Quality evaluation of insulating parts by fusion of classifiers issued from tomographic images

Lionel Valet a,*, Emmanuel Ramasso a, Sylvie Teyssier b

a Université de Savoie, Laboratoire d’Informatique, Systèmes, Traitement de l’Information et de la Connaissance, Domaine Universitaire, B. P. 806, 74016 Annecy cedex, France
b Schneider Electric, DST – Lab. de Recherche Matériaux, Site 38 tec, Bat. T3, 37 Quai Paul Louis Merlin, 38000 Grenoble, France

Received 28 January 2005; received in revised form 8 May 2006; accepted 15 May 2006

Abstract

The industrial manufacturing of insulating parts must meet strict requirements in order to be used in disturbed environments. Experts know that the moulding process has an impact on the final product quality. However, the phenomenon is so complicated that the relation between the manufacturing process and the product quality is difficult to identify. Some non-destructive methods are nowadays used in the industry to obtain information from inside the parts. In this paper, 3D tomographic acquisitions are used in order to analyse the parts. From the huge set of data obtained, several attributes have been computed to characterize images. A fusion system based on the Decision Templates method is proposed in this paper. Adaptations of the initial method are proposed to be more effective for image segmentation. The fusion approach capabilities are analysed on real data in the context of insulating part analysis.

Keywords: Image classification; Classification fusion; 3D tomographic images; Decision templates

1. Introduction

Nowadays, a growing number of industrial applications use image acquisition to improve product manufacturing. Vision tools are mainly used in the medical field to help complex disease detection [1–4] but also in many other industrial fields [5–8]. The observed growth in the last few years is mainly due to the great advances in acquisition devices which are now affordable for more industrialists. Moreover, the increasing demands in the quality requirements of the products are a great incentive to apply vision tools which allow a better understanding of the impact of the manufacturing process on the product quality. The end-users of such tools are not specialists in image analysis. Thus, there is a need for adapted tools to extract and manage information from these images. Many of these tools deal with decision support systems where end-users interact with the system. In many cases, end-users are able to bring knowledge on the relevant regions of the image according to their experience.

The industrial application concerned in this paper deals with the quality evaluation of insulating parts manufactured by the Schneider Electric Company. The parts are used in a strongly disturbed environment and they must meet strict requirements in order to be resistant enough in many situations. Used in low and medium voltages, they must be able to limit electric arc propagation. This is achieved by healthy elements having excellent mechanical and dielectrical performance. Parts are mainly composed of glass fibres mixed with an organic matrix. 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. The measure of the element quality is an important challenge in order to identify the most
efficient process and the most adapted composite materials to manufacture the part. It must also provide information for the adjustment of the numerous parameters, for instance the glass fibre length.

Schneider Electric are now using a method based on X-rays to acquire information inside a part without destroying it. 3D tomographic images are acquired at different resolutions to analyse the internal organization of the parts. These images have high dimensions and they require time and experience from experts to be completely analysed. In order to help experts in their task, the Schneider Electric research team has decided to implement image analysis methods to automatically detect the relevant regions in the images. Several classification algorithms have been applied and work is under progress to find other efficient methods.

It has been observed that each computed classification is adapted for measuring a given image characteristic and they are not directly related to the output classes. If taken into account simultaneously, computed classifications can lead to a more complete and understandable detection. An adapted fusion system must be able to:

- Use the existing classifications as such.
- Easily accept new coming classifications.
- Take expert knowledge on the sought-after regions into account.
- Be interpretable by non-specialists in information fusion system.
- Have a short time execution.

Many classification fusion methods exist in the literature and several taxonomies have been proposed [9]. The choice of a decision fusion technique was guided by the requirements linked to the industrial application and the retained classifier fusion method was the Decision Templates proposed by Kuncheva et al. [10]. This approach is based on two main steps: (1) the learning of the decision templates based on reference regions given by experts and (2) the decision-taking according to the learnt decision templates. This method is considered for its short execution time and for its versatility. It is a supervised approach which is able to handle different classifier output types. However, in its initial version, the method does not include contextual treatments and it is not possible to manage an output class for which there are no reference regions. Several adaptations are proposed in this paper to improve the relevance of this fusion tool in the context of insulating part quality evaluation. The capability of the proposed approach is then analysed according to the obtained results on insulating part analysis.

