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ORIGINAL ARTICLE

The recycling of wool clothes: an artificial neural network colour classification tool

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Abstract Recycling of clothes is a straightforward approach for the supply of a coloured raw material which does not involve the cost of the colouring process. A real time and completely automated colour classification tool for woollen clothes to be recycled is proposed. The tool uses the combination of a statistical method, called matrix approach, of a self-organizing feature map (SOFM) and a feed-forward backpropagation artificial neural network (FFBP ANN)-based approach, to correctly classify the clothes by respecting the selection criteria provided by human know-how. The developed tool, which uses an appositely developed workbench with a spectrophotometer, is aware of the way the different coloured clothes to be recycled combine each other to create a new one. The tool has been validated using a set of 5,000 differently coloured clothes to be recycled and the classification error in classifying the clothes is within 5%, i.e., lower than the one resulting from the use of an expert human operator.

Keywords Recycling · Neural networks · Picking · Spectrophotometry · Colour

Abbreviations

ANN artificial neural network
SOFM self-organizing feature maps
FFBP feed forward back propagation

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Nomenclature

$\boldsymbol{d}_{i,j}$	Numeric first order derivative of matrices $\boldsymbol{m'}_{i,j}$.
$\boldsymbol{C}_{i,j}$	Reference matrices.
$C_{i,j}^{(k)}$	k-th Extended spectrum
$\boldsymbol{e}_C$	Classification error without the re-picking operation.
e_K	Vector of network error at Kth training epoch.
h	Number of hidden units.
$\boldsymbol{I}$	New extended spectrum.
J	Jacobean matrix of network error function.
$\boldsymbol{M}_i$	Database matrix i.e., the representative matrix of the i-th class
$\boldsymbol{m}_{i,j}$	j-th sub-matrix of $\boldsymbol{M}_i$
$\boldsymbol{m'}_{i,j}$	Training set.
$\boldsymbol{m''}_{i,j}$	Early stopping set.
$\boldsymbol{m'''}_{i,j}$	Validation set.
MSE	Mean square error.
MSE_{ES}	Mean square error corresponding to the early stopping set.
$\boldsymbol{out}$	Neural network output vector.
out_{ES_K}	Neural Network output vector at Kth training epoch using the early stopping set.
$\boldsymbol{out}_{EXT}$	Extended spectrum for the output vector $\boldsymbol{out}$.
$\boldsymbol{out}_K$	Neural network output vector at Kth training epoch.
$\boldsymbol{P}$	New acquired spectrum.
P_i	Value of reflectance vs. wavelength of the new acquired spectrum.
Q	Number of examples (spectra) given as training set
$\boldsymbol{T}$	Target matrix.
$\boldsymbol{T}_s$	s-th column of the target matrix.
$\boldsymbol{t}_{ij}$	Sub-matrix of the target matrix.

W_K Weight matrix at Kth training epoch

$\boldsymbol{X}_{i,j}$ Confidence value vector for the matrix approach.

$\boldsymbol{X}_{iv}$ Maximum confidence value for the matrix approach.

Δs difference between the absolute maximum value and the absolute minimum value for all the spectra composing the database

Δd difference between the absolute maximum value and the absolute minimum value for the numerical derivatives of all the spectra of the database.

δ number of spectra contained in the matrices $\boldsymbol{m}_{i,j}$.

ϑ Confidence value vector for FFBP ANN approach.

ϑ_v Maximum confidence value for FFBP ANN approach.

μ Training parameter.

ξ Scale factor that serves to make the spectrum and the derivative variability ranges equal.

$\boldsymbol{\rho}_{i,j}$ Euclidean distance vector between $\boldsymbol{I}$ and $\boldsymbol{C}_{i,j}$.

ψ Euclidean distance vector between the extended spectrum $\boldsymbol{out}_{EXT}$ and each of the columns of the matrix $\boldsymbol{T}$

Ψ_i i-th element of vector ψ

1 Introduction

In Italy the wool industry produces a volume of approximately 50,000 ton/year of which 35,000 ton/year in the textile district of the city of Prato, in central Italy. The costs sustained by the wool industry are estimated at approximately 500 million euro. A wide range of products are thereby obtained by applying recycling techniques since the final product is often obtained using only one raw material. Accordingly, recycling is a basic approach for the supply of a raw material which does not involve the cost of the colouring process, since it comes from already coloured clothes. The common practice for companies performing wool recycling consists of providing the customer with a catalogue of the available colours. Depending upon the customer's choice, the company starts to search its storehouse for correctly coloured clothes. These are selected on the basis not only of the similarity of their colour to the desired one, but also of the knowledge of the recycling process. This process may lead to some little changes of the colour of a cloth. So the company's operators required to classify the clothes (called "pickers"), have to be aware of the way the different colours combine to create a new one. Some spectra that seem similar to other classes are classified by the pickers in two different classes. Moreover some spectra that seem to be similar are classified by the pickers in the same colour class. As a result highly specialised and well-trained operators must perform the selection process. Currently, several different methods for classifying the objects on the basis of their colour can be employed; for instance, the use of colour cameras [1] and colour histogram [2]. As already mentioned, in the classification of woollen clothes it is possible to have differently coloured clothes grouped together in colour classes, while apparently similar ones can be separated. For instance a cloth that seems to be classified in the colour class 29 (red), may be then washed (and this operation is known by the company staff) and after this operation it becomes a different colour (class 31). So in the classification, even if the spectrum is very similar to most of the spectra of colour class 29, the cloth is classified as colour class 31.

