Mining Linguistic Information for Configuring a Visual Surface Inspection System

D. Martín, D.M. Guinea, M.C. García-Alegre, D. Guinea

Industrial Automation Institute (IAI), Spanish Council for Scientific Research (CSIC)
28500 Arganda del Rey, Madrid, Spain
Email: {dmartin, dmguinea, maria, domingo}@iai.csic.es

Abstract— *The configuration of a surface inspection vision system as a complex task, requires mining associations among attributes due to the variability of the surface and the environment in real-time production process. The surface inspection task has to change to deal with different elements such as, wood, stainless steel or paper inspection and, in the case of stainless steel, with reflectance and thickness variations.*

This work is an approach to mine linguistic information based on the fuzzy transform method, capable of finding associations among features. We are interested in the linguistic form of the observed associations, derived from numerical data, as the configuration task needs such linguistic knowledge. This linguistic knowledge is handled by the dynamic cognitive architecture (ARDIS), here propose, to deal with the system knowledge, represented by means of IF-THEN rules, required to configure a specific inspection system.

Keywords— Cognitive Architecture, Fuzzy Transform, Knowledge-based Vision Systems, Configuration Task, Surface Defects, Visual Inspection.

1 Introduction

The configuration of a surface inspection system requires mining associations among attributes, to avoid the data analyses performed by a human expert, due to the variability of the surface in the real-time production process. The surface inspection task changes, for different materials such as wood, stainless steel or paper and, in the case of stainless steel, the reflectance, thickness or stainless steel type varies.

This work proposes the use of the fuzzy transform method [1,2], capable of finding associations from a set of numerical features. The linguistic expressions of the observed associations, derived from numerical data is an input for the configuration of the dynamic knowledge-based architecture (ARDIS) [3], which uses IF-THEN rules to configure a specific inspection system.

Visual systems for inspecting surface defects have always been present in the laminated materials industry [4]. Nevertheless, these systems still show several drawbacks, such as the vision system reusing, as they are designed for a particular surface inspection application and do not offer the possibility of changing either the objectives or the inspection goals. They are designed for a specific application and are not ready to hold unexpected variations. This fact entails a high cost as each new visual inspection task has to be redesigned, from the superficial defect analysis to the overall inspection system by a human expert. The solution here proposed points to extract linguistic knowledge on surface visual inspection, which is easily differentiated in types, by means of associations. This would allow changing or reconfiguring the components related to the inspection process that vary, in the production line, due to changes on either camera, surface or defect type.

To this aim a visual inspection architecture, namely ARDIS, is proposed to surface dynamic inspection in laminated materials based on the configuration of a specific visual system to obtain a good quality control of the manufacturing surface. The configuration task for surface inspection is analysed at the knowledge level and the task is decomposed into simple subtasks to reach the inference level, the most basic tasks. This task is solved as a Configuration-Design task following the CommonKADS methodology [5] leading to the knowledge-based dynamic architecture (ARDIS), which can account with all the knowledge involved in the process. The surface inspection generic knowledge is differentiated among environment, image quality, real-time and computer vision techniques to be integrated in ARDIS.

The injection of surface inspection knowledge from the human expert is an essential issue in the configuration process of any visual inspection system. For instance, the change of the surface thickness or lighting in a production line implies a variation that is not considered in current inspection systems. In this case, the distance between the camera and the surface varies and the camera gets out of focus, generating blurred images. Thus, expert knowledge is necessary to solve the problem as human experts do. But often, we lack knowledge from the expert, so mining linguistic information from numerical data will aid the architecture to re-configure, just in time, the inspection system.

In ARDIS, the surface inspection task, at the domain knowledge level, is analysed and decomposed into simple subtasks to reach the inference level that allows differentiating the Environment (E), Image Quality (IQ), Real-Time (RT) and Computer Vision Techniques (CVT) requirements.

This work is a first approach, to obtain the associations among E, IQ, RT and CVT, to configure the parameters of the inspection system to carry out a specific surface inspection task. In stainless steel inspection, real-time parameters could affect the more the CVT parameters.

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To reach the proposed goal, numerical data from E, IQ, RT and CVT are obtained and evaluated over a set of stainless steel and wood images. Results are shown where CVT is selected as a dependent attribute and E, IQ, RT are independent attributes.