The paper is organized as follows: Section 2 presents the context of the concerned industrial application and the existing classifications. Section 3 describes the Decision Templates method with the proposed adaptations to be more efficient in the context of image analysis. Section 4 illustrates the proposed approach on the real data concerning insulating part quality evaluation. The main advantages and drawbacks of the approach are then summarized in the conclusion.

2. Part quality assessment presentation

2.1. An industrial problem

The study particularly concerns a great family of composites which includes an organic matrix reinforced by fibres: the SMC (Sheet Moulding Compound) and BMC (Bulk Moulding Compound). They are composite materials containing unsaturated polyester, mineral filler and glass fibres, used in the industrial departments of automotive and electrical engineering. In the electrotechnical industry, the insulating parts for low and medium voltages must meet strict quality requirements:

- The parts must stand relatively high temperatures and great mechanical strains.
- They have to present good dielectric properties.

Part manufacturing requires the setting of an important number of parameters, among which the manufacturing process and the geometry of the part itself. Parts are often

![Fig. 1. Examples of insulating parts. (a) A corner of a part and (b) reconstructed 3D view of another part.](image-url)
bulky and have complex shapes. Moreover, parts can be moulded according to three different processes:

- Compression.
- Injection–compression.
- Injection which allows a better productivity.

Fig. 1 gives an illustration of two of the studied parts. For confidential reasons, Fig. 1(a) is a closed up view of the part and Fig. 1(b) is a reconstructed 3D view of another manufactured part which shows its complex shape and geometry.

For Schneider Electric, the improvement of the robustness, the reliability and the reproducibility of the properties are at stake. In addition, experts of Schneider Electric wish to have a better understanding of the material. The aim of this study is to exploit a new way of optimization of the unsaturated polyester parts, based on the analysis of the structural characteristics. It is 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 inside the parts are extremely varied in nature, shapes and sizes. Experts know that the distribution of the reinforcement, and in particular the orientation of glass fibres influences the mechanical properties [11–13]. Moreover, their endeavours are to avoid porosity in order to guarantee satisfactory dielectric properties.

2.2. Internal part measurements

The method chosen by Schneider Electric to analyse the parts is based on X-ray computed tomography (CT). It is a reliable non-destructive evaluation technique that was designed for medical diagnosis in the 1970s. It proves to be the most effective method of non-destructive testing to detect all the types of structural heterogeneity in electro-technical parts [14,15]. CT uses the measurement of radiation intensity transmitted from many angles around an object to reconstruct image cross-sections of that object. The clear images of interior planes of an object are achieved without the confusion of superposition of features often found with radiography. The CT images are maps of the relative linear X-ray attenuation coefficients of small volume elements (voxels) in the object. The X-ray linear attenuation coefficient measurements are directly related to material density and to the atomic number in the volume elements.

CT acquisitions offer the additional advantage of being multi-scale. Indeed, it is possible to reach very high spatial resolutions (lower than the micron). Today, the most powerful tool involves the use of synchrotron radiations (like the European Synchrotron Radiation Facility1). The measurements obtained from CT examinations can be usefully employed during the development of new materials and processes because they allow measurements in complex structures.

The CT results are 3D grey-scale images which provide data about the organization of the internal morphology. Fig. 2(a) presents a 2D tomographic slice corresponding to a studied part. This part is manufactured by injection process and with a glass fibre length of 25 mm. The resolution of this acquisition is 60 μm per voxel. The interpretation of such cross-sections, based on analysis of experts in composite parts, emphasizes four main regions:

1) **Porosity regions:** This term indicates all the voids, bubbles or cracks, possibly present. They can be spherical or lengthened. In Fig. 2(b), they correspond to the easily identified black spots.

2) **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.

3) **Oriented 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.

4) **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.

---

1 ESRF-Grenoble (http://www.esrf.fr/).
2.3. Tomographic image analysis

Tomographic images provide a vast amount of information and experts need a system to assist them in their exploitation. The currently encountered approach in the literature consists in computing different measures on the image. For example, in [5], orientation angles, the mean values on different areas or intensity line profiles are computed on tomographic images for studying the salt distribution in ham. In [8], the Voronoï diagram is used to determine the spatialized pore size distribution in soils. In [4], different measures computed on the cooccurrence matrix obtained from the image are evaluated. In [6,7], orientation and particle displacement are obtained by second- and fourth-order tensors or gradient tensors. Statistical methods are also encountered in medical applications of tomographic images [2,3,1]. In the case of this application, previous studies have been made to compute four attributes from the tomographic images [16].