This peculiarity, due to the way differently coloured wools combine into a newly coloured one, implies that no ordinary colour identification [3] and classification tool can be effectively used for clothes picking [4] with the result that human operators are needed to correctly perform the classification task. The coloured woollen clothes classification tool proposed in this work is designed to achieve an automatic and real-time classification of the clothes on the basis of their reflectance spectrum in order to select them, taking into account both the similarity of their colour and the knowledge of the recycling process. The proposed system provides a classification error for the clothes within 5% compared to the picker's selection criteria.

2 Background

Usually the selection procedure adopted by the companies' pickers for classifying the coloured clothes is split into two phases. First the clothes are grouped by colour families (red, blue, white etc.) and then the clothes belonging to a family are additionally classified in colour classes (for example six classes for the red family, nine classes for brown, etc.). In order to guarantee a correctly coloured final material, it is necessary to work in strictly controlled light conditions. It is important to emphasise once more that within a given class significantly different colours may be found while similar ones may belong to different colour classes or even families. From the description given above, it is evident that the selection method relies heavily on the judgment of the operators and consequently may vary remarkably depending on the operator's skill, colour perception and tiredness. Moreover, this method is characterised by a low and non-constant productivity. The catalogue used for the presented research provided by a textile company working in Prato (Italy) consists of a set of 85 recycled wool samples, demonstrating all the colours available to the customer. Each sample represents a colour class; the classes are grouped in 10 colour families as can be seen in Table 1 (the total number of classes is 85). A cloth that has to be recycled must be classified in one of the catalogue families, and then in a class, even if there are significant differences between its colour and the one of the coloured sample in the catalogue.

Table 1 Families and classes provided by the catalogue

Families	*Classes*	*Number of clothes*
White	1, 2	200
Beige	3, 4, 5, 6,13	500
Brown	7, 8, 9, 10, 11, 12, 14, 15,16	900
Orange	17, 18, 19, 20, 21, 22, 24	700
Pink	23, 25, 26, 27, 28, 30, 32, 36	800
Red	29, 31, 33, 34, 35, 37	600
Violet	56, 57, 58, 59, 60, 61, 62, 63, 64	900
Blue	40, 41, 42, 45, 47, 50, 53, 54	1,700
	38, 39, 43, 44, 46, 48, 49, 51, 55	
Green	52, 75, 77, 80, 82, 84, 86	1,600
	73, 74, 76, 78, 79, 81, 83, 85, 87	
Black and grey	65, 66, 67, 68, 69, 72	600

3 Method

The final goal of the presented work is to provide a tool for classifying coloured woollen clothes, with the aim of recycling them into a reusable bulk material. The tool is required to do the following:

- be capable of respecting the selection criteria provided by human know-how;
- be highly automated;
- be capable of performing real-time classification;
- provide repeatable selections;
- exhibit a low classification error.

This was carried out by two basic steps:

1. Data assembly.
2. Colour classification tool development.

The purpose of the first step is to collect and properly pre-process by using a self-organising feature map (SOFM) the significant data for the development of the colour classification tool. The second step consists in the development of the classification tool by means of a statistical method, called "matrix approach" and a feed forward back propagation artificial neural network (FFBP ANN) based method created on the basis of the information gathered from the first step i.e., using the significant data as a training set for the network.

3.1 Data assembly

The data assembly is performed in three consequential procedures:

- database creation; a relevant number of differently coloured clothes is stocked and their spectra are acquired by means of a portable spectrophotometer.
- SOFM development; A SOFM is developed in order to process the spectra collected in the database so that a relevant sub set of spectra can be identified.
- Training data assembly; the spectra selected by the SOFM are used for creating the training, early stopping and validation sets for the FFPB ANN which will be described later.

3.1.1 Database creation

In order to create a database capable of representing almost all the wool clothes colours, 10,200 differently coloured clothes are collected. These have to be classified by the company staff into families and then classes. As already stated the picker first groups the clothes in 10 families (red, green, etc.) and then groups the clothes of each family in a certain number of colour classes (six classes for the red family, 9 for the green one etc). Normally this operation is not error free. Accordingly it is necessary to ask the opinion of several pickers in order to obtain a completely error free classification. This operation, called "re-picking", not only is time consuming but also requires continuous revision during the entire process. The classification error without the re-picking operation is in the range $e_c = 7 - 10\%$.

