A 3D image-segmented evaluation procedure in a cooperative fusion system context

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Abstract—This paper deals with a cooperative fusion system parameter adjustment based on an evaluation quality of the fusion system output. The concerned application is an electro-technical part quality evaluation in which geophysicists need time and experience to analyze the 3D tomography of the parts. To help them in their task, a fusion system was designed to aggregate some measurements extracted from the image. The Choquet integral was used to achieve the fusion. The adjustment of the fusion system is difficult to do by the end-user. This paper presents a procedure to guide experts in the use of the system. First of all, classified images obtained by the fusion system are evaluated. The problematic of image evaluation is addressed and an evaluation based on both quantitative and qualitative criteria is proposed. Then, some actions are defined and presented as guidelines to the expert in order to adjust the parameters in a structured way. The approach is illustrated on the classification of the 3D tomographic bloc.

Keywords: image classification, cooperative fusion system, image evaluation, Choquet integral.

I. INTRODUCTION

Image and video acquisition systems have always known a strong development. CCD captors are more and more advanced while being low price. The use of such device is now encountered in almost all domains. Specific and advanced measurement tools which were first specialized for a given domain become now usable. It is the case for X-ray tomographic acquisition which was first set up and tuned for medical applications, and now employed in many other fields for non-destruction control and analysis. This generates new needs in image analysis and in information treatment in order to propose some adapted systems to the newcomer end-users.

This paper focuses on a non-destructive process based on X-Ray for insulating part quality control manufactured by Schneider Electric company. The parts (fig. 1) are used in a strongly disturbed environment and they must meet strict requirements in order to be resistant enough in many situations. This is achieved by healthy elements having excellent mechanical and dielectrical performances. Parts are mainly composed of glass fibres mixed with an organic matrix. The experts know that the organization of the glass fibres inside the part is correlated to its quality. Moreover, there are several different moulding processes which could have an impact on the final part architecture. 3D tomographic images are taken to acquire information from inside the part without destroying it and to analyze the internal organization.

Now, in the case of this industrial application, the 3D tomographic images are analyzed manually by geophysicists. They scan the images section by section, in several directions, to identify and to bound manually the interesting regions. They use in their analysis an important knowledge based on their long experience on the material behavior and on the part manufacturing process. The experts are not confident in an automatic treatment in which they don’t understand well what happens and how the results are obtained.

For this reason, a cooperative fusion system [1] was designed in order to help the experts in their time-consuming task. The proposed approach involves the experts in the different stages leading to the detection. The chosen aggregation method is the Choquet integral. This mathematical tool belongs to the fuzzy integral family and it has understandable parameters. These parameters express the weight of each input in the obtained result but also the existing interaction between inputs. The proposed fusion system has in input several measures obtained by image analysis technics and it gives a complete classification of the 3D tomographic bloc. The system uses the experts’knowledge to learn the Choquet integral parameters. A class of reject was introduced to affect voxels which do not match the regions. This system has given promising results but a specific procedure is needed by the end-users to adjust by themselves the system parameters.
This is directly correlated to the evaluation of the obtained detection.

In image analyses, the result evaluation is always a difficult task mainly due to the subjective definition of the sought-after regions. In the literature, there are a lot of quantitative measurements to quantify the classification performance. However, in such this kind of application in which the experts work in cooperation with the system and in which an entire reference set does not exist, the quantitative measurements are not enough to achieve a relevant evaluation. They must be complete with another kind of subjective information. This paper presents an image classification process which includes qualitative opinion in the global evaluation. Then we also give guidelines for the experts to adjust the fusion system parameters according to the evaluation in an efficient way. Always in a cooperative context, the experts take part in the proposed evaluation and in the fusion system adjustment.

Section II presents the fusion system developed for part quality assessment. Section III presents how the problematic of the image evaluation is dealt with in the literature. The proposed evaluation and adjustment procedure is explained in section IV and illustrated on real data in section V. Finally the last section is devoted to the conclusion and the perspective of this work.