2 ARDIS a cognitive architecture

The cognitive architecture, ARDIS, is proposed to deal with the complex task of visual inspection of laminated surfaces in industrial environments displaying a high variability in lighting, reflectance and real-time defect detection conditions. The generic expert knowledge on surface visual inspection and the deep knowledge on the inspection restrictions and defects characteristics that has the line inspector, is used in the design of a visual inspection system.

The architecture has to offer an adaptive behaviour for detecting different defects or inspecting different type of surfaces. To this aim the cognitive architecture is designed so as to be able to configure in real-time a visual inspection system, adapted for each specific type of laminated surface and defect.

The proposed architecture allows using generic knowledge on surface inspection to configure a specific system of visual surface inspection for different laminated materials such as, metal or wood. This knowledge, in the static roles of the architecture, is codified by means of crisp and fuzzy rules.

The configured visual inspection system is composed of a set of components, design elements, and their parameters. Each configured component depends on the type of surface and defect to be inspected. An environment component can be the lighting device or the camera, which could be composed of several sub-components, each one described by a set of parameters.

The method Propose-&-Revise used to solve the visual surface inspection task is displayed in Figure 1, showing the diagram of subtasks and inferences. This main method shows how the ARDIS architecture operates in three steps: (1) the initialization process, (2) the extension of the initial inspection skeleton and, (3) the revision process of the overall inspection system.

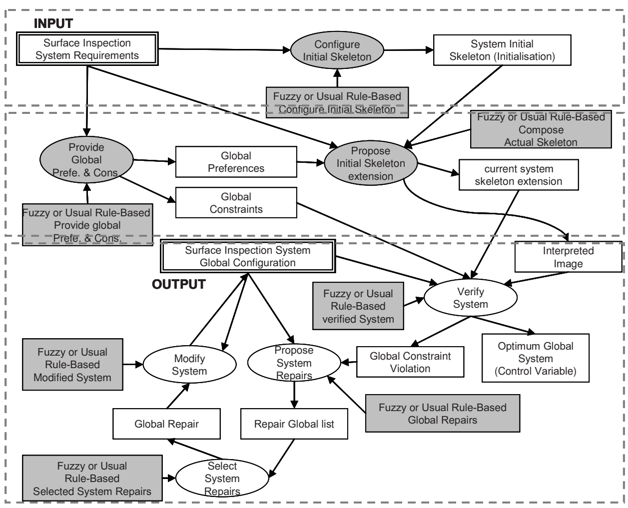

Figure 1: Subtask and inference diagram of the method Propose-&-Revise to solve the surface inspection task.

2.1 *The domain generic knowledge on surface inspection*

The domain generic knowledge on surface inspection is composed of different types of generic knowledge on real-time restrictions, image quality control restrictions, environment conditions and computer vision techniques. This differentiation of the type of knowledge makes possible to distinguish the knowledge used in each inference, making easier the specification of components and their interactions. Thus, the ARDIS architecture has been provided with all the necessary functionalities required to configure a specific complete system of visual inspection where knowledge is partitioned to be ease reused.

The relationships between the knowledge types are described in Figure 2. Here, the environment knowledge is related to real-time knowledge, such as image acquisition rate or lighting components that can influence real-time components in one or another way. So, during the configuration step of an inspection system, if an environment component is configured this has to be taken into account in the configuration of the real-time components.

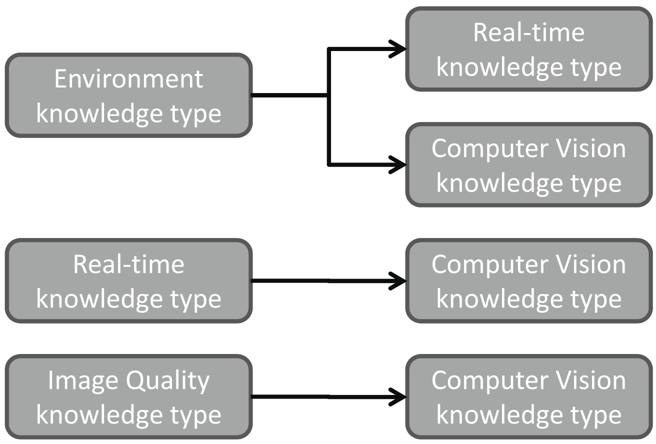

Figure 2: Influence diagram in the surface inspection process

2.2 *Dynamic configuration using ARDIS architecture*

The dynamic configuration process relies on (i) the cognitive architecture ARDIS, (ii) the domain generic knowledge on surface inspection and (iii) the line inspector knowledge who selects the requirements of the inspection system. This dynamic configuration process allows the inspection of each specific surface in a production line. Consequently, it is possible to inspect stainless steel or wood laminates in the same production line. Following the control structure of the ARDIS architecture, requirements and generic knowledge are integrated into crisp and fuzzy rules. This process gives rise to the configuration of the components of the surface inspection system. The Table 1 shows the set of rules used to configure the environment components of the inspection system.

