Artificial vision based inspection of marbled fabric

ROCCO FURFERI, LAPO GOVERNI, MATTEO PALAI, YARY VOLPE
Department of Mechanics and Industrial Technologies
Università degli Studi di Firenze
Via Santa Marta, 3 - Firenze
ITALY
matteo.palai@unifi.it   http://www2.dmti.unifi.it

Abstract: - Marbling effect on fabrics is a relevant aesthetic feature, increasing its diffusion specially in the field of textiles for technical applications. The fabric aesthetic anisotropy, characterizing the marbling effect, has a strong impact on the perceived quality: a high-quality marbled fabric to be used in automotive textiles, for instance, is characterized by a tiny quantity of veins and spotted areas. A large amount of "veins" and/or discolored areas may induce a customer to consider the fabric as "defected". In common practice, the identification of whether the fabric is defective or not is performed by human experts by means of visual inspection. As a consequence, fabric inspection is performed in a qualitative and unreliable way; thereby the definition of a method for the automatic and objective inspection is advisable. On the basis of the state of the art, the present work aims to describe a computer-based approach for the automated inspection of marbling effect on fabrics, resulting in the classification of fabrics into three quality classes. The devised apparatus is composed by a machine vision system provided with an image processing-based software. The processing software is able to determine the anisotropy of a fabric using edge segmentation and image entropy and defining a "fabric entropy curve". The proposed method proves to be able to classify the fabrics into the correct quality class in 90% of the cases, with respect to the selection criteria provided by human operators.

Key-Words: - Artificial vision, fabric inspection, image entropy, edge detection, marbling effect.

1 Introduction

A marbled fabric is characterized by a spotted, speckled or veined appearance usually created by "calendering", a finishing process used on cloths where fabric is folded in half and passed under rollers at high temperatures and pressures. In detail, the fabric is folded lengthwise with the front side (or face) inside and stitched together along the edges; the fabric is then run through rollers that polish the surface and make the fabric smoother and more lustrous. The result of the process is a fabric whose surface presents a series of veins, consisting of adjacent fibres with a preferred direction, and by some discolored areas. The size and the orientation of the stripes, so as the amount of discolored regions, characterizes the fabric anisotropy which has a strong impact on the perceived quality. For instance a first-rate marbled fabric used for automotive textiles requires a "small" quantity of veins and discolored areas; as a consequence a "large" amount of veins and/or discolored areas may induce a customer to consider the fabric as "defected". The identification of whether (and how much) the fabric is defective or not is a very hard task, mainly performed by specifically trained human experts (inspectors) by means of a qualitative visual inspection. However, the reliability of human inspection is limited by ensuing fatigue and inattentiveness [1]. Therefore, only about 70-80% of marbled fabrics are correctly classified by a single inspector. In the last years great efforts have been made to realize real-time fabric defect detection systems to be used during the finishing phase by means of non-intrusive systems like machine vision-based ones [2-4]. Several authors have considered defect detection on textiles. Kang *et al.* [5], analyzed fabric samples from the images obtained by transmission and reflection of light to determine its interlacing pattern. Islam *et al*. [6] and some of the authors of the present paper [7] developed automated textile defect recognition systems using computer vision and Artificial Neural Networks (ANNs). Wavelets, also, have been applied to fabric analysis by Jasper *et al.* [8]. Spectrophotometry is commonly applied as a method for evaluating colour defects on fabrics [9]. Unfortunately, no research has been addressed to the defect detection on marbled fabrics. Moreover, the use of spectrophotometers for determining the discolored areas is not suitable, since spectral response may be affected by some technological limitations originated by the small acquisition area, as will be demonstrated in Section 2.3. Therefore, an automated detection of marbling effect on fabrics is needed. Some of the advantages of such a tool are: it is a more reliable process when compared with human inspection; it is a non-contact inspection, thus avoiding problems that arise as a result of using contact inspection devices; it can result in lower labor costs and faster inspection [10]. The main objective of the present work is to provide a computer-based image processing tool for a non intrusive inspection of marbled fabric with the aim of assessing its "marbling condition" and providing an automatic classification into three quality classes. Such a tool, composed by an appositely devised machine vision system, is capable of extracting a number of numerical parameters characterizing the fabric veins and discolored areas. Such parameters are, then, used for fabric assessment which is finally compared to the one provided by fabric inspectors.