In order to have a sufficient variety of samples 120 different clothes for each class are collected. According to the described procedure, the database results to be made up of 10,200 clothes correctly classified by the company's expert staff. Once collected, the woollen clothes are processed by using an acquisition system consisting of a workbench on which is placed an Hunterlab Ultrascan XE reflectance spectrophotometer connected to a PC. The spectrophotometer provides the value of light reflectance in the visible wavelength range [400 – 700 nm], with a step of 10 nm. The resulting spectrum is obtained using a scattered light measurement in specular component excluded (SEC) mode [5]. The scan is made with a neutral white background using an 8 degree angle between the light source and the cloth. A zero calibration is used to compensate for the effects of stray light due to the changing flare characteristics of the optical system. The white calibration of the spectrophotometer is performed at the beginning of data acquisition using a Hunterlab-standard cap. The spectrophotometer is connected to a PC by a serial port and data are stored in the form of a 31 elements vector representing the reflectance values vs. the wavelength for an examined cloth.

Furthermore, a label is automatically assigned to each spectrum, according to the coding a/b where a is an integer in the range 1 – 10200 representing cloth sample number, whilst b is an integer in the range 1 – 85 representing the colour class. For example the label 736/23 identifies the spectra obtained for the cloth number 736 classified by the picker as belonging to the 23rd colour class. All the spectra of each class are collected in matrices; for a single class we have 120 clothes, that is 120 spectra. Accordingly it is possible to build a database matrix $\boldsymbol{M}_{\mathrm{i}}$, where i is the generic class, made up of 120 columns (number of spectra) and 31 rows (values of reflectance in the range 400–700 nm). In Fig. 1 some of the spectra collected in matrix $\boldsymbol{M}_{55}$ (one of the blue classes) are shown, while in Fig. 2 some spectra belonging to the class 52 (one of the green classes) are shown. The comparison of the spectra plotted in Fig. 1 and in Fig. 2, shows that, as already mentioned, considerably different colours are grouped in the same class while very similar ones are placed in different classes or even families.

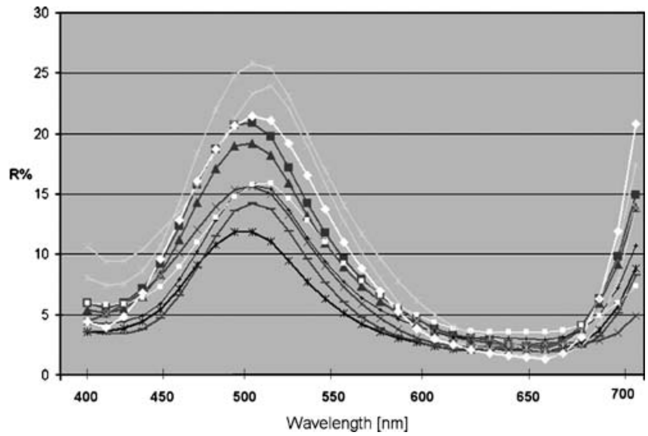

Fig. 2 Some of the spectra collected in the matrix $\boldsymbol{M}_{52}$ i.e., in one of the green classes

3.1.2 Self Organizing Feature Map (SOFM) development

The colour classification required by the customers is not easily performed using an unsupervised technique such as a SOFM [6], because of the necessity of classifying the clothes on the basis of the pickers knowledge of the recycling process. This implies that a supervised learning technique like the FFBP ANN can be used. Nevertheless, as will be shown, a SOFM is useful for properly treating the data prior to the creation of the FFBP ANN [7].

In order to develop a FFBP ANN it is necessary to define a training set [8]. The spectra collected in the matrices $\boldsymbol{M}_i$ are used for this task as described in the following paragraphs. Nevertheless, not all of them are to be used for the training set since an excessively large training set may lead to overtraining or missed training [9]. Moreover, even if the spectra collected in the matrices $\boldsymbol{M}_i$ may differ considerably one from the other, generally among the 120 spectra (for each colour class) it is possible to choose a lower number of spectra assuming that they sufficiently characterise the selected class. This is shown, for instance, in Fig. 3 where some other spectra of class 17 are plotted; though all the spectra are different, it is possible to guess that they could be grouped on the basis of the similarity of their shapes. Including all the spectra of Fig. 3 in the training set would cause redundancy in the network upon training; accordingly selecting only one or two representatives for each group may be considered a much more efficient approach. On the basis of this principle, a SOFM has been developed in order to choose the most representative spectra of each colour class. The SOFM can map the distribution of an N-dimensional input data to a M-dimensional feature map, preserving the statistical properties of the input data distribution [10]. Usually the mapping is generated between input spaces of high dimension and a lower-dimensional map field [11]. Accordingly each of the matrices $\boldsymbol{M}_i$, can be mapped from a 31-dimensional input space to a M-dimensional map. This procedure can be performed by creating, for each matrix $\boldsymbol{M}_i$, a SOFM with the following characteristics:

- two dimensional map (i.e., M=2) with 4×3 neurons;
- input data: the matrices $\boldsymbol{M}_i$;