II. PART QUALITY EVALUATION BY INFORMATION FUSION

The study particularly concerns a great family of composites which includes an organic matrix reinforced by fibres. They are composite materials containing unsaturated polyester, mineral filler and glass fibres, used in the industrial sectors of the automotive and the electrical engineering. In the electro technical industry, the insulating parts (fig. 1) for low and medium voltages must answer strict quality requirements. The structural heterogeneities, contained inside the parts, are extremely varied in natures, shapes and sizes. For Schneider Electric, the stakes relate to the improvement of the robustness, the reliability and the reproducibility of the properties. In addition, the experts from Schneider Electric wish to have a better understanding of the material. They appear essential to characterize the architecture of the parts thanks to a multi-scale and non-destructive method of control. The functional properties of a part depend on the quality of its morphology. The structural heterogeneities, contained inside the parts, are extremely varied in natures, shapes and sizes. The experts know that the distribution of the reinforcement, and in particular the orientation of glass fibres influences the mechanical properties [2]–[4].

The parts are first scanned by X-ray computed tomography which allows nowadays to reach very high spatial resolutions. The obtained 3D images provide a vast amount of information and the experts want a system to assist them in the exploitation of the images. The main experts’ request concerns the recognition of the sought-after regions. The main regions are:

1) Lack of reinforcement regions: These areas contain only resin (or paste) and no glass fibres. They appear in clear and homogeneous gray on the images.
2) Orientated regions: They are regions which have a regular and organized texture with a single preferential orientation. They are made up of long white fibres giving the impression of a flow.
3) Disordered regions: These regions appear as not organized on the images, locally “chaotic”, i.e. for which there is not a clearly defined principal orientation.

The developed system to help the experts in tomography analysis is illustrated on figure 2. The approach consists of extracting partial information from the original image by means of several image analysis methods and then to fuse its by an information fusion system based on the Choquet integral. Among the possible existing tools to extract information [5], two of them are used in this paper: One devoted to the orientation measurement. It is based on an analysis of the intensity voxel variations. The second one is a texture measurement based on the cooccurrence matrix. They are illustrated on figure 3 for a specific section of the studied bloc (fig. 4).

The 2-additive Choquet integral [6], [7] is used to aggregate the extracted measurements. This mathematical tool allows to
take the weight of each measurement as well as the interaction between them into account. It clearly models the redundancy, complementarity and independence of the measurements. A Choquet based aggregation is applied for each sought-after regions (fig. 5). The obtained numerical results are all in the $[0..1]$ interval and they can be interpreted like similarity degrees of a studied voxel to each sought-after region. Finally, a decision step affects to the voxel the label of the region which has the maximum similarity degree. This decision is contrained by a threshold $s$ ($s \in [0..1]$): when all the similarity degrees are inferior to $s$, the voxel is affected to a class of reject.

The use of the Choquet integral requires to find out the weights and interaction values. In this application, we have proposed in [1] a parameter identification based on the expert knowledge and experience. Experts want a cooperative system in which they can understand what happens and in which they can manipulate it. In this context, we have proposed a system working on reference regions pointed by the experts. These regions noted $Ref$ on fig. 5 are examples of the sought-after regions. The reference regions used in this paper are illustrated on figure 4. The proposed algorithm for the parameter identification is based on the intensity distribution of the reference regions. In the aggregation process [1], a local intensity distribution for each voxel is also computed on a given neighbourhood. The neighbourhood sizes noted $n_r$ is specific for each sought-after region $r$. The parameters $s$ and $n_r$ are initially set to initial values ($s = 0.7$, $n_{oriented} = 3$, $n_{disordered} = 3$ and $n_{lack} = 3$) and then the experts can adjust it according to the quality of the output.

