Neural Network based classification of car seat fabrics

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***Abstract* —**Car seat fabrics are uniquely fashioned textiles. A number of them is branded by a sponged-like appearance, characterized by spots and slightly discoloured areas. Their surface anisotropy is considered to be a relevant aesthetic feature since it has a strong impact on customer perceived quality. A first-rate car seat fabric requires a "small" quantity of spots and discoloured areas while fabrics characterized either by a large number or by a low number of spots, are considered to be of lower quality.

Therefore, car seat fabric quality grading is a relevant issue to be dealt with downstream to the production line.

Nowadays, sponged-like fabric grading is performed by human experts by means of manual inspection and classification; though this manual classification proves to be effective in fabric grading, the process is subjective and its results may vary depending on the operator skills. Accordingly, the definition of a method for the automatic and objective grading of sponged-like fabrics is necessary.

The present work aims to provide a computer-based tool capable of classifying sponged-like fabrics, as closely as possible to classifications performed by skilled operators.

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 discoloured areas. Such parameters are, then, used for training an Artificial Neural Network (ANN) with the aim of classifying the fabrics in terms of quality. Finally, a comparison between the ANN-based classification and the one provided by fabric inspectors is performed. The proposed method, tested on a validation set composed by 65 sponged-like fabrics, proves to be able to classify the fabrics into the correct quality class in 93.8% of the cases, with respect to the selection provided by human operators.

***Keywords*—** Car seat fabrics, Artificial Neural Networks, Machine Vision, Grading.

I. Introduction

Some typologies of car seat fabrics whose diffusion has been growing for the last 5 years in the automotive industry, are characterized by sponged-like appearance (Fig. 1) which can be obtained by means of different manufacturing processes. In most the cases the sponged-like effect is due to adjacent fibres with a preferred direction, and to some "discoloured" areas. The size and the orientation of spots, so as the amount of discoloured regions, characterizes the fabric anisotropy which has a strong impact on the perceived quality. For instance a first-grade sponged-like fabric requires a "small" quantity of spots and discoloured areas. When fabrics are characterized either by a large number or by a low number of spots, they are considered to be of lower quality.

Though fabric quality grading is an important issue to be dealt with, it is usually carried out by skilled operators performing a manual inspection.

Fig. 1 Car seats coated with first-grade sponged-like fabrics.

Though manual inspection usually proves to be effective for correct grading, the process is inevitably very subjective and its result, thereby, varies from an operator to the other. Unfortunately, skilled operators are seldom capable of providing a description of quantifiable parameters which could be taken into account in order to make the process more objective [1].

According to the general trend of providing automatic tools for quality classification and defect detection on fabrics, a number of methods, often based on artificial vision, can be found in the scientific literature [2-8].

Several authors have considered defect detection on textiles. Kang *et al.* [9], analysed fabric samples from the images obtained by transmission and reflection of light to determine its interlacing pattern. Islam *et al*. [10] 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.* [11]. Spectrophotometry is commonly applied as a method for evaluating colour defects on fabrics [12, 13].

None of the presented approaches, however, have been recognized to be effective in automatic grading of sponged-like fabrics. Moreover, the use of spectrophotometers for determining the discoloured areas is not suitable, since spectral response may be affected by some technological limitations originated by the small acquisition area. A method for automatically inspecting marbled fabrics has been proposed by the authors in a prior publication [14]; it allows the definition of a procedure based on quantitative parameters for classifying marbled fabrics into a number of classes. The approach is based on the definition of a threshold value which, under some circumstances (i.e. for particularly dark or saturated colours) may lead the automated system to misclassifications with respect to experts' judgment.

Moreover, the system described in [14], assumes a preliminary colour classification is performed in order to use the appropriate parameters.

The main objective of the present work is to provide a computer-based tool capable of classifying marbled, spotted and sponged-like fabrics, as closely as possible to classifications performed by skilled operators, thereby generalizing the usage and improving the performance of the above mentioned method.

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 discoloured areas. Such parameters are, then, used for training an Artificial Neural Network (ANN) with the aim of classifying, in terms of quality, the fabrics. Finally, a comparison between the ANN-based classification and the one provided by fabric inspectors is performed.