2 Method

With the aim of devising a system for real-time marbled fabrics inspection able to perform a qualitative classification, the following tasks have been carried out:
- Machine vision architecture development.
- Data collection.
- Image acquisition and parameter extraction.
- Classification parameter extraction.

2.1 Machine Vision architecture development

The morphology of marbled fabrics is, usually, inspected by human experts disposing the fabric under a diffuse grazing light obtained by means of a D65 standard illuminant (Fig. 1).

Fig. 1: a portion of a marbled fabric for automotive industry. Some discolored areas are visible in the image.

As a consequence, in order to implement an automatic inspection system able to match the inspectors' classification, a sealed cabin hosting a plane where the fabric samples are displaced and a high resolution (2560 x 1920) uEye UI-1480 camera (provided with a ½ inches CMOS sensor and with a frame rate of 6 fps) has been realized. The camera is equipped with a 8.5 mm fixed focal length lens. In order to emphasize the structure of the fabric surface, a CIE Standard Illuminant D65 lamp (with a temperature of 6504 K, roughly corresponding to midday sun in Western / Northern Europe) has been chosen and arranged into the cabin with the aim of providing a grazing diffusive light. The illumination system has been chosen in order to perform a repeatable and controlled acquisition, able to preserve the colors of each fabric to be classified. The distance between the camera and the fabric is about 500 mm. Accordingly, the area of any acquired image is about 500x600 mm^2. Using the maximum allowable resolution of the camera, the spatial resolution results in 0.098 mm/pixel. Since the average diameter of a vein is 0.15 mm (depending on the fabric manufacturing process and composition), the selected resolution is sufficient for discriminating the defects possibly present on the fabric surface.
The camera is connected to a PC by means of an USB 2.0 port and the images are managed by means of a graphical user interface (GUI) appositely developed in Matlab® environment.

2.2 Data Collection

In order to devise the computer-based image processing inspection tool, a number of different typologies of marbled fabrics for automotive industry, provided by a leading company operating in Prato (Italy), has been used in this work. In detail, 4 colour families (gray, brown, black and violet) each one composed by a number of fabric samples (see Table 1) have been inspected by a panel of 5 company experts (by visual inspection). Fabrics have been then classified into classes according to the following criteria:
- the fabric is classified in "Quality A (QA)" if, at least, 4 of the 5 experts classified it as "non-defected"; fabric in QA is assumed to be accepted as non-defected by all the customers.
- the fabric is classified in "Quality B (QB)" if 3 of the 5 experts classified it as "non-defected"; fabric in QB is assumed to be accepted as non-defected by most customers.
- the fabric is classified in "Quality C (QC)" if at least 3 of the 5 experts classified it as "defected"; fabric in QC is assumed not to be acceptable by any customer.

Table 1. Quality based classification of fabrics.

Colour family	Number of inspected fabrics	Ids.	Number of fabrics in QA	Number of fabrics in QB	Number of fabrics in QC
Gray	21	1 - 21	14	5	2
Brown	24	22 - 45	15	6	3
Black	27	46 - 72	16	6	4
Violet	18	73 - 90	10	4	4

According to the described fabric classification, the inspection tool is expected to perform a reliable classification into three classes: QA, QB and QC.
For each colour family a reference sample is selected. Classification, thereby, refers to a comparison between the other fabrics with the reference ones. In particular fabric with Id.1, Id.22, Id.46 and Id.73 have been used as references.

2.3 Image Acquisition and parameter extraction

In Fig. 2 the comparison between fabrics Id.1 and Id.5 of the same family (gray) is depicted. The two fabrics have been classified, respectively, in QA and QC. In order to demonstrate that colorimetric techniques are not suitable for discriminating the quality of the marbled fabric, a spectrophotometric acquisition has been performed by measuring the two fabrics spectral reflectances with a Minolta CM 700D spectrophotometer, and evaluating the CIELAB colour distance (DE_{CIELAB}) according to the following relationship:

$$DE_{CIELAB} = \sqrt{(L_{Id.1}*-L_{Id.2}*)^2 + (a_{Id.1}*-a_{Id.2}*)^2 + (b_{Id.1}*-b_{Id.2}*)^2} \quad (1)$$

In Fig. 2, small colour differences between the representative images of the two classes may be visually noticed. This visual deduction is confirmed by the evaluated CIELAB colour distance between the two fabrics (see Table 2) that is less than 0.75. Furthermore, for each of the analyzed families, the maximum CIELAB colour distance between a QA and a QC fabric is less than to 1.2.