2.3.1. Region growing algorithm

This method allows to create a partition of the image into homogeneous regions according to the grey level intensities. The process starts with small regions and then grows them according to a homogeneity criterion. The algorithm is based on the classical “blob colouring” algorithm: scanning image line by line, the current voxel is labelled according to the intensity difference with its 3D neighbouring voxels. A threshold \( t_0 \) is used to evaluate the similarity between the voxels. To increase the performance of this approach, the growing is performed iteratively. At each iteration, the threshold involved in the homogeneity criterion is changed [17] (the initial threshold \( t_0 \) is increased by \( \delta t_0 \) at each iteration). Fig. 3(b) presents the obtained results for an initial threshold of \( t_0 = 1 \), \( \delta t_0 = 1 \) and 6 iterations. This result is thus composed of several regions characterized by a weak grey level variance. Dark regions represented with black colours in Fig. 3(b) correspond to the sought-after porosity regions in the part.

2.3.2. Orientation measurement

Principal component analysis (PCA) of gradient vectors is an often used approach in image analysis for the recognition of different textures. First, 3D gradient vectors are computed for each voxel of the tomographic images. These vectors represent the local intensity variation and its corresponding orientation. To measure the organization of a given neighbourhood, a principal component analysis (PCA) is applied on the gradient vectors. A numerical combination of the obtained eigenvalues [16] gives a degree of organization of the texture in the image. Fig. 3(e) presents the obtained attribute. The oriented regions (black voxels) are well located on the bottom of the part where the flow is not perturbed by obstacles. However, the disordered regions (bright voxels) are located near the holes. It is also difficult to differentiate the lack of reinforcement

Fig. 3. Attributes extracted from the tomographic block. (a) Original tomographic slice, (b) region growing attribute, (c) Haar partial decision, (d) Gabor partial decision and (e) PCA of gradient vectors.

Please cite this article as: Lionel Valet et al., Quality evaluation of insulating parts by fusion of classifiers issued from tomographic imagesInformation Fusion (2006), doi:10.1016/j.inffus.2006.05.002
regions from the oriented regions with this kind of measurements.

2.3.3. Wavelet coefficient based classification

The wavelet transform is a multi-resolution analysis consisting of applying a set of filters to the image to get information about different frequency bands. This is performed by the convolution of the image with a wavelet function [18].

The Haar wavelet transform is first computed for two scales on a neighbourhood of $5 \times 5 \times 5$ voxels. The obtained wavelet coefficients are used to compute energy coefficients corresponding to different scales and directions. In a final step, the voxels are classified according to the energy coefficients using an unsupervised classifier ($K$-means algorithm) in order to identify five classes in the image. The unsupervised approach was chosen because wavelet coefficients have no meaning for the experts. The number of output classes was set according to the number of sought-after regions including a class of rejects (Fig. 3(c)).

The Gabor filter uses directional wavelets. It is applied on the tomographic images for six directions equally spread between $0^\circ$ and $180^\circ$. Due to time computing reasons, the considered directions are only in the 2D main slice of the part. The application of this filter gives, for each direction, a complex image of wavelet coefficients. These coefficients are also used to extract energy coefficients which are classified by means of the same unsupervised classifier ($K$-means algorithm) as the one used previously to segment the image into five regions (Fig. 3(d)).

2.4. Information fusion approach

The information extracted from the tomographic block measures specific characteristics of the part. Some of them are directly related to the sought-after regions. For example, the region growing based attribute is enough for the detection of the porosity regions. This is mainly due to the simplest definition of the porosity in the grey level space. For other regions like the lack of reinforcement ones or the oriented ones, they cannot be directly detected using one attribute alone. Moreover, some measurements are not directly understandable by the experts like the wavelet based attributes. However, they allow to identify regions within the block which are stable according to the wavelet coefficients. A global detection could be built by taking simultaneously all the pieces of information brought by each measurement into account.

All the measurements presented can be seen as classifications and a multiple classifier fusion is proposed to build the sought-after regions. Many classification fusion methods exist and several taxonomies have been proposed [9]. The literature also proposed many experimental studies [10], and theory-oriented works [19,20]. Some combination methods can work without a priori information as minimum, maximum, majority vote, average, sum, i.e. by applying them directly on classification results. They differ from supervised methods as Decision Templates, neural networks and fuzzy integral that are trainable classifier fusion methods which require expert knowledge (a learning set) to build templates, rules and to optimize the setting of parameters used in the fusion process. These supervised fusion methods are well adapted when a relevant reference data set is provided. Besides, boosting and bagging have been successfully coupled to such methods to improve classification performance [21,22].