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Table 1: Knowledge Base for configuring the surface inspection system.

KNOWLEDGE BASE USED IN THE INFERENCES OF THE SUBTASK Propose Environment Skeleton Extension
IF ProductionLineSpeed is high THEN ExpositionTime is short
IF IlluminationSystem is ExteriorLaserIllumination THEN CameraSensorGain is automatic
IF IlluminationSystem is ExteriorLaserIllumination THEN Camera-IlluminationRelativePosition is 45degrees
IF IlluminationType is GreenLaserSource THEN ImageChannel is Green

3 Stainless steel and wood images

The work departs from a set of images from inspections of residual oxide scale on cold stainless steel strip and wood. The first visual system is configured to detect 50 microns size defects and the second one to inspect larger defects in a wood surface. The images are obtained with a robust laser technique for diffuse illumination which allows stainless steel or wood industrial inspection with the same system. This visual technique for surface inspection consists on a smart vision system based on a green laser diode diffuse illumination, thus images display a green predominant colour.

The Figure 3 shows a set of images of stainless steel to inspect micro oxide defects, and Figure 4 displays a new laminated material, wood, where knot defects and wood irregularities have to be inspected in the same production line. The wood and stainless steel images have been acquired with an experimental system based on green laser illumination which allows inspecting defects ranging micro to five millimetres size. The acquisition visual system utilizes magnification 1.

4 Defining parameters from images

The analysis of the images has been accomplished with a HP xw4600 Workstation and “Intel(R) Core(TM)2 Quad CPU Q6600 @ 2.40GHz” processor. The numeric parameters have been calculated using the image processing toolbox of MATLAB [6].

Parameters of environment (E), image quality (IQ), real-time (RT) and computer vision techniques (CVT) are differentiated and obtained from the original image acquired by the visual inspection system. The E, IQ, RT and CVT parameters are all derived from an image, either stainless steel or a wood, and the evaluation is performed under the same conditions.

Several features are obtained from images but no associations among them. At this point, some additional knowledge is required to establish the priority on the selected parameter (E, IQ, RT) for the configuration of the inspection system.

The numerical data and F-transform will aid to mine the influence of the E, IQ and RT parameters on the CVT parameters. This knowledge will be, later on, used to set the priority in the configuration process. Then, fixing a CVT segmentation technique, we will try to find the influence between “E, IQ and RT” and the CVT technique. Thus, a segmentation technique could be more influenced by real-time inspection than a non-uniform lighting in the environment.

The linguistic information obtained for configuring a visual surface inspection system has the following structure: IF SegmentationTechnique is CVT and SurfaceInspection is StainlessSteel THEN ParameterPriority is Real-Time.