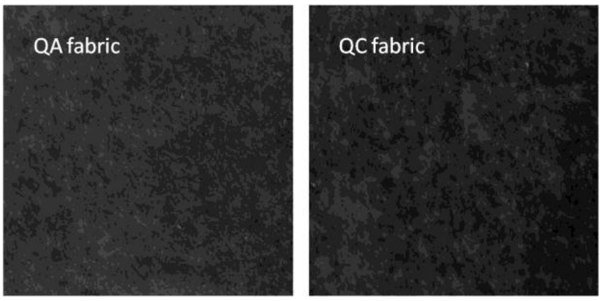

Fig. 2: comparison between a QA and a QC marbled fabric.

Table 2. Colour distances between two fabrics classified in different classes.

Fabric	R	G	B	L*	a*	b*	DE LAB	DE RGB
QA	64.23	43.82	37.94	20.13	8.63	7.30	0.72	0.74
QC	64.54	43.21	38.21	20.01	9.23	6.93		

Since textile companies, and colorists, consider that two fabrics are of the same colour when CIELAB colour distance is in the range 0.6 – 0.8 [11], colorimetric measurement is not helpful for inspecting the quality of marbled fabrics: the effect of marbling implies small colour changes that may be confused with the actual colour changes of the fabric or, in the worst case, may be missed by a colour-based control. For instance, as depicted in the example provided in Table 2, the difference in colour between two fabrics may be considered negligible, while the manual classification of the fabrics leads to two different quality classes. Since a spectrophotometric method is not capable of discriminating the marbling effect of fabrics, a completely new image processing based method has been implemented. Once fabric images are acquired by means of the system previously defined, the subsequent processing phase consists of the following tasks:

- Iterative Canny edge detection.
- Image entropy evaluation (for each iteration).
- "Fabric Entropy Curve" analysis.

2.3.1 Iterative Canny edge detection

As widely known [12] the canny method finds edges by looking for local maxima of the gradient of an image. The gradient is evaluated using the derivative of a Gaussian filter (with a proper value of sigma). The method uses two thresholds to detect strong and weak edges, and includes the weak edges in the output only if they are connected to strong edges. The result of edge detection is a binary image where the edges are represented by pixel with value 1 and the background by pixel with value 0. Edge detection strongly depends on the sigma value of the Gaussian filter and on the two threshold values (defining a vector T). In the present work, in order to reduce the image background noise, the value of sigma has been set to 5. Since canny filter has to be applied to images with different colors, with the aim of extracting differently sized veins and discolored areas, the threshold values cannot be set independently from the fabric typology. Accordingly for each acquired image of the fabric the canny method is applied, iteratively, varying the threshold values i.e. defining a threshold vector $T = [t_{\min}, t_{\max}]$ whose values vary into a range defined according to the following procedure:

i) a first-attempt threshold vector T_0 is defined as follows: $T_0 = [0.3t_{0\max}, t_{0\max}]$ where $t_{0\max}$ is evaluated according to Otzu's method [13] on the reference fabric (for each colour family a $t_{0\max}$ value is evaluated).

ii) the minimum value T_{min} of the threshold vector is set equal to 0.1 T_0, so that $T_{min} = [0.03\ t_{0\max}, 0.1\ t_{0\max}]$.

iii) the maximum value T_{max} of the threshold vector is set equal to $2T_0$, so that $T_{max} = [0.75\ t_{0\max}, 2\ t_{0\max}]$.

iv) the step for iteration is set equal to $(T_{max} - T_{min})/20$.

As may be noticed the only parameter $t_{0\max}$ needs to be evaluated prior to the iterative edge detection.

In Fig. 3 the results of Canny edge detection (binary image) obtained using T_{min} on the Id.1 (QA) and Id.5 (QC) fabrics are superimposed on the images of Fig.2.

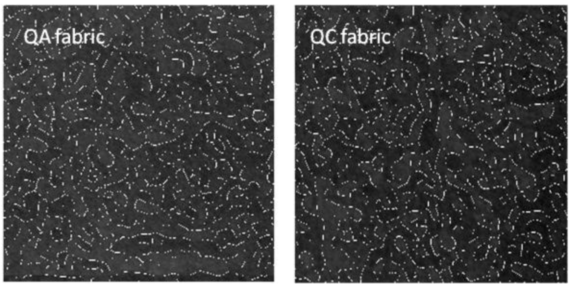

Fig. 3: superimposition of the canny edged image and the original one for a QA and a QC marbled fabric.