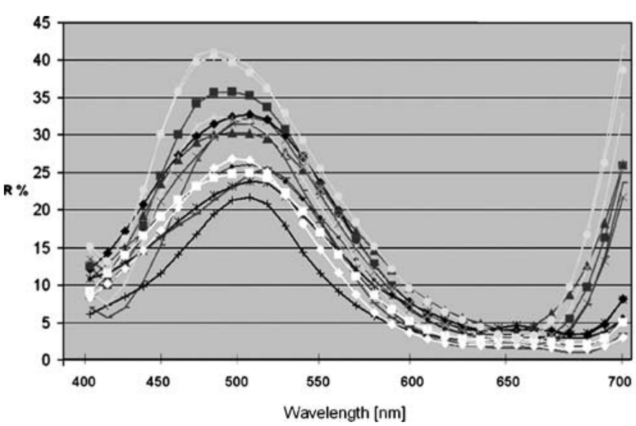

Fig. 1 Some of the spectra collected in the matrix $\boldsymbol{M}_{55}$ i.e., in one of the blue classes

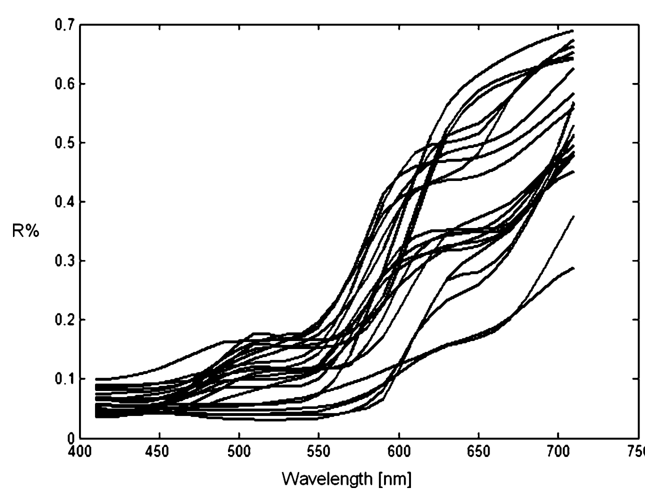

Fig. 3 Some other spectra of class 17; it is possible to guess that they could be grouped on the basis of the similarity of their shapes

- topology function: hexagonal; this means that the neurons of the SOFM are arranged in an hexagonal grid;
- Distance function: Euclidean distance;

Training the SOFM for 500 epochs the 120 spectra collected in each of the matrix $\boldsymbol{M}_i$ are mapped (divided) in 12 sub-matrices $\boldsymbol{m}_{i,j}$ (j=1...12), being $\boldsymbol{m}_{i,j}$ the jth sub-matrix of $\boldsymbol{M}_i$. For instance the spectra collected in matrix $\boldsymbol{M}_{17}$ are split into the matrices $\boldsymbol{m}_{17,1}$, $\boldsymbol{m}_{17,2}$, ..., $\boldsymbol{m}_{17,11}$, $\boldsymbol{m}_{17,12}$. Each sub-matrix is composed of a different number δ of spectra i.e., the size of the matrices $\boldsymbol{m}_{i,j}$ is 31×δ where δ varies over the range [0, 120] as shown in Table 2. In Fig. 4 the spectra shown in Fig. 3 are collected in four different sub-groups by using the described SOFM. The final result of this approach is to split the 85 matrices $\boldsymbol{m}_i$ in 1020 matrices $\boldsymbol{m}_{i,j}$ i.e., to split the 85 colour classes in 1,020 sub-classes.

3.1.3 Training data assembly

The data needed for properly training the FFBP ANN described in the next paragraphs comprise different data sets: training, early stopping and validation sets. These data sets can be effectively identified using the matrices $\boldsymbol{m}_{i,j}$, whose columns are the spectra of the clothes collected in the database re-arranged by the use of the SOFM. The matrices $\boldsymbol{m}_{i,j}$ are divided into three subsets:

- Training set. The first subset is composed of the 1,020 matrices $\boldsymbol{m}'_{i,j}$ (size 31×δ) made of half the columns of each matrix $\boldsymbol{m}_{i,j}$ (rounded off). Accordingly, these elements represent the training set, which is used for training the network. The remaining spectra make up, for each sub-class, a matrix $\overline{m}_{i,j}$ (size $31 \times \frac{\delta}{2}$) that is further divided into the subsets described below.
- Early stopping set. The second subset is made of a matrix $\boldsymbol{m}''_{i,j}$ (size $31 \times \frac{\delta}{4}$) whose columns are the first half columns of each matrix $\overline{m}_{i,j}$. This subset is used for evaluating a parameter serving as a stopping criterion of the learning process [12].
- Validation set. The third subset is a matrix $\boldsymbol{m}''_{i,j}$ (size $31 \times \frac{\delta}{4}$) whose columns are the remaining spectra of the matrices $\overline{m}_{i,j}$. 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 networks.