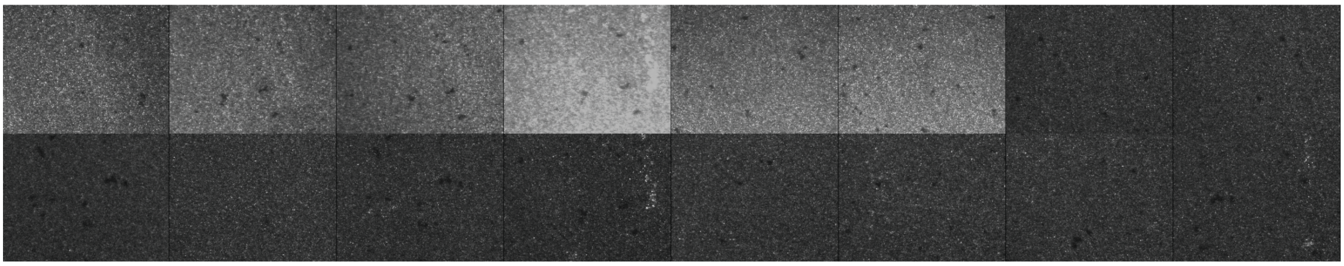

Figure 3: Images of stainless steel with micro oxide defects

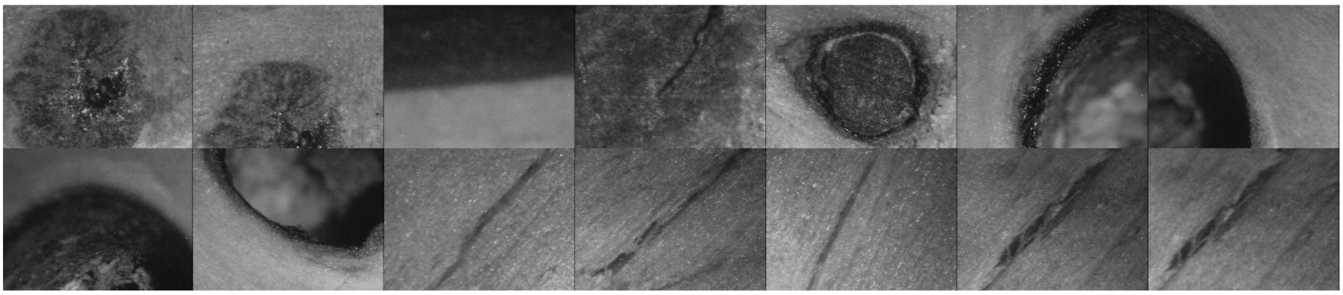

Figure 4: Images of wood with knot defect and other wood irregularities

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The parameters chosen to evaluate the E, IQ, RT and CVT properties over the acquired image, selecting the Mean-Shift algorithm [7] as the segmentation technique, are:

1) Evaluation of the Environment (E): the lighting non-uniformity of the image is used to measure the influence of the environment in the image. This environment evaluation will be an independent attribute or parameter and the corresponding contexts are $E_{StainlessSteel}$= [0.0736 8.1698], E_{wood}= [8.0138 50.2337]. Figure 5 shows data obtained from stainless steel and wood images.

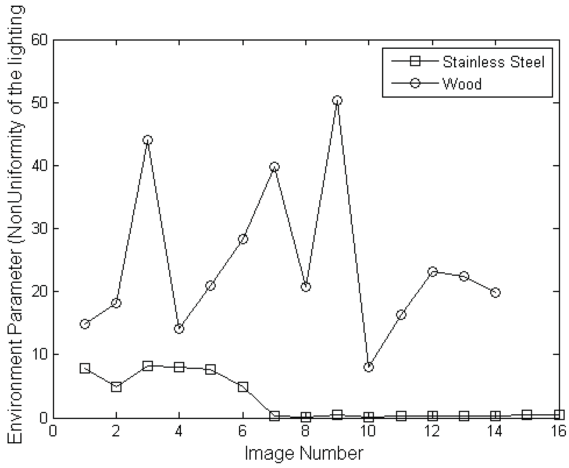

Figure 5: Evolution of the lighting in Stainless Steel and Wood images.

2) Evaluation of the Real-Time (RT): the computation time of the Mean-Shift algorithm [7] is used to estimate a Real-Time parameter in the image. The Real-Time evaluation will be an independent attribute or parameter and the corresponding contexts are $RT_{StainlessSteel}$ = [8.3594 12.3281], RT_{Wood}= [10.1719 13.7813]. Figure 6 shows data obtained on a set of stainless steel and wood images.

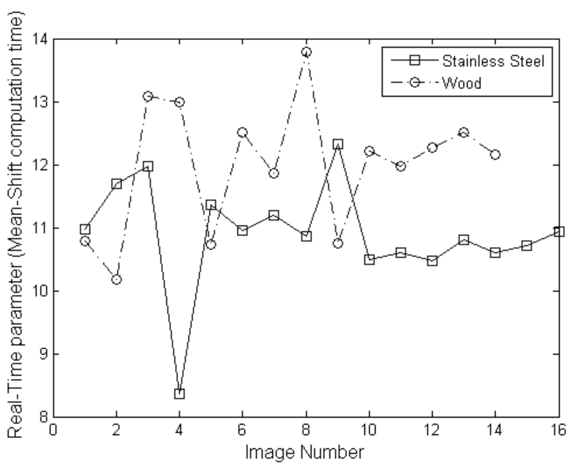

Figure 6: Evolution of the Mean-Shift computation time in Stainless Steel and Wood images.