III. EVALUATION IN IMAGE ANALYSIS

The image quality assessment plays an important role in various image processing applications. A great deal of effort has been made in recent years to develop objective and subjective image quality metrics that correlate with perceived quality measurements. Generally speaking, an image quality metric has three kinds of applications:

- First of all, it can be used to monitor image quality control systems. For example, an image and video acquisition system can use the quality metric to monitor and automatically adjust itself to obtain the best quality image and video data. A network video server can use it to examine the quality of the digital video transmitted on the network and control video streaming.
- Secondly, it can be employed to benchmark image processing systems and algorithms. Supposing we need to select one of multiple image processing systems for a specific task, then a quality metric can help us, to evaluate the one that provides the best quality images.
- Thirdly, it can be embedded into an image processing system to optimize the algorithms and the parameter settings. For instance, in a visual communication system, a quality metric can help the observer.

The quality of the task performance depends not only on the task and imaging system but also on the means by which the task is performed, or the observer. For classification tasks, the observer is often a human, such as a photo interpreter, and some measurements of classification accuracy can be used as a figure of merit for the combined performance of the imaging system and the observer. Alternatively, the images can be classified by computer algorithms or mathematical models.

(a) Orientation measurement

(b) texture measurement

Fig. 3. Measurement stage

Fig. 4. Sample of the sought-after regions

Fig. 5. Fusion system based on Choquet Integral
The best way to assess the quality of a result in image processing is perhaps to look at it, because the human eyes are the ultimate receivers in most image processing environments. The subjective quality measurement Mean Opinion Score (MOS) has been used for many years. However, the MOS method is too restricting, slow and expensive for practical use. The goal of the objective image quality assessment research is to supply quality metrics that can predict perceived image quality automatically. Peak Signal-to-Noise Ratio (PSNR) and Mean Squared Error (MSE) are the most widely used objective image quality/distortion metrics, but they are widely criticised as well, for not correlating well with perceived quality measurements. In the past year, a great deal of effort has been made to develop new objective image quality assessment approaches that include perceptual quality measures by considering human visual system (HSV) characteristics. A number of limitations of HSV based methods are discussed in [8]. To sum up, this has to do with the extrapolation of the vision models that have been proposed in the visual psychology literature to image processing problems.

Some objective image quality assessment methods proposed in the literature [9], [10] are not useful in our application, because they are full-reference (FR), methods that require full access to the original images as references. Therefore, it is highly desirable to develop quality assessment algorithms that do not require full access to the reference images.

Unfortunately, a non-reference (NR) or “blind” image quality assessment is an extremely difficult task [11]. Most proposed NR quality metrics are designed for one or a set predefined specific distortion type that may not be generalized for evaluating images. One interesting recent development in image quality assessment research is to design reference (RR) methods for quality assessment [12]. These methods do not require full access to reference images, but only need partial information, in the form of a set extracted features. Conceptually, RR methods make the quality assessment task easier than NR methods by paying the additional cost of transmitting some information to the users.

There are several forms of performance characterization. All of them have their own particular motivation and benefits:

- **The technology evaluation** concentrates on understanding the behavior of specific algorithms designed to do similar tasks. The testing can be carried out off-line using standardized data. The results are therefore repeatable and depend on the size and scope of the test data set. The results are performance characteristics which may be presented in terms of output parameters, their variations and density functions.

- **The scenario evaluation** defines a particular use application of specific algorithms within a prototype system potentially including other components which may be more or less well-characterized. The input data is based on a controlled real world and is therefore only partly reproducible. The results are given in terms of metrics that a system user has to understand such as reliability, accuracy and precision.

- **The operational evaluation** concerns the use of a complete system for a specific task for an end-user. It may be used as a benchmark to decide whether a system reaches a certain requirement or not. The evaluation must be computed in-line and on-line and is therefore not precisely repeatable. Small changes in the conditions and context of use may have quite dramatic effects on the system performance, especially when human users are involved.

Test data consist of three elements (1) the test data, (2) the corresponding ground truth and (3) other information about the data such as their origin and conditions of capture. The ground truth is an estimate of what is thought to be in the test data. It may be determined by an independent method, or it may be manually defined. Manual annotation provides a partial ground truth which is subjective. In fact unless the data is synthetically generated, ground truth will always have some residual error rate (bias and imprecision) due to administrative or instrumental error.