Table 2 δ values for each sub-matrix $\boldsymbol{m}_{i,j}$;δ varies over the range [0÷120]

Matrix	δ	Matrix	δ
$\boldsymbol{m}_{17,1}$	8	$\boldsymbol{m}_{17,7}$	12
$\boldsymbol{m}_{17,2}$	12	$\boldsymbol{m}_{17,8}$	10
$\boldsymbol{m}_{17,3}$	4	$\boldsymbol{m}_{17,9}$	5
$\boldsymbol{m}_{17,4}$	6	$\boldsymbol{m}_{17,10}$	15
$\boldsymbol{m}_{17,5}$	12	$\boldsymbol{m}_{17,11}$	6
$\boldsymbol{m}_{17,6}$	16	$\boldsymbol{m}_{17,12}$	14

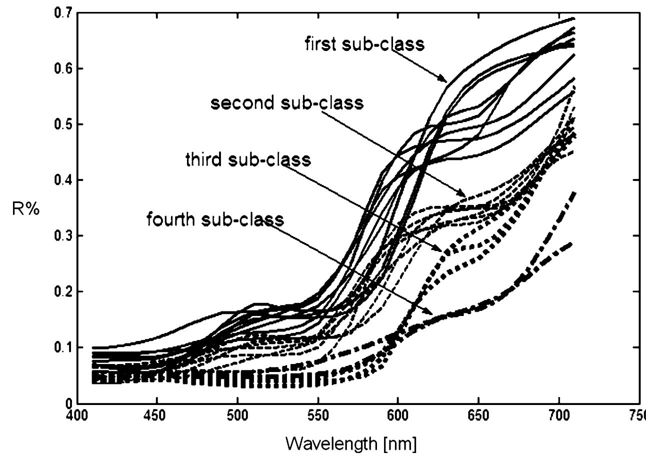

Fig. 4 Some spectra of class 17 collected in four different sub-groups by using a SOFM

The number of spectra collected for the training set is reported in Table 3.

3.2 Colour classification tool development

Once the data assembly task is carried out, the colour classification tool can be developed. As already mentioned this was performed by combining the matrix approach with a FFBP ANN as described in the following paragraphs.

3.2.1 Matrix approach

For each spectrum composing the matrices $\boldsymbol{m}'_{i,j}$ it is possible to evaluate, column by column, the numerical first order derivative $d_{i,j}$ thus obtaining a new matrix $C_{i,j}$ composed of k=120columns representing the spectral derivatives and 30 rows representing the wavelength values. So, it is possible to build a data matrix $C_{i,j}$, called “reference matrix”, containing both spectra and their derivative:

$$C_i = \begin{bmatrix} m_{i,j}-- \\ \xi \cdot d_{i,j} \end{bmatrix} = \begin{bmatrix} R_{11} & R_{21} & \dots & R_{k1} \\ : & : & \dots & R_{k2} \\ R_{1,31} & R_{2,31} & \dots & R_{k,31} \\ \xi \cdot D_{11} & \xi \cdot D_{22} & \dots & \xi \cdot D_{k1} \\ : & : & \dots & : \\ \xi \cdot D_{1,30} & \xi \cdot D_{2,30} & \dots & \xi \cdot D_{k,30} \end{bmatrix}_i \quad (1)$$

Where ξ is a scale factor that serves to make the spectrum and the derivative variability ranges equal.

Table 3 Number of spectra collected for the training set

Matrix	*Number of elements*	*Matrix*	*number of elements*
$\boldsymbol{m'}_{17,1}$	4	$\boldsymbol{m'}_{17,7}$	6
$\boldsymbol{m'}_{17,2}$	6	$\boldsymbol{m'}_{17,8}$	5
$\boldsymbol{m'}_{17,3}$	2	$\boldsymbol{m'}_{17,9}$	3
$\boldsymbol{m'}_{17,4}$	3	$\boldsymbol{m'}_{17,10}$	8
$\boldsymbol{m'}_{17,5}$	6	$\boldsymbol{m'}_{17,11}$	3
$\boldsymbol{m'}_{17,6}$	8	$\boldsymbol{m'}_{17,12}$	7

Accordingly, the proper value for the coefficient ξ, can be obtained by the following equation:

$$\xi = \frac{\Delta s}{\Delta d} \tag{2}$$

Where Δs is the difference between the absolute maximum value and the absolute minimum value for all the spectra composing the database and Δd is the difference between the absolute maximum value and the absolute minimum value for all the derivatives of the spectra composing the database.

The generic kth column of matrix $C_{i,j}$ is called "extended spectrum"$C_{i,j}^{(k)}$.

The set of reference matrices obtained by the procedure described above is used as a term of comparison in the matrix approach. This approach is organised as follows:

i When a new cloth is to be classified, the system scans it in a single position using the settings described in Par. 3.1.1 thereby obtaining a new spectrum P:

$$P = [p_1, p_2, \ldots p_{31}]^T \tag{3}$$

ii On the basis of the spectrum, it is possible to evaluate the first order numeric derivative of vector$P$ and to obtain the new extended spectrum I as follows:

$$I = [p_1, p_2, \ldots, p_{31}, \xi \cdot dp_1, \xi \cdot dp_2, \ldots, \xi \cdot dp_{30}]^T \tag{4}$$

I is a column vector of 61 elements.

iii In order to properly classify the new cloth we can evaluate the Euclidean distance vector$\rho_{i,j}$ between the vector I and each of the columns of the reference matrices $C_{i,j}$:

$$\rho_{i,j} = \left[\left\| C_{i,j}^{(1)} - I \right\|, \left\| C_{i,j}^{(2)} - I \right\|, \ldots, \left\| C_{i,j}^{(k)} - I \right\| \right] \tag{5}$$