With the aim of devising a system for real-time fabrics inspection able to perform a qualitative classification, the following tasks have been carried out:

- Fabric collection and manual classification
- Machine vision architecture and image acquisition
- Parameters extraction.
- Neural Network training.
- Neural Network validation.

II. Fabric collection and manual classification

In order to devise the automatic inspection tool, a number of different typologies of spotted and sponged-like fabrics for automotive industry, provided by a leading company operating in Italy, has been used in this work. In detail, 8 colour families (gray, brown, black, violet, cyan, green, yellow and red) each one composed by a number of fabric samples (see Table 1) have been inspected by a company expert (by visual inspection).

Fabrics have been placed on a commercial inspection workbench illuminated with a grazing D65 CIE standard light (with a temperature of 6504 K, roughly corresponding to midday sun in Western / Northern Europe). The expert examined, separately, the fabrics and classified them into a quality class (5 classes are available) by visually comparing the new fabrics with a set of 5 reference ones. The expert can also classify the new fabric as belonging to multiple classes (e.g. class 3-4)

Tab. 1 – Colour families and number of inspected fabrics.

Colour family	**Number of inspected fabrics**	**Ids.**
Gray	21	1 - 21
Brown	24	22 - 45
Black	27	46 - 72
Violet	18	73 - 90
Cyan	16	91 – 106
Green	20	107 – 127
Yellow	18	128 – 146
Red	23	147 - 170

According to the described fabric classification, the inspection tool is expected to perform a grading as closely resembling as possible the one provided by the human operator.

In the proposed approach, as explained in the following sections, the results of the manual classification are used to both training and validating the ANN-based tool described in section V.

III. Machine Vision architecture and image acquisition

As stated in the previous Section, the morphology of spotted fabrics is inspected by human experts disposing the fabric under a diffuse grazing light obtained by means of a D65 standard illuminant. Accordingly, in order to implement an automatic inspection system able to match the experts' classification, a system similar to the one described in [14] has been used. Such a system comprises a sealed cabin hosting a plane (size 600 mm x 600 mm) where the fabric samples are displaced and a high resolution (2560 x 1920) uEye UI-1480 colour camera (Fig. 2). The camera is equipped with a 8.5 mm fixed focal length lens. In order to emphasize the structure of the fabric surface, the same CIE Standard Illuminant D65 lamp has been chosen and arranged into the cabin with the aim of providing a grazing diffusive light. The illumination system has been selected in order to perform a repeatable and controlled acquisition, able to preserve the colours of each fabric to be classified. The distance between the camera and the fabric was set to about 500 mm. Accordingly, the area of any acquired image results to be about 500x600 mm^2. Such an extension has been proved to be sufficient in order to provide a robust classification. Using the maximum allowable resolution of the camera, the spatial resolution is equal to 0.098 mm/pixel. Since the minimum characteristic dimension of a spot is 0.5 mm (depending on the fabric manufacturing process and composition), the selected resolution is adequate for discriminating the appearance of the fabric surface.

For each fabric to be inspected, once displaced on the plane inside the sealed cabin, a single digital image is acquired by means of the previously described acquisition system. The result is a colour image I (size 2560 x 1920 x 3) described by three matrixes of R, G and B values respectively.

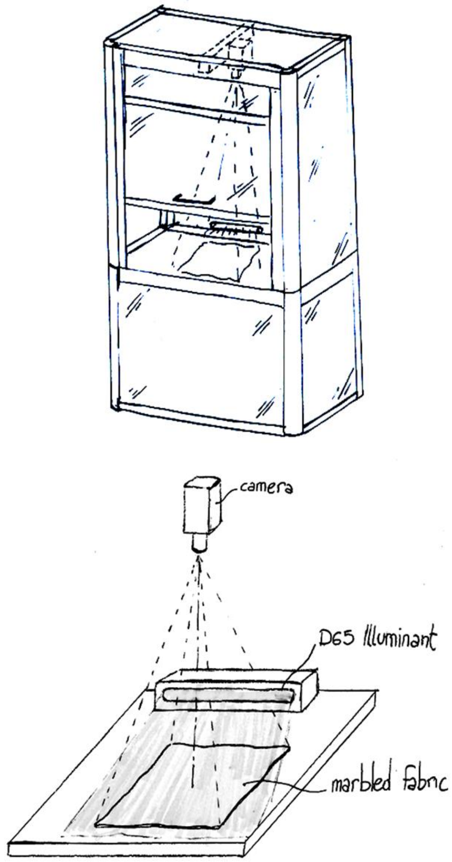

Fig. 2 MV system

In Fig. 3 three examples of images acquired for three spotted fabrics are shown. In order to highlight the sponged-like effect, a mesh plot of the R channel for each of the three images is also depicted in the same figure.