In our application, the result is given to the expert by a segmentation in several regions of interest. A review of segmentation evaluation techniques [13] identified two classes of empirical evaluation: reliable methods that attempt to quantify the quality of the output image based on measures of the region shape, uniformity and contrast; and discrepancy methods that compare the segmentation results with some ground truth based on measures of pixel misclassification (number or location) and number of regions. The studies in [14] use measures of true and false regions with a specified overlap compared to a manual segmentation as a way of determining the degree of over and under segmentation. For unsupervised classification only reliable methods seem applicable, but these are unsatisfactory (biased) if they correspond to the optimization criteria used in the segmentation algorithm being evaluated. Other metrics have been suggested [15].

In our application, relevance feedback is necessary. It has emerged as a necessary powerful tool for many content-based image retrieval (CBIR) architectures. This is an on-line learning strategy, which adapts the response of a system by exploiting users’ interaction. It improves the performance of the system since (a) it reduces the gap between high-level semantics that the humans ‘use to perceive the rich visual information and low-level features often extracted to describe the image content, and (b) it confronts the problems arising from the subjectivity of human’s perception who often interpret the same visual content in different ways under different conditions [16].

Usually, relevance feedback schemes are distinguished into two different types of actions; actions that modify the query originally issued by the users (possibly considering multiple query points) and actions that modify the similarity measure used for ranking and retrieving image data in a CBIR system, for example. To perform the evaluation, both subjective and objective criteria are used [17]. In our application, we give the experts objective and subjective results (quantitative and qualitative criteria). The expert can adjust the system’s parameters
to improve the detection result.

IV. A COOPERATIVE EVALUATION PROCESS

In this application, the interest of the proposed system is mainly based on the created cooperation between the experts and the developed method. Moreover, any possible feedback from the result quality to the parameter setting must pass through the experts. An automatic evaluation only based on quantitative measurements is therefore utopian.

A. Classification evaluation principle

The experts want the system to give us a detection of all the interesting regions simultaneously. Moreover, the result visualization in 3D space needs time and experience to easily navigate into the segmented bloc. The global quality of a result depends on the detection quality of each kind of region and the objective to reach is also different depending on the kind of region. After some discussions with the experts about the main features they look out, six characteristics were retained for each kind of region:

- Is the reference set used in the learning process correctly classified and what is the generalization capability of the classifier? There are two well-known notions in supervised classifier domain and they can be easily evaluated using measurements coming from the confusion matrix.
- How many objects have been detected? This feature interests the experts because it is directly correlated to the global quality of the part. A great number of lack of reinforcement regions is interpreted completely differently to a great number of oriented region.
- What is the main form of the detected region? In the same way, the form of the regions is important for the experts. They are able to correlate this kind of information to the geometry of the part and to the location of the region.
- Are the regions of a given kind all detected? This concerns all the regions present in the bloc that were not detected by the system.
- Does the detection have “over-detection”? On the contrary, this concerns the detected regions that were misclassified by the system.
- Is the detection split up? This concerns the fragmented aspect of the detection. For example, an area composed of many small oriented regions could be considered as a drawback if the experts wish a single and more global region.

Of course even if these features expressed in a linguistic and human understandable form are redundant, they are always complementary. For example, a fragmented aspect could lead to a specific form of the region.