The choice of a decision fusion technique between so many methods was guided by the requirements linked to the industrial application:

- First, the 3D tomographic images are of high resolution and their analysis is time-consuming. Furthermore, the classification fusion is processed at the end of the information processing chain. Therefore, the fusion method has to be fast enough.
- Then, the primary classifier outputs have different dimensions and the fusion approach must accommodate all of them.
- Since a voxel cannot represent anything when it is considered on its own, the neighbourhood has to be included in the image analysis method in order to provide a contextual treatment.
- Finally, experts who analyse the insulating parts have great knowledge on the sought-after regions and they request supervised systems in order to interact with them.

According to these constraints, the retained classifier fusion method is the Decision Templates proposed by Kuncheva et al. [10]. This choice is motivated according to results presented in [10], where an experimental comparison of Decision Templates vs 14 other fusion techniques, previously described, is achieved on several datasets. The results have shown the good performance for the versatility and the classification rate obtained with this approach.

Roughly, the Decision Templates fusion method consists in measuring the dissimilarities between previously learnt templates and a decision profile built from the individual classifier. Another strong point of this method is that it requires no strong assumptions compared to probability-based methods. Furthermore, it is less sensitive to the size of the learning set (overtraining) than other methods. The Decision Templates is also intuitive, so understandable by experts, and is not time-consuming.

3. Tomographic image analysis by classifier fusion

3.1. Decision Templates method

Decision Templates is a supervised fusion method, proposed by Kuncheva et al. [10]. Its principle is based on
the comparison between models of classes and results provided by classifiers. The final decision consists in selecting the closest model in terms of a chosen dissimilarity measure.

Framework: Kuncheva has introduced the decision profile (DP) to gather all the classification results presented in Section 2.3 for data \( x_i \):

\[
\text{DP}_{x_i} = \begin{bmatrix}
    d_{1,1}(x_i) & \cdots & d_{1,nb_{cl}}(x_i) \\
    \vdots & \ddots & \vdots \\
    d_{L,1}(x_i) & \cdots & d_{L,nb_{cl}}(x_i)
\end{bmatrix}
\]  

(1)

where \( L \) is the number of classifiers and \( nb_{cl} \) the number of classes. Each row of a \( \text{DP}_{x_i} \) is a vector representing the values of the base classifications. These values are also normalized so that their sum equals 1 (\( \sum_{\text{cl}} d_{i,cl}(x_i) = 1 \ \forall i \)). Notice that, in a class-indifferent interpretation [10], the line of the matrix \( \text{DP}_{x_i} \) could be semantically independent. In this case, a column of the matrix does not always represent the same class. When classifiers have different output dimensionalities, the \( \text{DP}_{x_i} \) matrix is completed by null values which are neutral at all the computation stages.

Step 1: Decision Templates learning — Models are built from reference points for which the output class is known. The reference points are gathered in a learning set noted \( E \) such that: \( E = E_{C_1} \cup \cdots \cup E_{C_{nb_{cl}}} \) with \( E_{C_c} \) a set of reference points belonging to the output class \( C_c \), \( \forall c \in \{1 \ldots nb_{cl}\} \).

One decision template \( \text{DT}_{C_c} \) is associated to one output class \( C_c \). Each decision template is the aggregation result of the decision profiles of points belonging to the sub-learning set \( E_{C_c} \). In this application, the decision templates \( \text{DT}_{C_c} \) are computed using the arithmetic mean of the decision profiles related to the class \( C_c \):

\[
\text{DT}_{C_c} = \frac{1}{|E_{C_c}|} \sum_{x_i \in E_{C_c}} \text{DP}_{x_i}
\]  

(2)

This aggregation function is simple but well adapted to the design and the validation of the fusion system. It could be changed later by, for example, the Choquet integral which is a more complete and complex aggregation function.

Step 2: Decision-taking — In the fusion stage, the input points are denoted by \( x_i \) with \( i \in \{1 \ldots nb_{in}\} \). Each \( x_i \) is characterized by a decision profile \( \text{DP}_{x_i} \). The fusion by Decision Templates is a point-by-point process which measures a dissimilarity between the decision profile of the current point and the decision template \( \text{DT}_{C_c} \). The class \( C_c \) is affiliated to the point \( x_i \) when \( C_c \) is the class of the likeliest model. The expression “likeliest” depends on the chosen measure of dissimilarity (noted \( S \)).