IV. Parameters extraction

With the aim of training a ANN able to correctly classify the fabrics, a series of parameters describing their appearance have been extracted by means of image processing-based algorithms; such data are used as a training, validation and testing set for the ANN. In detail, as described below, three kinds of parameters are extracted: colorimetric data, entropy curve and area subtended to the entropy curve.

A. Colorimetric assessment

Since fabric types are mainly defined by colour (fabrics are usually divided into colour families), this parameter cannot be discarded when trying to perform an automatic grading. As a consequence the first parameter to be considered is colour.

As previously mentioned, for each of the images acquired by means of the MV system, R, G and B values (matrixes) are available. Accordingly, a colorimetric analysis of each image may be performed as follows:

i) for each fabric image the mean values R_{mean}, G_{mean} and B_{mean} of R, G and B are evaluated (they are the mean image pixels value for each of the three channels);

ii) R_{mean}, G_{mean} and B_{mean} for each fabric image undergo a colour space conversion from RGB to CIELAB according to widely known colour conversion equations [15,16].

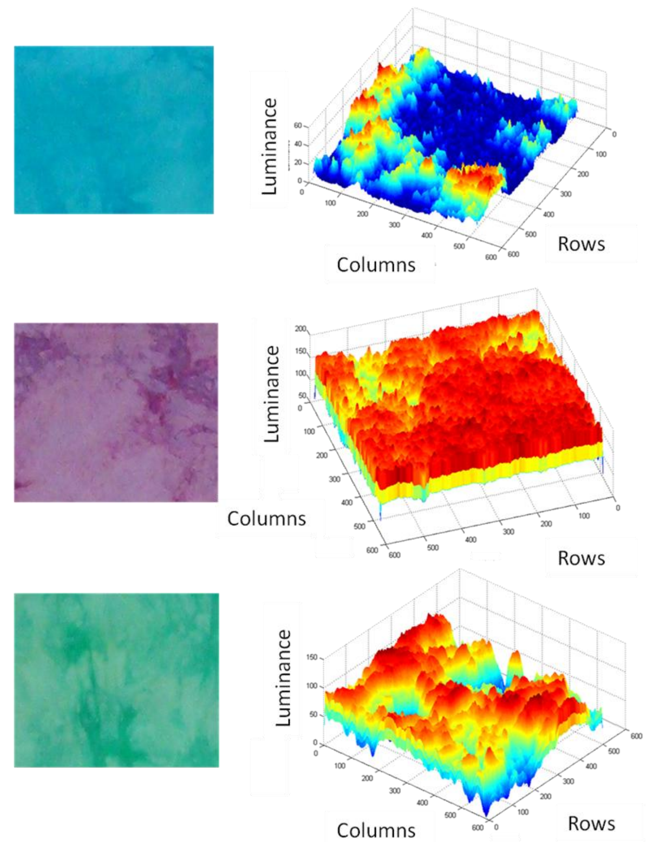

Fig. 3 Three examples of images acquired for three veined fabrics a mesh plot of the R channel for each of the three images is also depicted in the same figure (on the right).

The result is a set of L*, a* and b* values. Among them, the only parameters related to colour are a* and b* since L* component closely matches human perception of lightness [17]. Collecting colour information is extremely relevant, not only in order to identify the colour family of the fabric to be examined, but also for discriminating its appearance. Let us consider, as an instance, to compare two fabrics belonging to the same family but classified in different quality classes. In Fig. 4 the comparison between fabrics Id. 91 and Id.105 (cyan family) is depicted. Small colour differences between the images of the two may be visually perceived. These two fabrics, actually, have been differently graded.

It is possible to evaluate the CIELAB colour distance (DE_{CIELAB}), according to the following relationship:

$$DE_{CIELAB} = \sqrt{\left(L^*_{Id.91} - L^*_{Id.105}\right) + \left(a^*_{Id.91} - a^*_{Id.105}\right) + \left(b^*_{Id.91} - b^*_{Id.105}\right)} \qquad (1)$$

where the values for L*, a* and b* are listed in Tab.2.