According to this linguistic analysis, several measurements have been selected to quantify (when possible) the above criteria. For those which are not measurable, the experts are requested to answer the criteria. The partial evaluation for a given kind of region \( r \) \((r \in \{lack, oriented, disordered\})\) are noted \( C^r_i \) with \( i \) the criterion index. For each kind of region \( r \), the detection has given a set of objects noted \( R^r_j \) with \( j \in [1..\text{card}(r)] \) in which \( \text{card}(r) \) is the cardinality for the region \( r \) (number of detection objects for this kind of region). In this context, the following criteria are defined:

- \( C^r_1 = \frac{\text{number of correctly classified voxels}}{\text{number of reference voxels}} \) the classification rate obtained from the confusion matrix.
- \( C^r_2 = \frac{\text{card}(r)}{\text{card}(r)} \), the number of objects of the region \( r \)
- \( C^r_3 = \sum_{j=1}^{\text{card}(r)} \text{comp}3D(R^r_j) \) with \( \text{comp}3D(R^r_j) \) the 3D compactness of the object \( R^r_j \). The 3D compactness definition is an extension of the 2D case. An object has a compactness value equal to 1 when it is a sphere and it is over 1 when its surface is relatively more important than its volume. Its expression is: \( \text{comp}3D(R^r_j) = \frac{\text{vol}3D(R^r_j)}{\frac{4}{3} \pi \left( \frac{\text{surf}3D(R^r_j)}{4 \pi} \right)^{3/2}} \). In this equation, \( \text{surf}3D(R^r_j) \) is the surface of the object \( R^r_j \) and \( \text{vol}3D \) is the volume of the object \( R^r_j \).
- \( C^r_4 \rightarrow \) “Is the detection complete?” It is a quantitative feature and the experts must analyze the result and answer themselves the question according to the objective they assign for the region \( r \). At present \( C^r_4 = [\text{YES, NO}] \)
- \( C^r_5 \rightarrow \) “Over-detection?” In the same way: \( C^r_5 = [\text{YES, NO}] \)
- \( C^r_6 \rightarrow \) “Is the detection fragmented?” In the same way: \( C^r_6 = [\text{YES, NO}] \)

This evaluation is both quantitative with the criteria \( C^r_1, C^r_2, C^r_3 \) and qualitative with the criteria \( C^r_4, C^r_5, C^r_6 \). Computed on every obtained detection, it brings some information in the classification evaluation. The global quality of a classification is a combination of these partial evaluations. Only the experts can achieve this global evaluation according to the objective they give for every kind of region. For example, it is important to detect all the lack of reinforcement regions whatever the number or the compactness of these regions. On the contrary, the orientated regions are generally not compact and not very fragmented. This can also change according to the studied part. Indeed, the constraints will not be the same depending on the shape of the part and to its final use.

B. Fusion system adjustment guidelines

The selected criteria have the advantage to correspond to well-understandable features for the experts. According to these partial evaluations, a fusion system parameter adjustment is proposed to the experts in order to improve the detection. Even if the retained fusion system parameters are quite understandable by no specialist in image analysis and in the Choquet integral, it remains a non-natural task for the experts. Since more information, they change the parameters randomly. In order to help them, some actions are proposed according to every criterion evaluation. They are gathered together in table I under the form of guidelines. For example, if the experts judge that the detection contains too many objects for the orientated region (criterion \( C^r_2 \) oriented too important), we advocate first to increase the neighbourhood size for the region \( r \). If the
problem persists, they can in a second time, decrease the severity degree. In the case in which the proposed actions are not enough to obtain a satisfying detection in few interactions, it will be necessary to come back to the measurement stage and to improve the extracted information according to the final objective. We focus in this paper only on the fusion system parameter adjustment to explain the approach on a reduced context.

V. ILLUSTRATION ON A STUDIED PART

Initially, the experts give the reference regions presented on figure 4 and a detection is computed using the default values of the fusion system: the neighbourhood for every kind of sought-after regions is 3, the severity degree is 0.70. The obtained detection is presented on figure 6. On this result, the orientated regions are in grey level, the disordered ones in white, the lack of reinforcement in dark grey level and the region of reject in black.

![Fig. 6. Detection obtained with default parameter values](image)

This initial detection is evaluated according to the defined criteria (table II). The experts focus on the lack of detection of the lack of reinforcement regions. They achieve action 11 which consists in decreasing the severity degree in order to balance the decision between the output classes. They fix it to 0.50. The iteration 1 on fig. 7 presents the newly obtained result.