Since the initial threshold value is low (10% with respect to the Otzu's threshold) in both cases a large number of edges have been detected by the canny method due to the fabric morphology (texture, filling and warp yarn). As threshold increases, the Canny method detects a decreasing number of edges in both images; however the number of edges detected in QC fabric tends to be larger than the one detected in QA. This effect is demonstrated in Fig. 4 where the superimposition of edges on the original images is shown for increasing threshold values.

The result of the iterative Canny-based edge detection is to obtain, for each fabric, a subset of 20 binary images each one composed by a number of edges (value 1) on a black background (value 0).

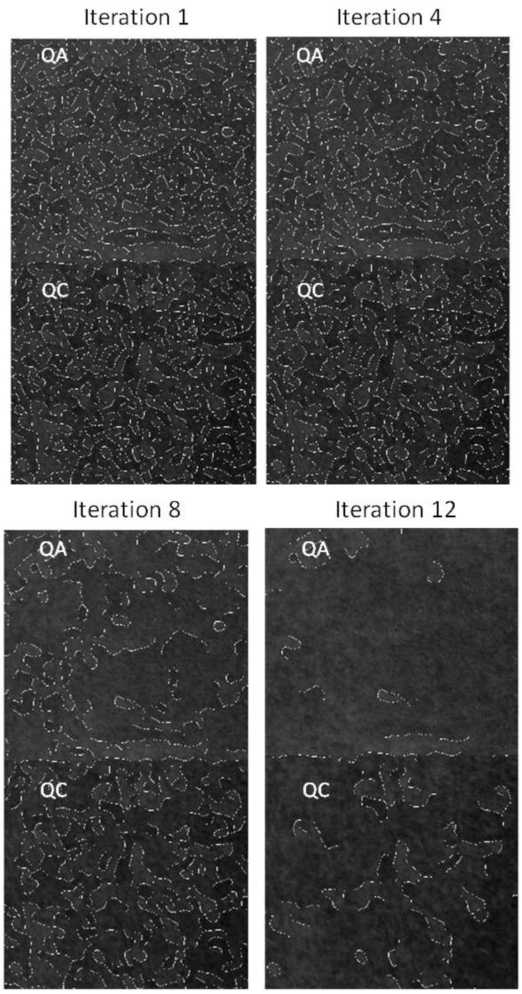

Fig. 4: edges superimposed on the original images for increasing iteration number (threshold value).

2.3.2 Image entropy evaluation

As already stated, the marbled effect heavily depends on the anisotropy of the fabric, i.e. by the number and the size of veins and discolored areas. By means of the iterative procedure described above, veins and spots have been detected as image edges. In order to identify image texturization a widely recognized method [14] consists of evaluating the image entropy. Since the outlines identified by edge extraction can be considered as a kind of image texturization, it appeared to be feasible to measure fabric aesthetic anisotropy by means of image entropy.

Let:

- I_j be the image of the fabric with Id. = *j*.
- C_{kj} be the kth thresholded (binary) image, with k = 1…20, obtained by applying iterative Canny method to image I_j.
- p_{ik} be the ith value of the histogram of image C_{kj}.

Image entropy S_{kj} for image C_{kj} is defined as follows:

$$S_{kj} = -\sum_{i=1}^{255} p_{ik} \log_2(p_{ik}) \qquad (2)$$

By definition, image entropy tends to zero if the image is uniform (flat) while it reaches its maximum value for highly disordered images. Accordingly, a high value of S_{kj} is expected in the first iteration while, as the threshold value increases, the entropy value decrease. The set of 20 image entropy values defines, for each image I_j, a 20-element vector S_j called "Fabric Entropy Curve (FEC)" given by:

$$S_j = [S_{1j}, S_{2j}, \ldots, S_{20j}] \qquad (3)$$

Referring to the example provided above (Id.1 and Id5), it is possible to plot two FECs (curves S_1 and S_5) as depicted in Fig. 5.

