metric was used to evaluate fusion performance by Qu and al [8]. Xydeas and Petrovic [4] evaluated the fusion performance by calculating the relative amount of edge information transferred from the input images to the fused image. Recently, an image quality index based on the structure metric proposed by Wang and Bovik [9] was improved for image fusion assessment by Piella and Heijmans [10] into a pixel by pixel or region by region method, giving weighted averages of the similarities between the fused image and each of the source images. These methods are classified as **no reference (NR)** methods. Cvejic and al. [11] also improved the structural metric by incorporating local measurements to estimate the amount of important information in the source images that can be represented in the fused image. One interesting development in image quality assessment research is to design **reduce reference (RR)** methods for quality assessment. These methods do not require full access to reference images, but only need partial information, in the form of a set of extracted features.

Most fusion systems are evaluated by comparing the similarity between the global result of the fused image and the source image. But here, we want to know the consequence of the adjustment of the parameters. So we proposed a **local evaluation**, which could inform the end-users on which part he must adjust parameters to have a better result.

3 Through a local evaluation

3.1 Formulation of subpart mission

A useful innovation which would be comforting for the end-user, is a system that not only offers a decision but also provides an explanation as to why a specific decision is made [5]. The global evaluation of the fused image does not provide such explanation, especially in the context of complex systems. The global evaluation does not make it possible to know the effect of parameter adjustments either. Possible conflicting impacts of two adjustments on the global result could be kept without more information. For example, considering the criterion which gives some information of the compactness of a region, it is difficult to guide the users to adjust the gradient window size according to the compactness. It is very difficult to explain the influence and the dependency of a parameter directly on the global result. Therefore there is a need for a **local measure** to adjust the subpart parameters. Another encountered difficulty is that the global result (3D segmented image) is not comparable to the extracted attributes and to the input image (different representation spaces). As a consequence, the defined measures for a global result evaluation are not applicable on the subpart output. The users are not able to define and express what the local evaluation must be either, because the local working spaces are not understandable for him.

A better way to adjust the fusion system is to focus on its subparts which do not completely achieve the functionality they were designed for. Thus this, the main mission of each subpart needs to be well-formulated and then, a mission achievement measurement will allow the performance of the subpart to be quantified according to its objective and independently to the method used inside the subparts.

The mission of the different subparts which compose the fusion system devoted to 3D image analysis can be expressed by:

- **Extraction subpart**: it extracts information from the original data. The output could contain a smaller quantity of information than the original image but it must bring a better separability between the sought-after regions. The results are presented in [12].

- **Representation subpart**: it consists in representing the extracted information in another commensurable space. The objective is to preserve the separability during the transformation.

- **Aggregation subpart**: this step aggregates the different information in order to build some new more interesting information, in reducing the information dimensionality while increasing its robustness.

This paper focuses on the **aggregation subpart** and proposes a process to evaluate its performance according to the mission it was designed for. The proposed indicator measures the separability between the regions obtained on the output of this aggregation subpart.

3.2 Aggregation subpart

The aggregation subpart is made by a Discrete Choquet integral. The Choquet integral with respect to a specific non-additive measure is a specific aggregation operator such as the *mean, median, max, min, trimmed means, Ordered Weighted Averaging operators, and voting operators* as well as more complex operators. Many of these operators are already used in fusion. The Choquet integral is a mathematical structure that can be used to optimize the aggregation operator for a specific application. The Choquet integral expressed under its 2-additive form [13] is given by:

$$C(s_1, s_2, ..., s_n) = \sum_{i=1}^{n} \nu_i . s_{(i)} - \frac{1}{2} \sum_{i=1}^{n} \sum_{j=i+1}^{n} I_{ij} |s_{(i)} - s_{(i-1)}| \quad (1)$$

where $s_{(i)}$ is the similarity degree given by the attribute $M_{(i)}$, ν_i is the weight of attribute $M_{(i)}$, and I_{ij} is the interaction between attributes $M_{(i)}$ and $M_{(j)}$.

The attribute weight can be interpreted as the relative importance of an attribute on the detection problem. The interaction coefficient expresses the redundancy and the complementarity of the attribute [14].