3) Evaluation of Image Quality (IQ): gray-level co-occurrence matrix from images, was used to calculate the contrast property from the gray-level co-occurence matrix which returns a measure of the intensity contrast between a pixel and its neighbour over the whole image. The Image Quality evaluation will be an independent parameter and the corresponding contexts are $IQ_{StainlessSteel}$ = [5.0702 35.2404], IQ_{Wood} = [0.2268 10.5327]. Figure 7 shows data obtained from stainless steel and wood images.

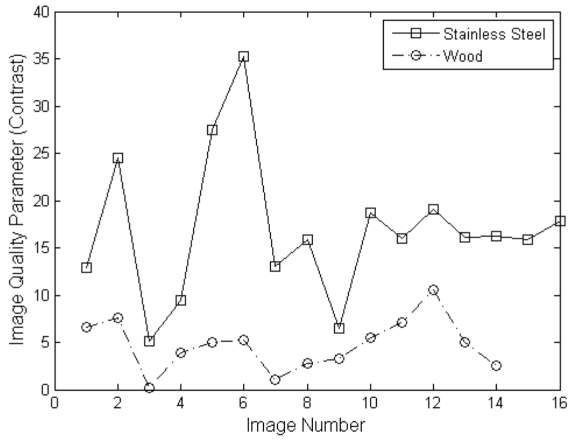

Figure 7: Evolution of the contrast in Stainless Steel and Wood images.

4) Evaluation of the segmentation technique (CVT): the Mean-Shift technique is used as the segmentation technique and the evaluation is based on the number of Mean-Shift regions located by the algorithm. This CVT evaluation will be the dependent parameter and the corresponding contexts are $CVT_{StainlessSteel}$ = [919 2968], CVT_{Wood} = [8 243]. Figure 8 shows data obtained from stainless steel and wood images.

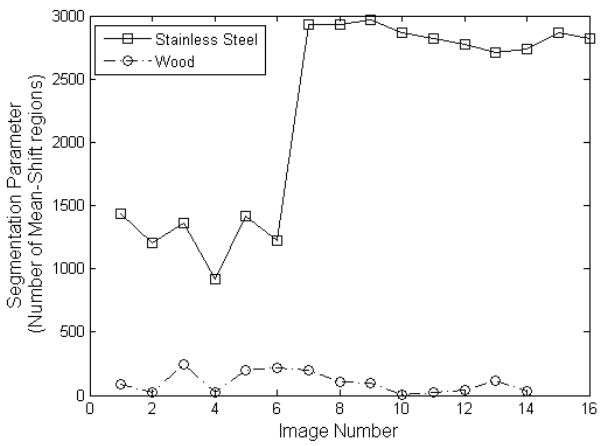

Figure 8: Evolution of the number of Mean-Shift regions in Stainless Steel and Wood images.

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5 Membership functions for data analysis

The membership functions map points in the input space to a membership value (or degree of membership) between 0 and 1.
If X is the input space and its elements are denoted by x, then a fuzzy set A in X is defined as a set of ordered pairs.

$$A = \{x, \mu_A(x) \mid x \in X\}$$

Where $\mu_A(x)$ is the membership degree of x in A.

Gaussian functions are selected to represent membership functions, due to their smoothness and concise notation. These curves have the advantage of being smooth and nonzero at all points.
The membership functions selected for the environment (E), real-time (RT), image quality (IQ) and computer vision techniques (CVT) parameters are shown in the Figures 9, 10 and the vectors of nodes $\langle l_1,...,l_k \rangle$ which define the membership functions of the induced fuzzy sets on the E, IQ, RT and CVT parameters for Stainless Steel and Wood, are displayed in Table 2.

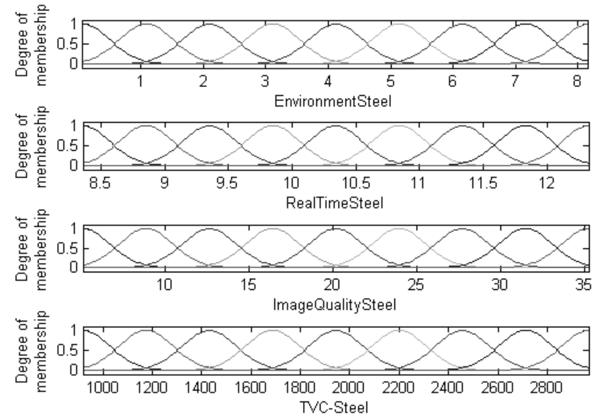

Figure 9: Membership functions with 9 nodes for E, IQ, RT and CVT parameters on Stainless Steel images.