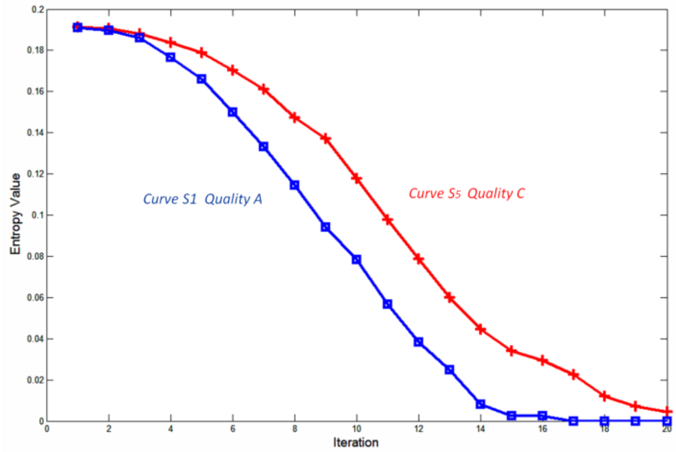

Fig. 5. Curves S_1 (QA) and S_5 (QC)

2.3.3 Fabric Entropy Curve analysis

Curve S_1 of Fig. 5 tends to zero more rapidly with respect to curve S_5. The same occurs if fabrics in QA and in QB are compared; in Fig. 6 the comparison between the FECs curves of fabric Id.2 and fabric Id.12, classified respectively in QA and in QB, are depicted.

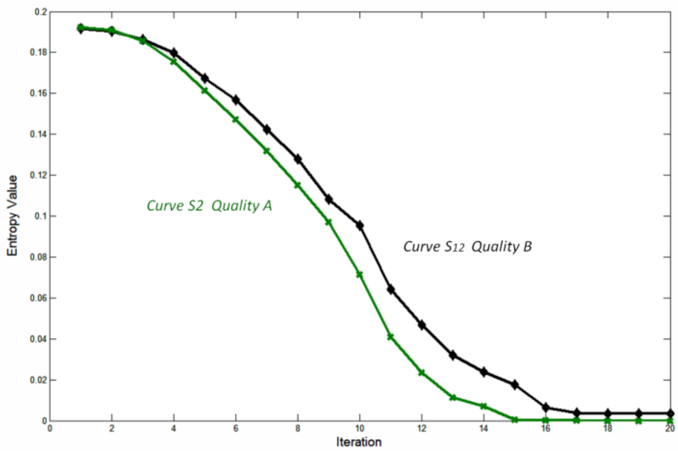

Fig. 6. Curves S_2 (QA) and S_{12} (QB).

Comparison between two fabrics of the same family and class (for instance fabrics with Id.46 and Id.47 belonging to the black family and both in QA) shows that the FECs are almost overlapped (Fig. 7).

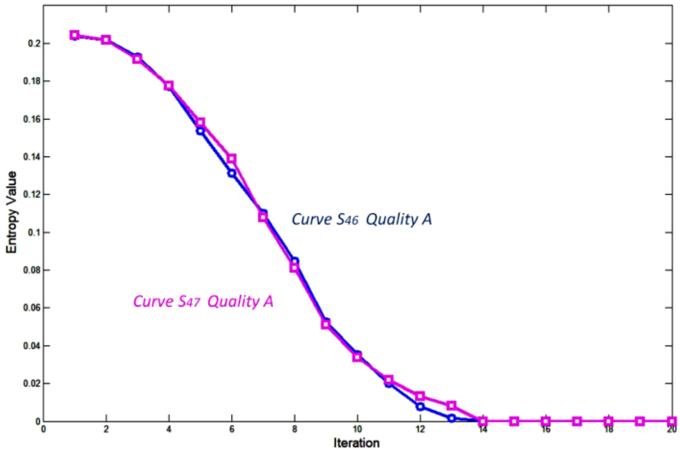

Fig. 7. Curves S_{46} (QA) and S_{47} (QA)

2.4 Classification parameter extraction

As mentioned in section 2.2., 4 fabrics are used as reference ones for the classification method. This allows to compare any FEC with its reference (e.g. curves from S_2 to S_{21} may be compared with curve S_1) in order to assess whether a fabric is in QA, QB or QC. Such a comparison is performed by evaluating, for each FEC S_j, the approximate area A delimited by S_j and S_{ref}:

$$A = \left| \sum_{k=1}^{20} S_{kj} - \sum_{k=1}^{20} S_{kref} \right| \qquad (4)$$

Generally speaking, A value tends to zero if the fabric is in QA class, while it increases as the fabric quality decrease (from B to C). The main problem is to determine which area value defines the boundaries between fabric classes. This important issue is faced up in the next session.