Manually tuning the aggregation parameters requires very good knowledge about the attribute computation. This is generally not the case for the experts since they are specialists in material science and not in image processing. In that context, a learning process based on the entropy notion proposed by Kojadinovic [15] is used to determine the Choquet integral parameters [6]. Several reference regions pointed out by the experts are used to build up the similarity maps and to learn the Choquet parameters. The other test regions are pointed out by the experts to evaluate the detection performance.

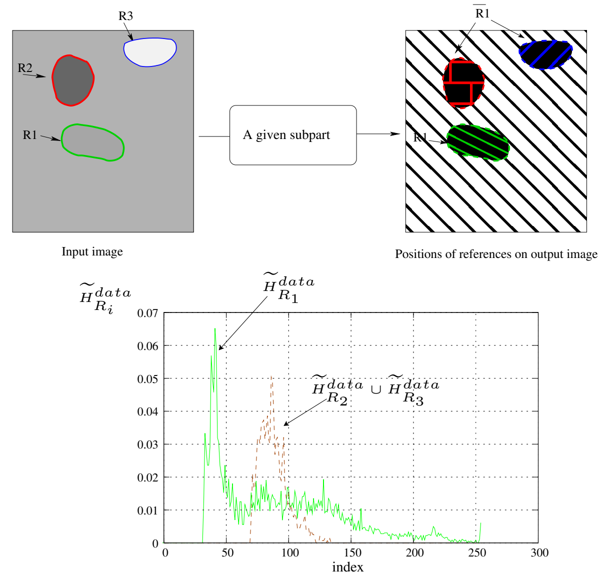

Figure 3: Utilization of the references given by the experts

3.3 Region separability measure

The reference of the sought-after regions pointed out by the experts will be used to compute the proposed region separability index. Indeed, even if the reference region expresses information into the output space of the fusion system, they contain both the type of the region and its localization. This information appears independent to the space they are superposed on. The idea is to report the reference regions into the intermediate space.

The evaluation process consists in comparing the voxel distribution of the attribute values between points of different sought-after regions. Figure 3 illustrates the approach. Voxels, whose output classes are well-known, are selected. Then, the distribution corresponding to a region can be compared to another one.

For example, considering three sought-after regions R_1, R_2 and R_3, the distribution of region R_1 is compared to the distribution of region $\overline{R_1}$ ($\overline{R_1} = R_2 \cup R_3$). The region separability measure is built comparing the two normalized histograms of regions R_1 and $\overline{R_1}$. This measure is, thus, part of the reduce reference (RR) method.

The expression of the distribution (noted H) for a *data* and for voxels v which belong to regions R_j is formulated by:

$$H_{R_j}^{data}(index) = \sum_{\forall v \in \mathcal{V} | class(v) \in R_j} \delta[data(v) - index] \quad (2)$$

with:

- $\delta[data(v) - index] = \begin{cases} 1\, if\ data(v) = index \\ 0 \quad otherwise \end{cases}$
- $data$ is an attribute A_i or a similarity map M_{ij} or a fusion result F_j
- R_j: a sought-after region of region set $\{R_1, \ldots, R_n\}$.
- $class(v)$ is (if it is known) the belonging region of voxel v and $class(v) \in R_j$.
- $\mathcal{V}$ is the set of voxels of the output image (Card($\mathcal{V}$) = total number of voxels in the image).
- $index$: represents abscissa values of the histogram, $index \in [0..255]$.

Thus, the obtained histograms are then normalized by the total number of points belonging to the regions they were computed for:

$$\widetilde{H}_{R_j}^{data}(index) = \frac{H_{R_j}^{data}(index)}{Card(\forall v \in \mathcal{V} | class(v) \in R_j)}$$

The region separability measure is finally built comparing two histograms $\widetilde{H}_{R_j}^{data}$ and $\widetilde{H}_{\overline{R_j}}^{data}$. Measures between histograms are numerous [16] and the choice was guided by the main objective: the separation between the two histograms independently on their forms and stretchness. In this case an intersection surface evaluation like the Manhattan distance is interesting. Its expression for two histograms is given by:

$$S_{R_j} = \frac{1}{2} \sum_{\forall index} |\widetilde{H}_{R_j}^{data}(index) - \widetilde{H}_{\overline{R_j}}^{data}(index)|$$

The obtained distance is equal to 1 when the two histograms have an empty intersection and 0 when they are completely overlapping. The Manhattan distance is symmetrical and respects the triangular inequality. Next section illustrates an utilization of the proposed separability index for the evaluation of the aggregation subpart.