Tab. 2 –Colour distances between two fabrics of the same family classified into different classes.

Fabric	R	G	B	L*	a*	b*	DE CIELAB
Id. 91	64.51	158.82	205.31	61.88	-12.63	-32.72	0.81
Id. 105	64.75	157.91	205.53	61.63	-12.04	-33.22	

The visual "deduction" is confirmed by the evaluated CIELAB colour distance between the two fabrics that is about 0.8. Since textile companies and colourists, consider that two fabrics are of the same colour when CIELAB colour distance is lower than 0.6 – 0.8 [18], colorimetric measurement is not helpful, if used as a sole criterion, for inspecting the quality of sponged-like fabrics: the effect of local colour unevenness may be confused with the global colour changes of the fabric or, in the worst case, may be completely 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 grades.

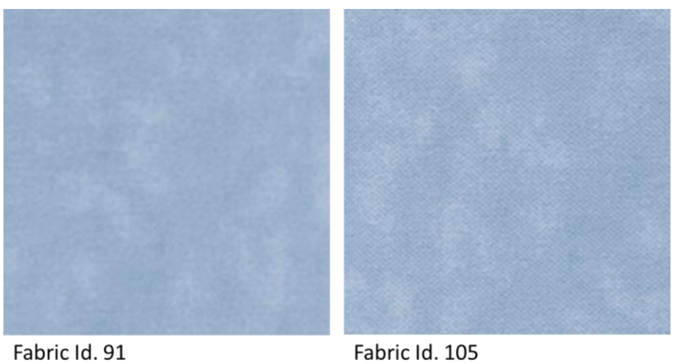

Fig. 4 Differences, in colour, between two differently graded fabrics.

Anyway, some differences in colour exists when quality degree varies. Moreover, colour differences are evident between families; as a consequence the a* and b* values may be used both for automatically discriminating families and as two auxiliary parameters for training the ANN since, as mentioned above, they preserve colour information regardless to image luminance.

B. Entropy curve

Since the spectrophotometric method is not, by itself, capable of discriminating the aspect of a fabric, the image processing based algorithm developed in a previous work has been applied and further developed with the aim of extracting a characteristic curve describing the anisotropy of a fabric surface to be used for training, validating and testing the ANN.

Once fabric images are acquired by means of the modified MV system, this algorithm performs:

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

These steps are basically the same ones described in [14] (with the exception of the necessary conversion of RGB to grayscale images), thereby they are not detailed here. It is relevant to recall, anyway, that the main result of the algorithm is to compute, for a generic image I_j, a 20-element vector S_j called "Fabric Entropy Curve (FEC)" given by:

$$S_j = [S_{1j}, S_{2j}, \dots, S_{20j}] \tag{2}$$

Where:

- $S_{kj} = -\sum_{i=1}^{255} p_{ik} \log_2(p_{ik})$ (3)
- p_{ik} is the ith value of the histogram of image C_{kj}.
- C_{kj} is the kth thresholded (binary) image, with k = 1…20, obtained by applying iterative Canny method to image I_j.

Referring for instance to the example provided above (Id. 91 and Id. 105), it is possible to compare the respective FECs (curves S_{91} and S_{105}) as depicted in Fig. 5.

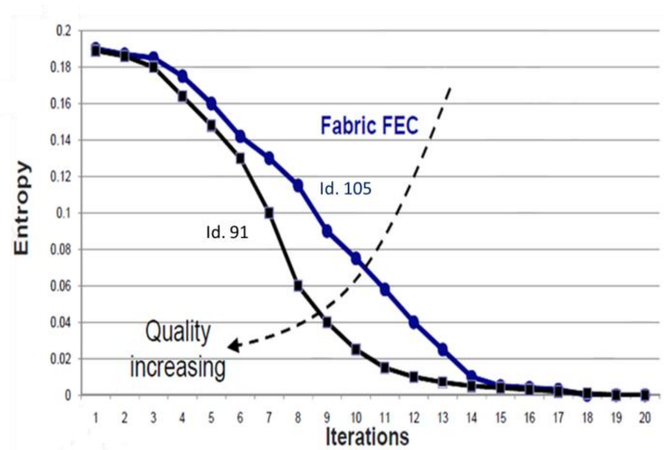

Fig. 5 Fabric Entropy Curves S_{91} and S_{105}.