The dissimilarity measure is another parameter of the Decision Templates. This is a flexible aspect of the method which allows to adapt it according to the applications. In [10], many dissimilarity measures have been studied and the squared-Euclidean distance has shown good performance on all the datasets, notably because it is an integral measure and thus is less sensitive to noise. The use of the squared-Euclidean distance leads to a nearest mean.

The fusion step consists first in calculating the distance between the decision profile from the current point \( \text{DP}_{x_i} \) to each decision template \( \text{DT}_{C_c} \) as

\[
S(\text{DT}_{C_c}, \text{DP}_{x_i}) = \sum_{l=1}^{L} \sum_{c=1}^{nb_{cl}} (\text{DT}_{C_c}(l, c) - \text{DP}_{x_i}(l, c))^2
\]  

(3)

A point is considered as similar to a decision template when the computed dissimilarity measure \( S \) is low (near 0).

To take the final decision for a voxel \( x_i \), the class associated to the smallest value of the dissimilarity measure \( S(\text{min}) \) is chosen as being the most similar to the decision profile \( \text{DP}_{x_i} \):

\[
x_i \leftarrow C_c/S(\text{min}) \quad \text{with} \quad S(\text{min}) = \min_{c=1 \ldots nb_{cl}} (S(\text{DT}_{C_c}, \text{DP}_{x_i}))
\]  

(4)

3.2. Class of reject managing

In image classification, a well known class of rejects [23] is usually used to represent the voxels which are too different from all the sought-after classes. This special output class could not be learnt like the others because there are no regions of reference associated to it. To introduce the class of rejects in the initial Decision Templates method, a threshold is applied on the dissimilarity measure. This threshold, noted \( T \), acts on the dissimilarity measure \( S(\text{min}) \) to reject unsatisfactory points. When \( S(\text{min}) \geq T \), the system considers that the current point is not similar enough to the sought-after class and therefore, assigns it to the class of rejects.

This adds a new parameter \( T \) to the method. To assist the end-users in its setting, the parameter has to be understandable. It can be demonstrated that the dissimilarity measure belongs to \([0,2 \times L]\) with \( L \) the number of classifiers and under the following condition: \( \sum_{\text{cl}} d_{i,cl}(x_i) = 1 \), \( \forall x_i \in E_{in} \) and \( \forall l \in \{1 \ldots L\} \) (probabilistic point of view of the input classification). Note that this bound is independent from the number of sought-after classes. Therefore, the dissimilarity measure has been linearly transformed from \([0,2 \times L]\) to \([0\%,100\%]\) to be efficiently interpreted and set by the user (Fig. 4).

![Fig. 4. Threshold interpretation according to the dissimilarity measure.](Image)
Hence, the threshold $\mathcal{T}$ can be interpreted as a strictness degree on the dissimilarity measure. The user can choose 100% if he wants the fusion system to affiliate the class corresponding to the best model only when the similarity is maximum ($S = 0$). In this case, the user relies completely on the templates learnt. If he chooses 0% then he lets the system affiliate the class whatever the dissimilarity measure. It can be noticed that the case 0% ($S = 2 \times L$) enables the user to use the initial Decision Templates as proposed by Kuncheva. The algorithm of the decision rule becomes:

$$\text{For } \forall x \in E_m \text{ Do}$$
$$\text{If } S_{\text{min}} \geq \left( \frac{-L}{50} \times (T - 100) \right) \text{ Then } x \leftarrow \text{Reject}$$
$$\text{Otherwise } x \leftarrow C_c$$
$$\text{End If}$$
$$\text{End For}$$

3.3. Neighbourhood processing

In image analysis, voxel classification is always achieved by taking the neighbourhood of the voxel into account. It allows to have a better spatial connexion of the output class and this yields detections which are closer to the reality.

The proposed contextual treatment is introduced within the fusion process and works on the dissimilarity measures taking the imprecision of the dissimilarity into account. It makes the assignment concerning the class of rejects more reliable by increasing the certainty in a class. The method consists in computing a global and contextual dissimilarity measure in the neighbourhood of the current point. A global dissimilarity measure is obtained for each class on which the previously described decision-taking principle is applied.

The global dissimilarity measure is the mean value $S^\text{mean}_{C_c}$ of the dissimilarity measures $S(DT_{C_c}, DP_{v})$ computed for each point $x_p$ in the neighbourhood $v$ of the current point and for this each class $C_c$, as follows:

$$S^\text{mean}_{C_c} = \frac{1}{\text{size}(v)} \sum_{P \in v} S(DT_{C_c}, DP_{v})$$

The final decision is taken by using Eq. (4) and by considering $S^\text{mean}_{C_c}$ instead of $S_{\text{min}}$. The 3D shape of the neighbourhood can also be adjusted to be more adapted to a specific region shape.