4 Experimental results

4.1 3D tomographic image interpretation

This application concerns the analysis of electrotechnical parts manufactured by Schneider Electric (Company). The studied parts are mainly composed of glass fibers mixed with an organic matrix. The quality of the parts is directly correlated to the fiber organization. Experts (geophysics, part designers, ...) try to understand the inside part organization to find the best fabrication process (fiber length, injection point, baking time, ...). Their main goal is to obtain healthy elements having excellent mechanical and dielectrical performance to be used in a low and high voltage environment. The method chosen by Schneider Electric to analyze the parts is based on X-ray computed tomography (CT). It is a reliable non-destructive evaluation technique. The CT results are 3D gray-scale images which provide data about the organization of the internal morphology. Figure 4 presents a 3D tomographic image corresponding to a studied part.

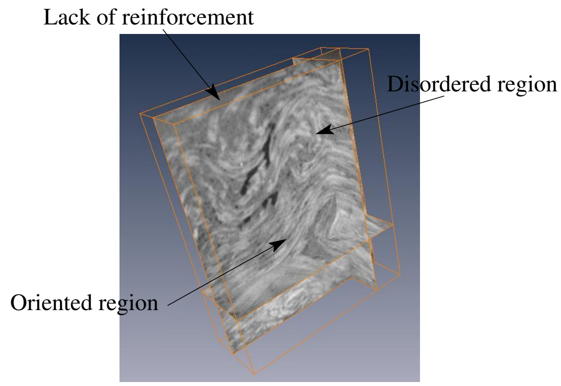

Figure 4: A 3D tomographic image sample

The first sought-after region is the *oriented region* (noted R_1) which has a regular and organized texture with a single preferential orientation of the glass fibers. They are made up of long white fibers giving the impression of a flow. The *Disordered regions* (noted R_2) do not appear organized on the images; they seem "locally chaotic", when the principal orientation is not clearly defined. The regions called *Lack of reinforcement* (noted R_3) only contain resin (or paste) and no glass fibers. They appear in clear and homogeneous gray level on the images.

4.2 Initial parameters

First, different image characteristic measurements based on image processing techniques have been implemented to acquire pertinent information on the sought-after regions. The main family measures are based on:

- *Local organization*: based on a voxel intensity gradient analysis. For example: α = Derich filter coefficient, (G_x, G_y, G_z) = gradient window size, (A_x, A_y, A_z) = ACP window size, t_1 = measure type, and d_1 = ajustment of the output dynamic
- *Texture measurement*: different methods are applied to the coocurrence matrix useful for texture characterization. For example:

(W_x, W_y, W_z) = window size for coocurrence matrix, (D_x, D_y, D_z) = the analyzing direction, t_2 = measure type applied on the coocurence matrix, and d_2 = adjustment of the output dynamic

- *Morphological measurement*: the specific forms of the object in the images are taken into account. For example: structural element (SE) form and dimensions, central point (x_c, y_c, z_c), operation type (top hat by closing, opening, closing, ...)

Each of these extractors can give several complementary measures which are then used simultaneously in the aggregation step. The representation step consists in building similarity maps M_{ij} for each attribute and for each sought-after region. All the information is thus expressed in common and commensurable space. Then, different Choquet integrals are applied to compute for each voxel a belonging degree to the sought-after regions.

Attribute	Parameters
A_1	$(W_x, W_y, W_z) = 7 \times 7 \times 7$, $(D_x, D_y, D_z) = (0, 5, 0)$, $t_2 \equiv$ contrast, $d_2 = 100$
A_2	$(W_x, W_y, W_z) = 8 \times 8 \times 8$, $(D_x, D_y, D_z) = (2, 2, 2)$, $t_2 \equiv$ homogeneity, $d_2 = 100$
A_3	$\alpha = 0.3$, $(G_x, G_y, G_z) = (15, 15, 15)$, $(A_x, A_y, A_z) = (5, 5, 5)$, $t_1 = 7$, $d_1 = 20$

Table 1: Initial parameters

Three attributes are computed: first two parameters A_1 and A_2 based on an intensity gradient and local homogeneity respectively are computed from coocurrence matrix (*texture measurement*), the third one A_3 based on gradient organization (*local organization*). The initial parameters were set approximately according to the structure resolution of the sought-after regions (Table 1).