The elements of $\rho_{i,j}$ represent the distances between the newly acquired extended spectrum and each of the ones contained in the database. The smaller is the distance $\rho_{i,j}$, the closer is the new extended spectrum to the correspondent one in the database.

iv On the basis of the $\rho_{i,j}$ elements, a confidence value vector for the matrix approach, $X_{i,j}$, is introduced by the following formula called radial basis function:

$$X_{i,j} = b \cdot \exp(-\rho_{i,j^2}) \tag{6}$$

The bias b allows the sensitivity of the radial basis function to be adjusted. Such a function has a maximum of 1 when its input is 0. As the distance between I and $C_{i,j}$ decreases, $X_{i,j}$ increases. The position of the maximum value in $X_{i,j}$ permits the identification of the extended spectrum that is most similar to the new one, while the maximum value X_{iv} represents the confidence of the result.

v The new extended spectrum is placed in the same class as the one in the database maximising the correspondent $X_{i,j}$ value.

In Fig. 5 the extended spectrum of a new cloth and the one selected by the classification tool in the database are compared. As can be seen, the database spectrum is very similar to the new one; consequently its class is also assigned to the new spectrum. The discontinuity in both the lighter and the darker trace in Fig. 5 is due to the fact that after the 31th value of spectrum is appended the numerical derivative of the spectrum itself.

The matrix approach, used as a stand-alone classification tool, is very useful when the cloth to be classified is very similar to at least one cloth found in the database. In this case we have a high confidence value for the cloth classification and an overall satisfactory behaviour of the classification tool. Furthermore, it is possible to detect which cloth is the most similar to the new one and, thereby, the operator can check the results by a visual comparison. On the other hand, when clothes very different from the

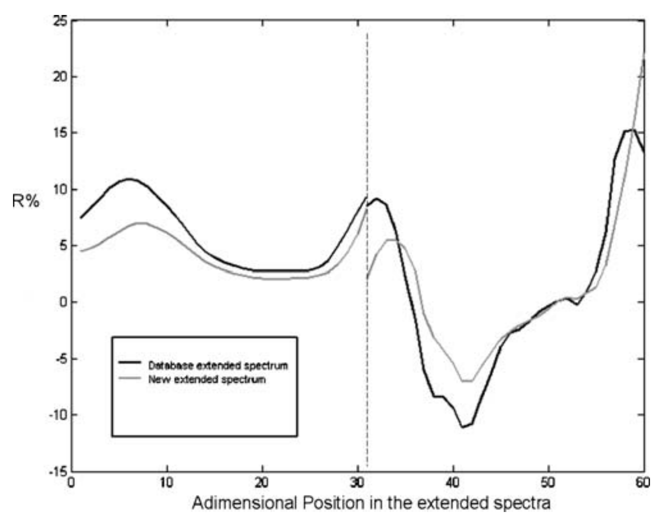

Fig. 5 Comparison between the extended spectrum of a new cloth and the one selected by the classification tool in the database. The database spectrum is very similar to the new one and consequently its class is assigned to the new spectrum

ones that are found in the database must be analysed, the method may lead to low confidence values.

3.2.2 FFBP ANN approach

To overcome the limitations described in the previous paragraph, a FFBP ANN was coupled with the matrix approach. The FFBP ANNs are known to be suitable for applications in the pattern classification field, especially where the limits of classification are not exactly defined [13]. A properly trained FFBP ANN is capable of generalising the shape of the spectra on the basis of the information acquired during the training phase. In order to properly teach the network to respect the classification made by the picker, a proper target set is required. This set is obtained by presenting to the network a target matrix T (size 1020× 31) whose columns T_s are the 1,020 mean, which can be obtained by averaging the spectra contained in the 1,020 $m_{i,j}$ matrices constituting the colour sub-classes identified by the SOFM approach. The ANN training can be made more efficient if the network training set, the validation set and the target set are properly pre-processed. It is known that, before training, it is particularly effective to scale the data so that they always fall within a specified range. In particular we can linearly scale all the values of the spectra contained in matrices $\boldsymbol{m'}_{i,j}$, $\boldsymbol{m''}_{i,j}$, $\boldsymbol{m'''}_{i,j}$ and T in the range [0 1].

The network devised for the classification system, whose structure is reported in Fig. 6, has the following characteristics:

- three layers: input, hidden and output layer.
- hidden layer made of logistic neurons followed by an output layer of logistic neurons again.
- 31 input, h hidden, and 31 output units. The number of hidden units was varied from 20 to 50 with a step of six units, monitoring the performance of response using the training and validation data. As described below the selected network is characterized by h=26 units.