The experts focus then on the number of objects belonging to the orientated and disordered regions. They judge that there are numerous and they decide to increase the neighbourhood sizes (action 6) for this two kind of regions. The obtained detection is presented on iteration 2. These actions give satisfying results for the concerned regions but it causes damage to the lack of reinforcement regions which is now not detected (lack of detection). Action 12 is thus applied to the parameters and the neighbourhood size for the lack of reinforcement is thus increased (iteration 3). Finally, in order to try to improve the lack of reinforcement detection, a new reference region pointed on the 140th section (fig.4) is given (action 12) to fight against the fragmentation. The obtained detection has weak variations compared to the previous one and the experts consider that the fusion system parameter is now set.

VI. CONCLUSIONS

The results coming from an image analysis is always difficult to evaluate due to the difficulty in finding a measurement representing the human perception. In a context in which the experts ask to be solicited during the information treatment in order to bring their experience and to be confident in the proposed result, this paper attends to the idea that the experts must participate in the evaluation stage. Indeed, they are the most competent to evaluate the subjective aspect of the result. Moreover, they only know the specificity of every studied electro-technical part, and so they are able to give different importance to every kind of region. The paper proposed an explicit expression of the subjective evaluation in the case of electro-technical part analysis. Based on the evaluation of six criteria for every kind of region, three of which are qualitative, some actions are defined to adjust the fusion system parameter. They are proposed as guidelines to the end-user to help him in changing the parameters in an efficient way. It is a means to
improve the implication of the experts in the detection process. We emphasise the fact that the experts are at the center of the information treatment. They drive the fusion process in giving reference regions (based on their knowledge), they participate to the result evaluation and they are able to act cleverly on the fusion system.

The proposed approach was, then, illustrated on the analysis of 3D tomographic images. In this application, the experts want to classify the 3D images in several regions of interest. In this paper we focus on three region types. First, the fusion system gives an initial detection with default value for its parameters. According to the evaluation of every sought-after regions, the experts achieve actions on the fusion system to improve the detection region by region. In this application, the approach allows to converge in few iterations to an arbitration detection.

When the quality improvement becomes weak following these actions, it means that the fusion system is at its maximum according to the output objectives. At this moment, it will be interesting to act on the measurement stage in adding new information or in tuning the measurements. This is the main perspective of this work. A need appears to explain to the experts how and when it is necessary to tune the information extraction parameters. A studied way is to use the learning coefficient of the Choquet integral to define the actions. Indeed, expressed on the 2-additive form, the Choquet coefficients are the weight and the interaction of the fusion system inputs. They bring interesting information on the impact of every input in the obtained result. The work is in progress to define actions on the measurement stage parameters according to those Choquet integral coefficients.