The results of the local evaluation of the extraction, representation and aggregation subpart are illustrated in Table 2. Detection rates T_{R_i} and T_{global} are obtained by computing a confusion matrix on the voxels of the reference image. Separability is considered interesting when the index S_{R_i} is greater than or equal to 0.70.

The aggregation subpart is composed of three similar maps M_{ij} and it has one output F_j. The local evaluation of this subpart is achieved thanks to the proposed separability measure S_{R_j}. Moreover, the mean μ of each similarity maps versus a region R_j and of the fused result F_j is also calculated (Table 3). According to the obtained values, the aggregation subpart correctly achieved its mission if it gains in separability between regions.

		A_1	A_2	A_3
Extraction	S_{R_1}	0.38	0.51	0.65
	S_{R_2}	0.32	0.27	0.90
	S_{R_3}	0.95	0.92	0.46
Representation	S_{R_1}	0.37	0.47	0.65
	S_{R_2}	0.32	0.13	0.92
	S_{R_3}	0.94	0.92	0.42
Aggregation	S_{R_1}	**0.87**		
	S_{R_2}	**0.93**		
	S_{R_3}	**0.96**		
Detection	T_{R_1}	76.31 %		
	T_{R_2}	52.78 %		
	T_{R_3}	99.95 %		

Table 2: Separability index and detection rate

Similarity Card		M_{1j}	M_{2j}	M_{3j}	F_j
R_1	μ	212.97	60.45	190.59	**190.32**
R_2	μ	250.91	52.54	121.86	**147.97**
R_3	μ	237.85	255	133.24	**250.10**

$T_{Global} = 74.50\%$

Table 3: Statistical parameters

We can note that the separability S_{R_i} between the extraction subpart and the representation subpart is very similar. So we can conclude that the representation subpart achieves properly its mission. The global detection rate obtained after the fusion is $T_{Global} = 74.50\%$ which is relatively weak. This is due to the strong redundancy between attributes A_1 and A_3 with A_2 and regions R_1 and R_2 have a weak separability. Thus A_1's parameters must be adjusted. We can notice that all separability value S_{R_j} after aggregation subpart are greater than those obtained after representation subpart. The mean μ are always between the minimum and maximum of the mean M_{ij} because of the compromise behavior of the Choquet integral. Aggregation subpart correctly achieved its mission.

4.3 Parameter adjustments

We decided to adjust the parameters A_1 by increasing the window size (W_x, W_y, W_z) of the coocurrence matrix.

Attribute	Parameters
A_1	$(W_x, W_y, W_z) = \mathbf{17} \times \mathbf{17} \times \mathbf{17}$, $(D_x, D_y, D_z) = (0, 5, 0)$, $t_2 \equiv$ contrast, $d_2 = 100$
A_2	$(W_x, W_y, W_z) = 8 \times 8 \times 8$, $(D_x, D_y, D_z) = (2, 2, 2)$, $t_2 \equiv$ homogeneity, $d_2 = 100$
A_3	$\alpha = 0.3$, $(G_x, G_y, G_z) = (15, 15, 15)$, $(A_x, A_y, A_z) = (5, 5, 5)$, $t_1 = 7$, $d_1 = 20$

Table 4: Adjustment parameters

This adjustment made a better separability of the sought-after regions possible. For example, the separability S_{R_1} of attribute A_1 increased from 0.38 to 0.71. We have the same results with the separability S_{R_2} of region R_2.

		A_1	A_2	A_3
Extraction	S_{R_1}	**0.71**	0.51	0.65
	S_{R_2}	**0.75**	0.27	0.90
	S_{R_3}	**0.98**	0.92	0.46
Representation	S_{R_1}	0.71	0.47	0.65
	S_{R_2}	0.47	0.13	0.89
	S_{R_3}	0.65	0.89	0.42
Aggregation	S_{R_1}	**0.92**		
	S_{R_2}	**0.97**		
	S_{R_3}	**0.99**		
Detection	T_{R_1}	79.44 %		
	T_{R_2}	75.93 %		
	T_{R_3}	100 %		

Table 5: Separability index and detection rate

After parameter adjustments, separability indexes are all greater than those obtained after the representation subpart, the mean μ of region R_2 has increased and is equal to 176.55. Region R_2 is well detected and detection rate T_{R_2} also increases.