4. Application to 3D tomographic image classification

The information extracted from the tomographic block and presented Section 2 is now aggregated by means of the Decision Templates. On the 113th slice of the block, experts have selected some reference regions corresponding to the four sought-after regions (Fig. 5) which have to be detected: disordered, oriented, lack of reinforcement and porosity. In the sequel, for simplicity’s sake, these classes will be denoted (DIS, ORI, LCK, POR) and REJ for the class of rejects. The voxels of these regions are used to learn the decision templates of each sought-after region. All tests are performed using a 10-fold cross-validation to assess the quality of the fusion. Confusion matrices are also given for relevant cases of study from which the total error rate (TER) [24] is extracted to quantify the reliability of the system. The rejection rate (RR) is also given.

4.1. Decision templates application

The result presented in Fig. 6 is the final classification obtained on the 113th slice of the tomographic block. The threshold is set to 50% and no neighbourhood is considered. All attributes are used in the fusion process and the results show that the system can aggregate pieces of information with different dimensionalities. Even if this detection is globally coherent, this result is judged unsatisfactory by experts. This is because the false detections are equally spread in the image and this phenomenon also appears in the confusion matrix presented in Table 1. This matrix emphasizes the fact that both oriented regions and lack of reinforcement regions are intermixed. The computational cost involved in this approach is low. Indeed, for each voxel, the classification requires a linear number of subtractions and multiplications according to the number of sought-after regions.

4.1.1. Threshold effect

The effect of the threshold on the detection is now studied. Fig. 7 presents three detections obtained for different thresholds. Fig. 7(a), with $\mathcal{T} = 0\%$, corresponds to the result obtained with the initial method proposed by Kuncheva. There is no class of rejects in this result, so all the voxels are classified into the four sought-after regions. On the contrary, detection in Fig. 7(b), with $\mathcal{T} = 75\%$, contains many more voxels classified in the class of rejects. Therefore, the higher the threshold the larger the class of rejects as could be expected. This behaviour well corresponds to the concept of strictness attached to this threshold. This is illustrated by the obtained confusion matrices in Table 2.
4.1.2. Neighbourhood effect

The neighbourhood acts on false detections as depicted in Fig. 8. Besides, for a given threshold, the higher the size of the neighbourhood, the higher the classification rate as shown in confusion matrices of Table 3. The use of the neighbourhood is necessary to reduce noise and increase the detection rate but also to obtain a more relevant classification in terms of the spatial region shape. It can be noticed that the complexity increases in $O(N^3)$ with $N$ the size of the neighbourhood.

4.1.3. Sensitivity to the threshold and the neighbourhood

Fig. 9(a) depicts the rejection rate (RR) related to the threshold and the neighbourhood. First, it can be noticed that, for a given threshold, the neighbourhood has a weak influence on the RR value. Furthermore, this figure shows that the threshold has a strong influence on the rejection rate with the limit of $\mathcal{F} \approx 70\%$. Thus, its setting can be quite critical. Fig. 9(b) shows the total error rate (TER) according to the threshold and the neighbourhood. The TER decreases more gradually with the neighbourhood size than with the threshold. The neighbourhood size of $3 \times 3 \times 3$ appears as a frontier between noise and denoise results: indeed, when $\mathcal{F} = 50\%$ and no neighbourhood, the TER equals almost $20\%$ while a neighbourhood of $3 \times 3 \times 3$ leads to a TER of almost $10\%$. Fig. 9(b) also emphasizes the sensitivity of the TER according to the threshold.

Quantitatively, the matrices show good performance for region detection. However, they show that it is difficult to differentiate oriented and lack of reinforcement regions. The confusion matrices of Table 3 show this problem: the mixing between both regions keeps on being high despite the threshold or neighbourhood adjustments. This error is due to the fact that no specialized classifier is used for lack of reinforcement regions. Furthermore, the analysis of the decision templates of both classes reflects this mixing. For instance, the similarity of both templates is up to $91\%$ based on the Euclidean distance. This similarity reaches its highest value when considering all the similarity between pairs of templates. The analysis of the templates is of great interest for a better understanding of the obtained detection and thus should deserve more attention.