As may be noticed, curve S_{91} of Fig. 5 tends to zero more rapidly with respect to curve S_{105}. In general it can be experimentally demonstrated that quality increases if the FEC curve tends to zero more rapidly.

C. Entropy Curve Area

The comparison between a FEC with its reference, whose entropy curve is S_{ref}, may be considered a straightforward method for assessing whether a fabric is classified into a quality class assuming a proper threshold value *Tr* can be defined. In detail, by evaluating, for a given FEC S_j, the approximate area A delimited by S_j and S_{ref} and comparing it with *Tr*.

As already mentioned, the use of a threshold may lead to discrepant grading results compared to the ones provided by the skilled operator. As a consequence, for each image I_j a new area parameter A_{FECj}, called "Entropy Curve Area" is defined as the area subtended to a FEC:

$$A_{FEC_j} = \sum_{k=1}^{20} S_{kj} \tag{4}$$

This parameter, together with S_j, a* and b* is used for the development of the ANN.

V. Neural Network training

All the parameters extracted by the image processing-based algorithms, previously described, are used for training a ANN capable of automatically grade the fabrics.

Artificial Neural Networks are known to be suitable for applications in pattern classification field, especially where the limit of classification are not exactly defined. A properly trained ANN is capable of generalizing the information on the basis of the parameters acquired during the training phase.

Once trained, the ANN is expected to be able to properly correlate training data and target ones. Obviously, in the present work, the ANN has to correlate a series of parameters extracted from fabric images with the expert's classification based on their appearance.

Accordingly, for each of the 170 fabrics listed in Tab. 1 it is possible to determine, on the basis of the procedure described above, the following parameters:

- colorimetric values a* and b* (2 parameters);
- FEC curve (20 parameters);
- A_{FEC} (1 parameter).

In other words it is possible to define a database of parameter represented by a matrix $\mathbf{T}$ (size 23 x 170) whose columns $\mathbf{T_h}$ are:

$$\mathbf{T_h} = \left[a_h^*, b_h^*, A_{FEC_h}, [FEC_h]\right]^T \tag{5}$$

The data needed for training the ANN comprise different data sets, training, early stopping and validation sets [19].

Accordingly the database has been split into three subsets as described below.

A. Training Set

Training set is composed by a matrix $\mathbf{P}$ (size 23 x 85) whose columns are all the odd column of matrix $\mathbf{T}$:

$$\mathbf{P}_{[23x85]} = \begin{bmatrix} a_1^{\ *} & a_3^{\ *} & \dots & a_{170}^{\ *} \\ b_1^{\ *} & b_3^{\ *} & \dots & b_{170}^{\ *} \\ A_{FEC_1} & A_{FEC_3} & \dots & A_{FEC170} \\ [FEC_1] & [FEC_3] & \dots & [FEC_{170}] \end{bmatrix} \tag{7}$$

This matrix is used for training the ANN.

B. Early stopping set

The second subset is made of a matrix $\mathbf{E}$ (size 23x20) whose columns are the first 20 even columns of matrix $\mathbf{T}$:

$$\mathbf{E}_{[23x20]} = \begin{bmatrix} a_2^{\ *} & a_4^{\ *} & \dots & a_{40}^{\ *} \\ b_2^{\ *} & b_4^{\ *} & \dots & b_{40}^{\ *} \\ A_{FEC_2} & A_{FEC_4} & \dots & A_{FEC_{40}} \\ [FEC_2] & [FEC_4] & \dots & [FEC_{40}] \end{bmatrix} \tag{8}$$

This subset is used for evaluating a parameter serving as a stopping criterion of the learning process [16].

C. Validation set

The third subset is a matrix $\mathbf{V}$ (size 23 x 65) whose columns are the remaining columns of matrix $\mathbf{T}$:

$$\mathbf{V}_{[23x65]} = \begin{bmatrix} a_{42}^{\ *} & a_{44}^{\ *} & \dots & a_{184}^{\ *} \\ b_{42}^{\ *} & b_{44}^{\ *} & \dots & b_{184}^{\ *} \\ A_{FEC_{42}} & A_{FEC_{44}} & \dots & A_{FEC_{184}} \\ [FEC_{42}] & [FEC_{44}] & \dots & [FEC_{184}] \end{bmatrix} \tag{9}$$

This set is used to assess the performance of the network thereby allowing the choice of the most efficient architecture within a set of candidate network topologies.