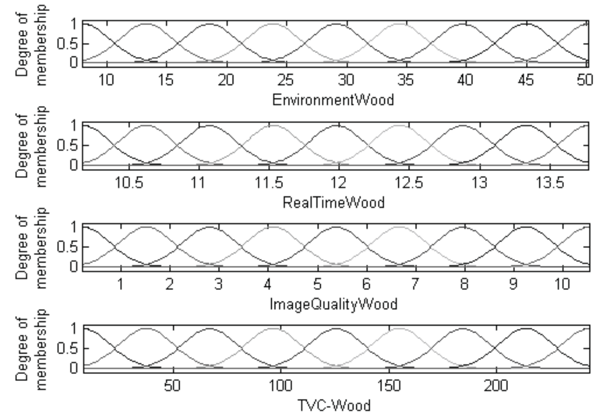

Figure 10: Membership functions with 9 nodes for E, IQ, RT and CVT parameters on Wood images.

Table 2: Vectors of nodes of the membership functions.

	Stainless Steel	*Wood*
Environment **(E)**	[0.0736, 1.086, 2.098, 3.11, 4.122, 5.134, 6.146, 7.158, 8.17]	[8.014, 13.29, 18.57, 23.85, 29.12, 34.4, 39.68, 44.96, 50.23]
Real-Time **(RT)**	[8.359, 8.855, 9.352, 9.848, 10.34, 10.84, 11.34, 11.83, 12.33]	[10.17, 10.62, 11.07, 11.53, 11.98, 12.43, 12.88, 13.33, 13.78]
Image Quality **(IQ)**	[5.07, 8.841, 12.61, 16.38, 20.16, 23.93, 27.7, 31.47, 35.24]	[0.2268, 1.515, 2.803, 4.092, 5.38, 6.668, 7.956, 9.244, 10.53]
Computer Vision Techniques **(CVT)**	[919, 1175, 1431, 1687, 1944, 2200, 2456, 2712, 2968]	[8, 37.38, 66.75, 96.13, 125.5, 154.9, 184.3, 213.6, 243]

6 Mining associations between environment, real-time, image quality and computer vision techniques parameters: A case study

The proposed method is based on F-transform to search dependence between the CVT segmentation technique and the E, IQ, RT parameters. These associations allow to determine the priority of the parameters E, IQ, RT for configuring a visual surface inspection system.
Following the applications of F-transform to data analysis [2], we look for dependences among some attributes having a general expression of the type: $X_z = H(X_1,...,X_k)$, where X_z is the dependent attribute, such as the CVT segmentation technique and $X_1,\ldots,X_k$ are the independent attributes as E, IQ, RT parameters. The evaluation of these attributes is carried out on a set of 16 images (objects $\{o_1,\ldots,o_j,\ldots,o_{16}\}$) for Stainless Steel inspection and 14 images (objects $\{o_1,\ldots,o_j,\ldots,o_{14}\}$) for Wood inspection.
This first approach selects a computer vision technique for image segmentation, such as the Mean-Shift algorithm and afterwards, the F-transform is used, as well as the "*degree of support*" (r) and "*confidence*" (γ) parameters [2], for mining associations in the data, finding hypothesis of potential dependences among the selected segmentation technique and the E, RT, IQ parameters. The *degree of support* (r) is defined by (1):

$$r = \frac{|\{o_j \mid Fn[l_1...l_k](o_j) > 0\}|}{m} \tag{1}$$

Where m is the number of objects, Fn $[l_1\ldots l_k](o_j)$ is the membership function of an induced fuzzy set on the set of objects $\{o_1,...,o_m\}$ and | · | denotes a number of elements of the given set.
The *degree of confidence* (γ) using the F-transform and inverse F-transform is formulated in (2):

$$\gamma = \sqrt{\frac{\sum_{j=1}^{m} (f_F(o_j) - F_{l_1...l_k})^2 \cdot Fn[l_1...l_k](o_j)}{\sum_{j=1}^{m} (f_{jz} - F_{l_1...l_k})^2 \cdot Fn[l_1...l_k](o_j)}} \tag{2}$$

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Where, $f_F(o_j)$ is an auxiliary function on the set of objects $\{o_1,...,o_m\}$ induced by the inverse F-transform with components $F_{l_1...l_k}$ of F-transform, and f_{jz} is the value of the dependent attribute X_z measured on the object o_j.