### Table 1

<table>
<thead>
<tr>
<th></th>
<th>DIS</th>
<th>ORI</th>
<th>LCK</th>
<th>POR</th>
</tr>
</thead>
<tbody>
<tr>
<td>REJ</td>
<td>10.9</td>
<td>1.5</td>
<td>2.1</td>
<td>2.7</td>
</tr>
<tr>
<td>DIS</td>
<td>85.2</td>
<td>0.0</td>
<td>0.8</td>
<td>12.4</td>
</tr>
<tr>
<td>ORI</td>
<td>0.0</td>
<td>67.7</td>
<td>8.4</td>
<td>0.8</td>
</tr>
<tr>
<td>LCK</td>
<td>0.4</td>
<td>25.9</td>
<td>80.4</td>
<td>6.5</td>
</tr>
<tr>
<td>POR</td>
<td>3.5</td>
<td>4.9</td>
<td>8.3</td>
<td>77.6</td>
</tr>
</tbody>
</table>

Fig. 6. Region detection results on the 113th slice of the block. (a) Detection of the four regions, (b) disordered region, (c) oriented region, (d) lack of reinforcement region and (e) porosity region.
Fig. 7. Detection obtained for several thresholds. (a) $T = 0\%$, (b) legend, (c) $T = 50\%$ and (d) $T = 75\%$.

Table 2
Confusion matrices for two extreme thresholds (top: $T = 0\%$, bottom $T = 75\%$)

<table>
<thead>
<tr>
<th></th>
<th>DIS</th>
<th>ORI</th>
<th>LCK</th>
<th>POR</th>
</tr>
</thead>
<tbody>
<tr>
<td>REJ</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
</tr>
<tr>
<td>DIS</td>
<td>85.4</td>
<td>0.0</td>
<td>0.8</td>
<td>12.4</td>
</tr>
<tr>
<td>ORI</td>
<td>0.0</td>
<td>68.2</td>
<td>8.5</td>
<td>0.8</td>
</tr>
<tr>
<td>LCK</td>
<td>4.5</td>
<td>26.9</td>
<td>82.1</td>
<td>7.3</td>
</tr>
<tr>
<td>POR</td>
<td>10.1</td>
<td>4.9</td>
<td>8.6</td>
<td>79.5</td>
</tr>
<tr>
<td>REJ</td>
<td>55.6</td>
<td>49.1</td>
<td>61.9</td>
<td>71.9</td>
</tr>
<tr>
<td>DIS</td>
<td>44.4</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
</tr>
<tr>
<td>ORI</td>
<td>0.0</td>
<td>41.8</td>
<td>2.7</td>
<td>0.0</td>
</tr>
<tr>
<td>LCK</td>
<td>0.0</td>
<td>9.1</td>
<td>34.4</td>
<td>0.4</td>
</tr>
<tr>
<td>POR</td>
<td>0.0</td>
<td>0.0</td>
<td>1.0</td>
<td>27.7</td>
</tr>
</tbody>
</table>

Table 3
Confusion matrices for two neighbourhoods (top: $9 \times 9 \times 9$, bottom: $15 \times 15 \times 15$) with $T = 50\%$

<table>
<thead>
<tr>
<th></th>
<th>DIS</th>
<th>ORI</th>
<th>LCK</th>
<th>POR</th>
</tr>
</thead>
<tbody>
<tr>
<td>REJ</td>
<td>1.1</td>
<td>0.7</td>
<td>0.0</td>
<td>0.0</td>
</tr>
<tr>
<td>DIS</td>
<td>98.9</td>
<td>0.0</td>
<td>0.0</td>
<td>2.7</td>
</tr>
<tr>
<td>ORI</td>
<td>0.0</td>
<td>83.2</td>
<td>1.3</td>
<td>0.0</td>
</tr>
<tr>
<td>LCK</td>
<td>0.0</td>
<td>15.7</td>
<td>97.6</td>
<td>7.5</td>
</tr>
<tr>
<td>POR</td>
<td>0.0</td>
<td>0.4</td>
<td>1.1</td>
<td>89.8</td>
</tr>
<tr>
<td>REJ</td>
<td>0.0</td>
<td>0.9</td>
<td>0.0</td>
<td>0.0</td>
</tr>
<tr>
<td>DIS</td>
<td>100.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.4</td>
</tr>
<tr>
<td>ORI</td>
<td>0.0</td>
<td>86.1</td>
<td>0.0</td>
<td>0.0</td>
</tr>
<tr>
<td>LCK</td>
<td>0.0</td>
<td>12.5</td>
<td>100.0</td>
<td>6.0</td>
</tr>
<tr>
<td>POR</td>
<td>0.0</td>
<td>0.5</td>
<td>0.0</td>
<td>93.6</td>
</tr>
</tbody>
</table>

Fig. 8. Influence of the neighbourhood size with $T = 50\%$. (a) Without neighbourhood, (b) $5 \times 5 \times 5$, (c) $9 \times 9 \times 9$ and (d) $15 \times 15 \times 15$.