D. Target set

As already stated, the devised ANN has to correlate the training set $\mathbf{P}$ with a proper target set. Since the ANN has to classify the fabrics into 5 classes, the target set for each column $\mathbf{P_h}$ of $\mathbf{P}$, is made of a binary vector $\mathbf{H_h}$ (size 5 x 1) defined as follows:

$$\begin{cases} \mathbf{H_h}(i) = 1 \\ \mathbf{H_h}(k) = 0 \quad (\forall k \in [1,5] \mid k \neq i) \end{cases}$$

when the fabric has been classified in class *i*;

$$\begin{cases} \mathbf{H_h}(i) = \mathbf{H_h}(j) = 0.5 \\ \mathbf{H_h}(k) = 0 \quad (\forall k \in [1,5] \mid k \neq i, j) \end{cases}$$

when the fabric has been classified in class *i-j* (i.e. the new fabric belongs to multiple classes).

As a consequence target set is defined by a matrix $\mathbf{H}$ (size 3 x 170) defined as follows:

$$\mathbf{H} = [\mathbf{H_1}, \mathbf{H_2}, \dots \mathbf{H_{170}}] \tag{10}$$

The entire target set is on its turn, divided into three subsets $\mathbf{H_P}$, $\mathbf{H_E}$ and $\mathbf{H_V}$ respectively used for training, early stopping and validation.

E. *ANN architecture*

The ANN devised for the classification system, whose structure is shown in Fig. 6, has the following characteristics: three layers (input, hidden and output layer); input layer processes 23 input, hidden layer is made of sigmoid neurons followed by an output layer of sigmoid neurons again with 5 output units. The number of hidden units was varied from 12 to 24 with a step of 3 units, monitoring the performance of response using the training data.

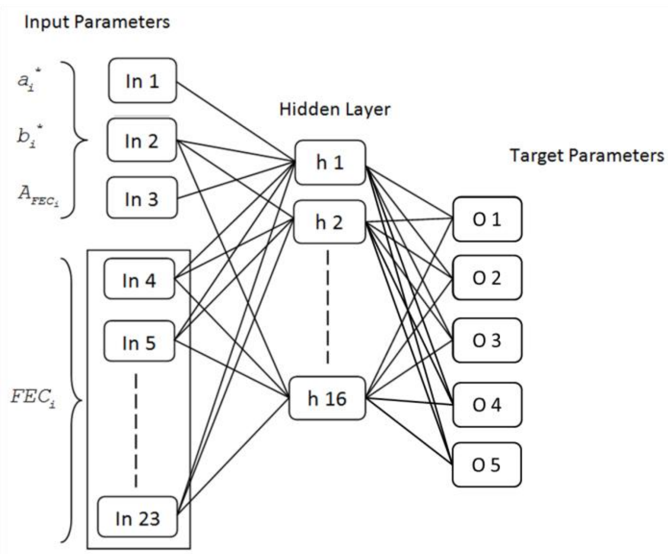

Fig. 6 ANN Architecture.

As widely known during the training, the weights and the biases of the network are iteratively adjusted to minimize the network error function. The network error used in this work is the mean square error (MSE) correspondent to the training set elements. The error is monitored during the training process and will normally decrease during the initial phase of the training, as does the MSE. However, when the network becomes excessively specialized in reproducing the training data, the early stopping error will typically begin to rise. When the early stopping error increases for a specified number of iterations, the training is stopped, and the weights and biases at the minimum early stopping error are returned [17].

The final network is characterized by *h* = 16 units. The training was carried out using a training rule based on the Levemberg-Marquardt algorithm [20,21] that is an effective method for training moderate-sized Feed-Forward Back-Propagation ANNs.

VI. NEURAL NETWORK VALIDATION

Once trained, the ANN is able to process new input data and to provide an output value performing a transformation $\Re^{23} \rightarrow \Re^{5}$.

In order to validate the ANN fabric grading performance, the validation set $\mathbf{V}$ is used as input set. The output of the trained ANN when it process matrix $\mathbf{V}$ is a matrix $\mathbf{Z}$ (size 3 x 65) whose elements have to be compared with the results of expert's classification of the same fabric samples considered in building $\mathbf{V}$.