Similarity Card		S_{1j}	S_{2j}	S_{3j}	F_j
R_1	μ	197.97	60.45	190.59	**190.29**
R_2	μ	223.43	52.54	121.86	**176.55**
R_3	μ	222.08	255	133.24	**249.80**

$$T_{Global} = 81.93\%$$

Table 6: Statistical parameters

With the parameter adjustment, the global detection rate obtained is now $T_{Global} = 81.93\%$, which becomes an interesting detection rate for such a kind of applications. Aggregation subpart correctly achieves its mission.

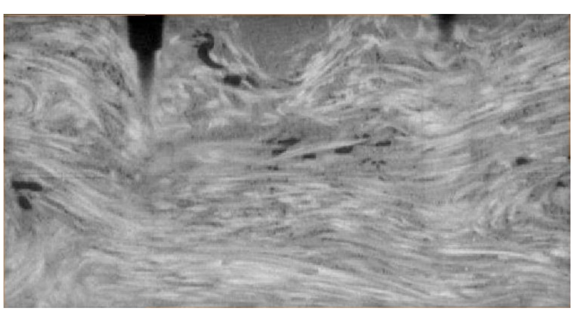

Figure 5: Original image: a cut in a 2D space

The approach makes a better performance possible compared to the previous one because each attribute characterizes one sought-after region (the complementary of information provided by the attributes) and thanks to the fusion process, a better mapping of the image can be obtained. Figure 6 and Figure 7 present the obtained classified image before and after attribute adjustment, white voxels represent the lack of reinforcement region, clear gray level voxels the disordered region, dark gray level voxels the oriented regions and black voxels are not classified voxels.

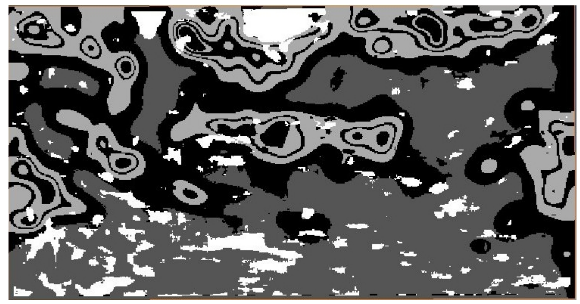

Figure 6: Cartography before parameter adjustments

We can notice that after parameter adjustments, regions are better separated and homogeneous, and there are few misclassified voxels (fewer black voxels in image Figure 7.

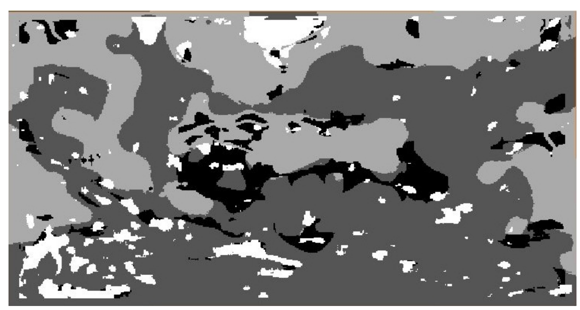

Figure 7: Cartography with parameter adjustments

5 Conclusions

In recent years, information fusion has been increasingly used in many domains and the need of an evaluation of the performance of these systems has become evident. Fusion systems are complex systems composed of different subparts having non-linear and non-continuous behaviors. A performance evaluation is needed in order to help both in the design of such systems validating the different methods used in the system and also in the numerous parameter adjustments. Generally the global evaluation is not sufficient to interact locally with the system.

This paper has expressed the problem of the evaluation of fusion systems by a local evaluation of each subpart the system is made of. As there is no reference in the output space of the subparts, a mission is expressed to describe the objective of the subparts. A mission achievement measure is then proposed to quantify the local performance of each subpart. The illustration of this approach is made on the aggregation subpart. In the context of 3D image interpretation, the defined mission concerns the separability between sought-after regions provided by an attribute. A separability measure based on the comparison of the histograms has been proposed. We have shown that this measure assesses the mission associated with each subpart. The aggregation subpart improves the results and fulfills its mission.

Even if the local evaluation indicates where to intervene on the system well, it does not indicate how to do it. It remains difficult to suggest image processing parameter adjustments guidelines to the end-user who is not a specialist in computing. The use of automatic optimization tools applied locally to select extracted attributes could be an interesting perspective to this work.

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