Please cite this article as: Lionel Valet et al., Quality evaluation of insulating parts by fusion of classifiers issued from tomographic imagesInformation Fusion (2006), doi:10.1016/j.inffus.2006.05.002
4.2. Generalization capability

The generalization capability of the fusion process is now analysed (Fig. 10). For this purpose, the Decision Templates (DT) learnt on the 113th slice are used for the fusion of classifiers computed ten slices further, i.e. on the 123rd slice, depicted in Fig. 10(a). The threshold was kept to 50%. The results of the detection of the four
sought-after regions are given for two different neighbourhoods (Fig. 10(c)–(d)). The results are detailed class by class for the neighbourhood of size 15 × 15 × 15 in Fig. 10(e)–(h).

The results show a good generalization but the mixing between oriented and lack of reinforcement regions clearly appears. This is due to the fact that the templates learnt on the 113th slice have a tendency to mix the former within the latter as discussed previously. The confusion matrices (Table 4), computed on reference regions given by experts on this slice, also illustrate this effect. One interesting comparison can be done with the porosity regions. Indeed, despite their size which is a priori smaller than for the lack of reinforcement regions, they are well detected, even though they are too large because of the neighbourhood. The confusion matrices show the improvement on the detection of this class. This comparison emphasizes that a specialized classifier is required for a correct detection of the lack of reinforcement regions as is the case for the porosity ones.

5. Conclusion

Vision tools are a means to access a lot of information on complex phenomena for which other measurements are not possible. Such techniques provide huge sets of data to be analysed and experts need decision support systems to help them in this complex task. In this paper, insulating parts manufactured by Schneider Electric are evaluated by means of 3D tomographic images. The quality of the parts mainly depends on the glass fibre distribution and experts have identified four different relevant regions. Due to the heterogeneity between the sought-after regions, several image analysis methods have been applied on the 3D tomographic images which have provided relevant information on three of these regions. Obtained results are presented as partial decisions, and some of them have no understandable meaning to the end-users.

To build a global classification for the end-users, a fusion system has been proposed which aggregates the primary information obtained at the image analysis stage. The retained fusion method is the Decision Templates one and adaptations were proposed to be more efficient in the context of this application. These adaptations concern the managing of a class of rejects in the output and the managing of the neighbourhood within the fusion process.

The obtained detections have shown that the proposed adaptations of the initial method are necessary to obtain relevant results in the context of image analysis. Indeed, the aggregated results lead to an easier image interpretation according to each partial decision. The contextual treatment inside the fusion process has led to a great improvement in classification training error as well as to a better interpretation by experts: regions are more homogeneous while some details are kept. The neighbourhood size must be great for large regions like oriented ones which do not have a precise bound. However, a too important size leads to an over large detection of the well defined regions like the porosity regions for example. The threshold $T$ introduced for the management of the class of rejects is also an interesting means for the experts to control the strictness of the detection.

This approach is also intuitive and elucidative information can be obtained from the decision templates. In the case of this application, the decision templates of the lack of reinforcement and of the oriented regions are very similar. This means that the input classification brings poor information to dissociate these two kinds of regions. To improve this aspect of the detection, new attributes must be added. Work is under progress to use cooccurrence matrices which will be more adapted for the recognition of the texture within the lack of reinforcement regions.

The fusion method needs adjustments to be effective. The choice of the arithmetic mean has been made to learn the decision templates. It is a simple way to implement the method and work is under progress to use the Choquet integral instead. The Choquet integral is a complex numeric aggregation operator. A simplified form of the Choquet integral called “2-additive”, proposes a generalization of the arithmetic mean by taking the interaction between inputs into account. This could be an interesting way to give more importance to several inputs in the fusion process.

The application has also shown that quantitative evaluation is a complex problem which in most of the cases mainly depends on the reference set. In this kind of application where experts interact with the system, it is necessary to involve the experts in the building of a more relevant evaluation indicator.

References