The training phase teaches the network to properly correlate the training set elements to the target ones. All the spectra of a given sub-class, i.e., the spectra of the matrix $\boldsymbol{m'}_{i,j}$, are associated to the correspondent target spectra T_i. The training was carried out using a training rule based on the Levemberg–Marquardt algorithm that is an effective method for training moderate-sized FFBP [14]. As known, during the training, the weights and the biases of the network are iteratively adjusted to minimise the network error function. The network error used in this work is the mean square error (MSE) correspondent to the training set elements:

$$MSE = \frac{1}{Q}\sum_{K=1}^{Q}(e_K)^2 = \frac{1}{Q}\sum_{K=1}^{Q}(T - out_K)^2 \tag{7}$$

Where Q is the number of examples (spectra) given as training set.

The network error function constitutes the error surface in the space of parameters W_{ij} [15]. After each training epoch the algorithm computes both MSE and the early stopping error i.e., the mean square error $MSE_{E.S.}$ correspondent to the early stopping set:

$$MSE_{ES} = \frac{1}{Q}\sum_{K=1}^{Q}(e_{ESK})^2 = \frac{1}{Q}\sum_{K=1}^{Q}(T - out_{ES_K})^2 \tag{8}$$

This 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 specialised in reproducing the training data, the early stopping error will typically begin to rise as shown in Fig. 7. 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. The training was carried out using an adaptive learning rate [16], which is the variation in the weights values between two epochs, until the mean square error MSE reached 1.10^{-5}. This goal was obtained in approximately 500 epochs.

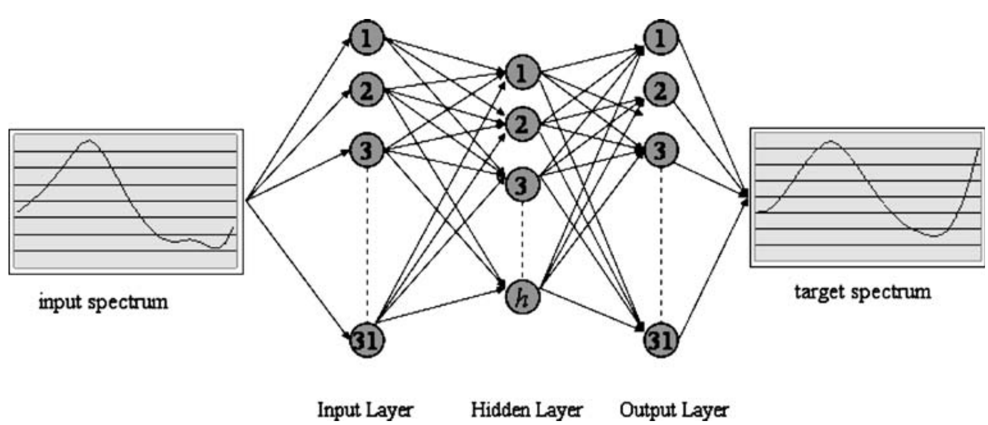

Fig. 6 Three layer FFBP ANN devised for the classification system; this is characterised by 31 input, 26 hidden, and 31 output units

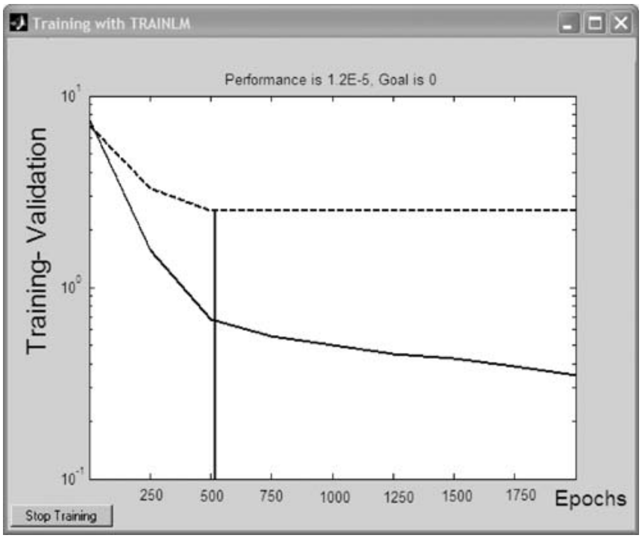

Fig. 7 Early stopping error value during the training phase of the FFBP ANN; when it increases for a specified number of iterations, the training is stopped, and the weights and biases at the minimum early stopping error are returned

3.2.2.1 Network behaviour validation Usually it is possible to choose the best network by estimation, for a given problem, of the network architecture and parameters within a set of candidate configurations. As anticipated in Par. 3.2.2, the number of hidden units h was varied between 20 and 50 with a step of six units thereby obtaining a set of five networks. Accordingly, the network is trained by the training set. For monitoring the network response, the matrices $\boldsymbol{m'''}_{i,j}$ are used as a new input. Accordingly, for a given network, an output made of 1020 new spectra each one similar to a target spectrum. Though all the networks were capable of reaching the minimum desired MSE value, the best network is considered the one that reached the minimum error in classifying the validation set. Accordingly the selected network is characterized by h=26.