Finally, each association is supported by the mean of the "*degrees of support*" (r_{mean}) and "*confidence*" (γ_{mean}) parameters, as each r and γ corresponding to the *k*-tuple of fuzzy sets $\langle Fn[l_1],\cdots,Fn[l_k]\rangle$ is analysed, therefore the mean value represents a meaningful value of r and γ.

The results are presented under the format (3):

$$(X_1 \ is \ \langle Fn[l_1],\cdots,Fn[l_k]\rangle) \underset{mean\ r,\ \gamma}{\overset{F}{\sim}} X_z(segmentation) \quad (3)$$

Then applying the F-transform, three associations for Stainless Steel and Wood are obtained, using the segmentation algorithm (Mean-Shift):

$$(E_{\substack{Stainless\\Steel}} \ is \ \langle Fn[l_1],\cdots,Fn[l_k]\rangle) \underset{\substack{mean\\ r=0.3194\\ \gamma=0.00021982}}{\overset{F}{\sim}} CVT_{\substack{Stainless\\Steel}}(Mshift)$$

$$(RT_{\substack{Stainless\\Steel}} \ is \ \langle Fn[l_1],\cdots,Fn[l_k]\rangle) \underset{\substack{mean\\ r=0.3889\\ \gamma=0.00040048}}{\overset{F}{\sim}} CVT_{\substack{Stainless\\Steel}}(Mshift)$$

$$(IQ_{\substack{Stainless\\Steel}} \ is \ \langle Fn[l_1],\cdots,Fn[l_k]\rangle) \underset{\substack{mean\\ r=0.3750\\ \gamma=0.0015}}{\overset{F}{\sim}} CVT_{\substack{Stainless\\Steel}}(Mshift)$$

$$(E_{Wood} \ is \ \langle Fn[l_1],\cdots,Fn[l_k]\rangle) \underset{\substack{mean\\ r=0.3968\\ \gamma=0.0547}}{\overset{F}{\sim}} CVT_{Wood}(Mshift)$$

$$(RT_{Wood} \ is \ \langle Fn[l_1],\cdots,Fn[l_k]\rangle) \underset{\substack{mean\\ r=0.4048\\ \gamma=0.0084}}{\overset{F}{\sim}} CVT_{Wood}(Mshift)$$

$$(IQ_{Wood} \ is \ \langle Fn[l_1],\cdots,Fn[l_k]\rangle) \underset{\substack{mean\\ r=0.3810\\ \gamma=0.0142}}{\overset{F}{\sim}} CVT_{Wood}(Mshift)$$

The linguistic approach of these associations for configuring a visual surface inspection system can be formulated as:

Stainless Steel:
"IF $CVT_{StainlessSteel}$ is Mean-Shift THEN ConfigurationPriority is IQ"
with *degree of support* r=0.3750 and *confidence* γ=0.0015.

The three Stainless Steel associations, highlight the fact that Mean-Shift technique has a stronger influence on image quality than do the others parameters, so the priority of the Stainless Steel configuration process is the image quality parameters. This association is quite obvious as a consequence of the influence of small defects and huge number of regions, Figure 8, detected by the Mean-Shift algorithm and the high frequency of the images.

Wood:
"IF CVT_{Wood} is Mean-Shift THEN ConfigurationPriority is E"
with the *degree of support* r= 0.3968 and *confidence* γ= 0.0547

The three Wood associations points that Mean-Shift has a larger influence on environment than the others parameters, so the priority of the Wood configuration process is the environment parameters. This association is also obvious due to the influence of huge defects and small number of regions, Figure 8, detected by the Mean-Shift algorithm and the low frequency of the images.

7 Conclusions

This work proposes a first approach to derive associations among environment, real-time, image quality and computer vision techniques, based on the F-transform and inverse F-transform.
This is the first step to tune the parameters of a visual inspection system to accomplish a specific surface inspection task, either on Stainless steel or Wood.
The mean of r and γ, is used to summarize the results instead of using individual r and γ values. The derived associations are quite obvious and suggest hypothesis that correspond to expert knowledge.
Future work will be performed on applications that use the linguistic form of the observed associations from numerical data as the configuration task for surface inspection that requires such linguistic knowledge.

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