REFERENCES

<table>
<thead>
<tr>
<th>Criteria</th>
<th>(in/de)crease</th>
<th>Actions</th>
</tr>
</thead>
<tbody>
<tr>
<td>classif. rate $C^r_1$</td>
<td></td>
<td>1 – Checking of the reference regions and removing the ambiguous ones.</td>
</tr>
<tr>
<td></td>
<td></td>
<td>2 – Decreasing the severity degree.</td>
</tr>
<tr>
<td></td>
<td></td>
<td>3 – Checking of the input attribute adequation.</td>
</tr>
<tr>
<td>cardinality $C^r_2$</td>
<td></td>
<td>4 – Decreasing the neighbourhood size for region $r$.</td>
</tr>
<tr>
<td></td>
<td></td>
<td>5 – Increasing the severity degree.</td>
</tr>
<tr>
<td></td>
<td>↘</td>
<td>6 – Increasing the neighborhood size for the region $r$.</td>
</tr>
<tr>
<td></td>
<td></td>
<td>7 – Decreasing the severity degree.</td>
</tr>
<tr>
<td>compactness $C^r_3$</td>
<td></td>
<td>8 – Making the outline of the reference region clear.</td>
</tr>
<tr>
<td></td>
<td>↘</td>
<td>9 – Adding new reference regions in the orientation of the lack of compactness.</td>
</tr>
<tr>
<td>lack of detection $C^r_4$</td>
<td>YES</td>
<td>11 – Decreasing the severity degree</td>
</tr>
<tr>
<td></td>
<td></td>
<td>12 – Increasing the neighbourhood size for the region $r$</td>
</tr>
<tr>
<td></td>
<td></td>
<td>13 – Adding new reference regions.</td>
</tr>
<tr>
<td>over-detection $C^r_5$</td>
<td>YES</td>
<td>14 – Decreasing slightly the severity degree.</td>
</tr>
<tr>
<td>fragmentation $C^r_6$</td>
<td>YES</td>
<td>15 – Decreasing the severity degree</td>
</tr>
<tr>
<td></td>
<td></td>
<td>16 – Adding a reference region on a nearest section of the bloc</td>
</tr>
</tbody>
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### TABLE I
**BOARD ACTIONS FOR FUSION SYSTEM PARAMETER ADJUSTMENT**

<table>
<thead>
<tr>
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<th>Regions</th>
<th>Parameters</th>
<th>Criteria</th>
<th>Action</th>
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<tr>
<td></td>
<td>$n$</td>
<td>$s$</td>
<td>$C^r_1$</td>
<td>$C^r_2$</td>
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<tr>
<td>Results obtained with the reference regions presented on fig. 4</td>
<td></td>
<td></td>
<td></td>
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</tr>
<tr>
<td>0 (Initial)</td>
<td>oriented</td>
<td>3</td>
<td>0.70</td>
<td>85.16 %</td>
</tr>
<tr>
<td></td>
<td>disordered</td>
<td>3</td>
<td></td>
<td>74.64 %</td>
</tr>
<tr>
<td></td>
<td>lack of reinforcement</td>
<td>3</td>
<td></td>
<td>1.17%</td>
</tr>
<tr>
<td>1</td>
<td>oriented</td>
<td>3</td>
<td>0.50</td>
<td>94.97%</td>
</tr>
<tr>
<td></td>
<td>disordered</td>
<td>3</td>
<td></td>
<td>74.69%</td>
</tr>
<tr>
<td></td>
<td>lack of reinforcement</td>
<td>3</td>
<td></td>
<td>62.21%</td>
</tr>
<tr>
<td>2</td>
<td>oriented</td>
<td>9</td>
<td>0.50</td>
<td>100%</td>
</tr>
<tr>
<td></td>
<td>disordered</td>
<td>9</td>
<td></td>
<td>87.68%</td>
</tr>
<tr>
<td></td>
<td>lack of reinforcement</td>
<td>9</td>
<td></td>
<td>11.10%</td>
</tr>
<tr>
<td>3</td>
<td>oriented</td>
<td>9</td>
<td>0.50</td>
<td>95.70%</td>
</tr>
<tr>
<td></td>
<td>disordered</td>
<td>9</td>
<td></td>
<td>80.06%</td>
</tr>
<tr>
<td></td>
<td>lack of reinforcement</td>
<td>9</td>
<td></td>
<td>15.20%</td>
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In adding the reference region presented on fig. 8

<table>
<thead>
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<th>Iteration</th>
<th>Regions</th>
<th>Parameters</th>
<th>Criteria</th>
<th>Action</th>
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<tr>
<td>4</td>
<td>oriented</td>
<td>9</td>
<td>0.50</td>
<td>95.70%</td>
</tr>
<tr>
<td></td>
<td>disordered</td>
<td>9</td>
<td></td>
<td>80.06%</td>
</tr>
<tr>
<td></td>
<td>lack of reinforcement</td>
<td>9</td>
<td></td>
<td>15.20%</td>
</tr>
</tbody>
</table>

### TABLE II
**CRITERION EVOLUTION**