For instance the first column of $\mathbf{Z}$, i.e. the ANN output when it process the first column of matrix $\mathbf{V}$ (or the 42th column of the training set) is given by:

$$\mathbf{z}_1 = [0.97, -0.04, 0.01, 0, 0]^T$$

In order to compare ANN outputs with target vectors, outputs need to be normalized by dividing each element of $\mathbf{Z}$ (z_r) by the sum of all the elements. The result is a normalized vector $\mathbf{z}^{\mathbf{norm}}$ given by:

$$\mathbf{z}^{\mathbf{norm}} = \frac{z(r)}{\sum_{r=1}^{5} z(r)} \tag{10}$$

In Tab. 3 some ANN outputs are provided togheter with their normalized values.

Tab. 3 – Some results of ANN validation.

$\mathbf{z}_i$	ANN output value	ANN normalized value
$\mathbf{z}_1$	[0.97,-0.04,0.01,0,0]T	$[1.03,-0.04,0.01,0,0]^T$
$\mathbf{z}_2$	[0.12,0,0.75,-0.12,0] T	$[0.16,0,1.00,-0.12,0]^T$
$\mathbf{z}_3$	[0.88,0.32,0,-0.13,0] T	$[0.82,0.29,0,-0.12,0]^T$
$\mathbf{z}_4$	[0,0.56,0.22,0.14] T	$[0,0.61,0.24,0.15,0]^T$
$\mathbf{z}_5$	[0,0.04,0.45,0.49,0] T	$[0,0.04,0.46,0.50,0]^T$
$\mathbf{z}_{30}$	[0.92,0.23,0.06,0,0] T	$[0.76,0.19,0.05,0,0]^T$
$\mathbf{z}_{31}$	[0.97,0.01,0,-0.01,0] T	$[1.00,0.01,0,-0.01,0]^T$
$\mathbf{z}_{32}$	[0.32,0.83,0,01,0.11,0] T	$[0.25,0.65,0.01,0.09,0]^T$
$\mathbf{z}_{33}$	[0.12,0.04,0.89,0.02,0] T	$[0.11,0.04,0.83,0.02,0]^T$
$\mathbf{z}_{34}$	[0.49,0.51,0.03,0,0,02] T	$[0.48,0.49,0.03,0,0]^T$
$\mathbf{z}_{35}$	[0.21,0.76,-0.11,-0.02,0] T	$[0.22,0.90,-0.13,-0.02,0]^T$

Normalized values must be converted in order to assume same form of the output provided by human operators (i.e. let the vector elements assume only values equal to 1 or 0.5).

This is done by assuming that *l* is the index of the first largest element of an output vector $\mathbf{z}^{\mathbf{norm}}$ and *m* is the index of the second largest element of $\mathbf{z}^{\mathbf{norm}}$.

Two vectors α_1 and α_2 are defined as follows:

$$\begin{cases} \alpha_1(l) = 1 \\ \alpha_1(k) = 0 \quad (\forall k \in [1,5] \mid k \neq l) \end{cases} \tag{11}$$

$$\begin{cases} \alpha_2(l) = \alpha_2(m) = 0.5 \\ \alpha_1(k) = 0 \quad (\forall k \in [1,5] \mid k \neq l, m) \end{cases} \tag{12}$$

An additional coefficient $\mu = \mu(z, g)$, called "grading confidence", is defined as:

$$\mu = (1\text{-}\mathbf{D}) \cdot 100 \tag{13}$$

where:

$$\mathbf{D} = \sqrt{\sum_{i=1}^{5} \left(z(i) - g(i)\right)^2} \tag{14}$$

The two corresponding confidence values are then computed replacing g by α_1 and α_2 respectively.

The final result provided by the ANN is assumed to be the one with higher confidence value.

Referring to the example provided above, the normalized value results to be

$$\mathbf{Z_1}^{\mathbf{norm}} = [1.03, -0.04, 0.01, 0, 0]^T$$

As a consequence:

$$\alpha_1 = [1,0,0,0,0]$$
$$\alpha_2 = [0.5,0,0.5,0,0]$$
$$\mu(\mathbf{Z_1}^{\mathbf{norm}}, \alpha_1) = 99.8$$
$$\mu(\mathbf{Z_1}^{\mathbf{norm}}, \alpha_2) = 47.7$$

The fabric is thereby classified in class 1 with a confidence equal to 99.8 and its corresponding vector is assumed to be $\alpha^{\star} = \alpha_1$.