3.2.2.2 Simulation of the network response with new inputs The new cloth that has to be classified is characterised by an acquired spectrum *P*as described in Par. 3.2.1. The ANN accepts the spectrum as input and computes the correspondent neural network output vector *out* that must be compared with all the 1020 spectra contained in the matrix *T*. The easiest way to perform this task is to use the matrix approach limitedly to the output vector. This approach is organised as follows:

It is possible to evaluate the extended spectrum for the output vector, out_{EXT} as follows:

$$out_{EXT} = \left[out_1, out_2, ..., out_{31}, \xi \cdot d(out)_1, \xi \cdot d(out)_2, ..., \xi \cdot d(out)_{30}\right]^T$$

The Euclidean distance vector ψ between the extended spectrum out_{EXT} and each of the columns of the matrix T is given by the equation:

$$\psi = \|out_{EXT} - T\| = [\psi_1, \psi_2, ..., \psi_{1020}] \tag{10}$$

The smaller is the distance Ψ_i the closer is the extended spectrum for the output vector to the correspondent one in the catalogue.

Now it is possible to compute the confidence value vector for the Neural network approach, ϑ, using radial bases function with a bias b=0.1:

$$\vartheta = -b \cdot \exp(\psi) \tag{11}$$

The vector ϑ (size 1×85) contains values between 0 and 1.

The position of maximum value of ϑ detects the target spectrum that is most similar to the new one while the value itself, ϑ_v, represents the confidence of result. If the picker considers the result to be insufficient for properly classifying the new cloth (this has proved to be when ϑ_v<0.4), the FFBP ANN is retrained with this cloth.

4 Colour classification system

The colour classification tool has been implemented in a purpose-built rig including a Hunterlab spectrophotometer and a commercial PC. The cloth to be classified is sent onto this workbench by means of a transport guide developed by the Research Centre Tecnotessile s.r.l. (Fig. 8). When the cloth reaches the spectrophotometer acquisition area, the acquisition is performed and the colour tool classify the clothes in about 5 seconds. Once classified the cloth is transported in the area of the depot where its family has been placed.

5 Results and discussion

The classification tool described in this work has been validated using a set of more than 5,000 differently coloured clothes to be recycled split in all the 85 colour families. In order to measure the performance of the classification system a reliability index, given by the following equation, is used:

$$\tau_C = \frac{T_{CC} + 0.2 \cdot T_{CF}}{T_C} \tag{12}$$

Where T_{CC} is the total number of the clothes correctly classified, T_{CF} is the number of clothes classified in the same family, but not classified in the proper class (so a weight of 0.2 is used for evaluating the system performance) and T_C is the total number of clothes to be classified. In Table 4 some of the results of the colour

Fig. 8 Transport guide developed by the Research Centre Tecnotessile s.r.l. in order to transport the cloths to be classified onto the measurement workbench

classification are provided. The mean value of τ_C is about 95% thus proving that the classification system respects all the objectives proposed for the work. The system tend to fail more for beige and brown families where the reliability of the system is about 90–92%. Although the system proved to be reliable and in particular is able to (1) recognise the new clothes with a mean error within 5%, (2) respecting the selection criteria provided by human know-how. Moreover it provides repeatable selections: several acquisitions have been performed for the same cloth, with different environmental conditions and this lead to the same final classification and to a confidence value within 0.3%. This error increase to 0.8% in case of different settings for the spectrophotometer (this is due, in particular, to the thermal drift of the spectrophotometer). The system is highly automated and is capable of performing real-time classification since the only required operation is to place the cloth to be classified on the spectrophotometer and to start the acquisition. Future works will be addressed to the colorimetric measurement and classification of cloths composed by different raw materials.

Table 4 Some of the results of the colour classification

Class	T_C	T_{CC}	T_{Cf}	τ_C
1	65	61	2	0.94
2	65	60	4	0.94
3	65	59	3	0.92
6	65	57	8	0.90
7	65	58	6	0.91
8	65	59	4	0.92
9	65	57	8	0.90
10	65	64	1	0.99
15	65	64	0	0.98
16	65	62	2	0.96
17	65	63	1	0.97
20	65	59	6	0.93
21	65	58	6	0.91
22	65	61	4	0.95
23	65	63	2	0.98
24	65	64	1	0.99
25	65	61	3	0.95
34	65	62	3	0.96
35	65	61	3	0.95
36	65	60	3	0.93
37	65	61	4	0.95
38	65	58	7	0.91
39	65	59	6	0.93
40	65	59	5	0.92
41	65	64	1	0.99
42	65	62	3	0.96
43	65	63	2	0.98
46	65	64	0	0.98
54	65	62	3	0.96
55	65	63	1	0.97
56	65	61	2	0.94
57	65	59	6	0.93
58	65	60	4	0.94
59	65	64	0	0.98
60	65	62	2	0.96
61	65	63	2	0.98
62	65	65		1.00
63	65	64	1	0.99
64	65	57	6	0.90
65	65	59	5	0.92
66	65	58	6	0.91
67	65	65	0	1.00
68	65	65	0	1.00
73	65	59	5	0.92
74	65	59	4	0.92
75	65	64	0	0.98
82	65	60	4	0.94
84	65	62	2	0.96
85	65	64	0	0.98

Mean value for τ_C 0.95
Variance for τ_C 0.001

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