3 Inspection Tool

In Table 3 the human expert judgments and the value of A for a number of fabrics are listed together with the results of automated classification (which will be defined later).
Analyzing Table 3 (and more in general the whole dataset) it can be observed that the fabrics classified by the human experts in QA generally produce a value of A lower than 0.40, while to the ones classified in QC correspond a value of A greater than 0.50. Consequently, the range [0.40 – 0.50] has been assumed to define the QB boundaries to be used during the classification process.
In other words:

- the fabric is classified in QA if $A < 0.4$;
- the fabric is classified in QB if $0.4 \le A \le 0.5$;
- the fabric is classified in QC if $A > 0.5$.

Table 3. Comparison between experts' and automated classification (bold characters denote discrepancy between human and automated classifications) .

Family	Fabric Id.	Quality (human experts)	A	Automated Classification
Gray	1	QA	0	QA
	2	QA	0.18	QA
	3	QA	0.23	QA
	5	QC	0.96	QC
	15	QC	1.04	QC
	12	QB	0.43	QB
	18	QB	0.45	QB
	21	**QB**	**0.38**	**QA**
Brown	22	QA	0	QA
	23	QA	0.09	QA
	24	QA	0.29	QA
	33	QC	0.97	QC
	37	QC	0.57	QC
	40	QC	0.83	QC
	26	QB	0.47	QB
	27	QB	0.49	QB
Black	46	QA	0	QA
	47	QA	0.33	QA
	50	QA	0.29	QA
	48	QC	1.21	QC
	65	QC	0.99	QC
	70	QC	1.39	QC
	55	**QB**	**0.51**	**QC**
	58	QB	0.48	QB
Violet	73	QA	0	QA
	75	QA	0.27	QA
	78	QA	0.34	QA
	81	QC	0.87	QC
	82	QC	0.72	QC
	74	QC	1.05	QC
	85	QB	0.50	QB
	87	QB	0.47	QB
	90	**QB**	**0.39**	**QA**

The fabric sample to be inspected is displaced inside the sealed cabin hosting the machine-vision system which acquires and transfer and high resolution image to a PC. This task is performed, averagely, in 0.4 s. An appositely built algorithm applies the iterative canny method and the FEC is evaluated. This is the most time consuming phase (a single iteration lasts about 0.3 s) and involves a total time of 6 – 6.5 seconds. Since the FECs of the reference fabrics are preliminarily computed and stored in the PC, the algorithm instantly evaluates the A value and performs the fabric classification.
The results of automatic classification, referred to 33 fabrics, are listed in the last column of Table 2. As highlighted in this Table, in few cases the automatic classification leads to a class different from the one assigned by human experts, since the area values are very close to the class boundaries.
In order to measure the reliability of the proposed system, a performance index η is defined as follows:

$$\eta = \frac{N_F}{N} \qquad (5)$$

Where N_F is the total number of the fabric samples correctly classified (i.e. the experts and the system classify the sample in the same quality class) and N is the total number of fabric samples. Referring to Table 3 the system performance index is equal to 0.91; however, it can be observed that, even in case of misclassification, the fabric sample is placed in a class which is contiguous to the correct one. With reference to the whole dataset the index η is equal to 0.90. This means that the average classification error is equal to 10%. Such a result proves that the proposed automatic inspection method can be effectively employed for performing a reliable classification of marbled fabrics. It is also important to remark that experts' classification is based on a subjective defect perception that changes over time, thus potentially increasing the number of classification errors. For this reason, the results provided in Table 3 can be considered to be excellent ones since it is probable, even if unlikable, that the experts themselves, sometimes, classify the fabrics into a quality class that is, actually, considerably different from the customer perception.

In order to assess the robustness of the developed tool, each fabric has been processed several times acquiring images from different regions. The maximum value for the area *A* between two different acquisitions of the same fabric proved to be less than 0.03. As a consequence the classification may be considered satisfactorily robust against the variability in selecting the fabric region which is used for classification.

4 Conclusion

In this work a method for carrying out a non intrusive inspection of marbled fabrics has been described. The proposed method proves to be reliable and, in particular, is able to classify the fabrics into the correct quality class in 90% of the cases with respect to the selection criteria provided by human experts. Moreover, it provides robust results: several acquisitions performed in different regions of the same fabric substantially lead to the same classification result. The acquisition and classification process is completely automatic and the only required operation is to place the fabric to be classified into the sealed cabin hosting the MV system. Future work will be addressed to the identification, the extraction and the processing of additional parameters characterizing veins and decolorized regions (possibly by means, for instance, of Hough transform and colour clustering) in order to increase the system classification performance.

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