The described confidence value can also be useful in order to assess the correctness of the classification. In particular, if $\alpha^{\star}$ is equal to the correspondent column of matrix $\mathbf{H_v}$, i.e. the classification result matches the one performed by the operator, confidence value $\mu(\mathbf{Z_i}^{\mathbf{norm}}, \alpha^*) = \mu(\mathbf{Z_i}^{\mathbf{norm}}, \mathbf{H_{vi}})$.

In Table 4, the $\alpha^{\star}$ values corresponding to the ones listed in Tab. 3 are compared with the correspondent targets; the confidence value is also evaluated.

Tab. 4 – ANN-based grading and grading coefficient.

$\alpha^{\star}$	**Target value**	**Manual Grading**	**ANN-based Grading**	**Grading Confidence**
$[1,0,0,0,0]^T$	$[1,0,0,0,0]^T$	1	1	99.80%
$[0,0,1,0,0]^T$	$[0,0,1,0,0]^T$	3	3	96.00%
$[1,0,0,0,0]^T$	$[1,0,0,0,0]^T$	1	1	86.91%
$[0,0.5,0.5,0,0]^T$	$[0,0.5,0.5,0,0]^T$	**2-3**	**2-3**	89.78%
$[0,0,0.5,0.5,0]^T$	$[0,0,0.5,0.5,0]^T$	**3-4**	**3-4**	99.68%
$[1,0,0,0,0]^T$	$[1,0,0,0,0]^T$	1	1	90.38%
$[1,0,0,0,0]^T$	$[1,0,0,0,0]^T$	1	1	99.96%
$[0,1,0,0,0]^T$	$[0,1,0,0,0]^T$	2	2	80.68%
$[0,0,1,0,0]^T$	$[0,0,1,0,0]^T$	3	3	91.74%
$[0.5,0.5,0,0,0]^T$	$[0.5,0.5,0,0,0]^T$	**1-2**	**1-2**	98.87%
$[0,1,0,0,0]^T$	$[0,1,0,0,0]^T$	2	2	92.43%

Referring to the examples given in Tab. 4 the ANN-based classification matches the manual grading with a minimum confidence of about 81%.

In order to determine the reliability of the proposed system, a performance index η is defined as follows:

$$\eta = \frac{N_F}{N} \tag{15}$$

Where N_F is the total number of the fabric samples correctly classified (i.e. the expert and the system classify the sample in the same class) and N is the total number of fabric samples. With reference to the whole validation set, since the ANN classified the fabrics in the correct class for 62/65 cases (93.8%) the index η is equal to 0.938. This means that the average classification error is equal to 6.5%. The minimum confidence for the whole validation set resulted to be 73%.

Such results prove that the proposed automatic inspection method can be effectively employed for performing a reliable classification of sponged-like 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.

Conclusions

In the present work a method able to carry out an automatic grading of car seat fabrics has been described. The method integrates an acquisition apparatus and a software tool in order to perform the classification.

The proposed method proves to be reliable and, in particular, is able to (with reference to the experimental tests performed on 65 samples used for validation):

- classify fabrics with a reliability index averagely equal to 93.8% with a minimum confidence of 73%;
- respect the selection provided by human know-how.

A comparison between the results of the proposed method and some others provided by scientific literature (adopted for evaluating the performance of different classification systems) may be carried out considering that most methods defines a dimensionless parameter (whose value is, usually, comprised in the range 0 – 1) for evaluating the classification performance. In [22], for instance, the correlation between measured and forecasted classifications of coloured textiles is stated to be in the range 0.85 – 0.98. In [24] the classification error of textured objects is less than 10%.

In the work described in [25] the misclassification rate (in the case of wood samples) varies from 1.1% and 8%. In [26] an accuracy varying in the range 87.6 – 97.1 % is obtained. Finally, in [27] an average classification rate for colored natural textures is defined and varies in the range 84.4% - 98.2%.

These results are comparable with the ones provided by the present work, thus allowing to state that a satisfactory performance has been obtained.

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