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Integrated Computer Vision and Soft Computing System for Classifying the Pilling Resistance of Knitted Fabrics

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Abstract
Fabric pilling is one of the important properties that affect fabric appearance. The testing of fabric pilling using the standard methods available, however, depends on subjective sample evaluation. Objective fabric pilling evaluation using image processing techniques comprises four main stages that include binarisation, segmentation, quantisation, and classification. Literature on the topic focuses only on one or more of these stages while there is a growing need for an integrated system that combines the most effective techniques of each stage and introduces them in a way that does not depend on the subjective evaluation of human operators. This work tries to tackle this problem and creates an integrated system for classifying the pilling resistance of knitted fabrics. The system introduced a new method for generating an image library based on photographs of the EMPA Standards to allow the training and testing of a soft-computing classifier. The method suggested was tested using knitted samples of different structures and colours and the results show their high robustness performance. The quantitative pilling classification produced from the system suggested shows high agreement with the subjective operators' evaluation with a Spearman's correlation coefficient of +0.85.

Key words: *pilling of knitted fabric, pill segmentation, pill quantisation, soft-computing classifier, artificial neural networks.*

Introduction

Fabric wear performance is a critical phenomenon equally for both manufacturers and consumers. Changes in the surface of a fabric during processing, use, and care may be obvious (e.g. the loss of structural integrity due to abrasion or the changes in fabric's colour and texture), or it may be as subtle as fuzzing and pilling. According to ASTM standard terminology related to textiles [1], pills can be defined as "bunches or balls of tangled fibres which are held to the surface of a fabric by one or more fibres". Although fabric pilling is less likely to affect the functional performance of textiles, it frequently results in consumer dissatisfaction and subsequent disposal of textile products before they reach the end of their useful wear life [2].

There is a wide range of parameters that affect fabric pilling that are related to yarn parameters (e.g. twist, hairiness… etc), spinning technology (e.g. ring spinning, rotor, compact spinning, etc), fabric producing technology (e.g. weaving, knitting, etc), as well as other processing parameters [3]. Knitted fabrics are commonly used because of their flexibility and cheap production costs. However, knitted fabrics are less stable than woven ones since they are produced from low twisted yarns and have slack constructions which lead to low abrasion resistance and pilling performance.

Although most theoretical and empirical research on surface wear dates back before the 1950s, when the durability of military uniforms was a priority[2], the majority of standard testing methods depend on accelerated fabric wear using laboratory devices that simulate the frictional mechanisms leading to surface wear and pilling formation. The standards available recommend comparing samples that have undergone this accelerated wear process, with standard photographs of different pilling grades, where expert operators can make their judgment on the samples, which makes their evaluation human dependent and a very subjective process. Although the majority of pilling standard evaluation methods assign a ranking system that ranges between 1 and 5 (where 1 is assigned to sever pilling and 5 to no pilling), the existence of different standards (e.g. ASTM, SN, EN ISO, etc) creates a lot of confusion as samples that are ranked using different standards may result in different pilling grades. This calls for researchers to find alternative objective evaluation methods that may help to standardise the standard ones [4].

The introduction of image analysis as a method for evaluating fabric pilling started in the late 80's with an attempt to replace the subjective evaluation methods applied [5]. The application of image processing and analysis in the evaluation of fabric pilling consists in four stages and the majority of the research work on this topic tried to focus on one or more of these stages to modify the total outcome of their systems. The main four objective pilling evaluation stages can be summarised as:

- Fabric's surface digitisation,
- Pill detection and segmentation,
- Pill quantisation (numerical description),
- Pill rating and classification,
- Fabric surface digitisation is the process of converting the fabric surface to a digital form that can be dealt with on computer systems. This process can be done using a digital scanner [6 - 10], camera [4, 11 - 13], light projected on a camera [14], a camera attached to a microscope [15], optical triangulation topographic reconstruction of the fabric surface [16 - 18], a laser line projected on the surface of the fabric specimen [19], or a stereovision surface reconstruction using two CCD cameras [19].

Pill detection and segmentation is the process of separating the surface fuzz and pills from the complicated fabric structure background. This process was obtained using simple techniques such as the application of a binarisation threshold on fabric images [5, 19], or after processing raw fabric images using spatial and spectral techniques. The raw image processing may include some filters for noise reduction or edge detection [9, 14], background dilation and erosion [11, 16], fabric pattern detection and isolation using Fast Fourier Transform (FFT) [4, 10, 11, 13, 20] or different techniques of wavelet transforms [6-8, 20-23]. Pill detection was also performed using a template matching algorithm[13]and edge flow detection [24, 25]. For the coloured images, pills were detected manually by blending the colour channels of the fabric image [15].

Pill quantisation is the next stage after segmenting pills from the fabric image. The process focuses on extracting some features that numerically represent the pill population to allow quantitative discrimination between the different images. The feature descriptors can be divided into two categories: one that depends on the final image of the segmented pills, and the other that utilises the spectral decomposition and analysis performed during the pill segmentation. The first category of features includes simple features such as the number of pills, the total pixel area of pilling, the mean area of pills, the relative area of pills to the total surface area, the sum of the gray values of pill images, the total volume of pills, as well as the distributions of pills, their shape, orientation angle, contrast, and density or uniformity of the pills' spatial distribution on the fabric surface [4, 5, 8, 10 - 13, 15, 16, 19]. The descriptor features can also be calculated from the gray-scale image of the processed surface or from the simulated fabric surface and includes roughness, skewness as well as the pill number, volume (total and average volumes), height (maximum and average), area (total and average), and fractal dimension [9, 14].

The second category of features includes the wavelet detail coefficients from the decomposition levels at horizontal, vertical and diagonal orientations [21].It can also be defined as the horizontal detailed coefficient (especially at a scale close to the inter-yarn distances in the fabric) [6], as well as the energies of the reconstructed sub-image's indifferent spatial orientations [22, 23]. Other statistical features can also be extracted from the wavelet decompositions, such as the range, interquartile range, variance, standard deviation, the mean absolute deviation, median absolute deviation, the standard error and the coefficient of variation [7].

The classification stage can be considered as the ultimate goal of the whole process, where a "successful" rating of images allows the trust of the method to replace the available subjective analysis. Classification models use the extracted set of features as inputs that can be used to generate the final rating of the image. For the classification models empirical and statistical methods may be implemented such as multi-variable linear regression [8, 13, 19]and discriminant analysis [7, 21, 22],or artificial intelligent methods such as the application of different types of artificial neural networks [14, 23].

It is worth noticing from the literature survey that the majority of published papers available are more oriented toward one or more evaluation stages by altering and detailing their techniques, while some papers may focus on one stage only [24, 25]. Therefore there is a lack of integrated systems that manipulate the efficient practices and techniques of each evaluation stage to create a robust and effective evaluation process. This paper tries to bridge this gap by creating a simple and user friendly integrated system for the pilling evaluation of knitted fabrics. The system suggested implements fast and efficient techniques for pill segmentation and quantisation. The system also introduces a new method for creating a sampling dataset that is large enough to suit training and testing processes required in building the artificial intelligent classifier applied.

Methods of analysis

Standard image preparation

The standard evaluation photographs used for comparison were obtained from the EMPA Standards (SN 198525). The EMPA standards characterise the size of the pill as large, medium, and small and assign a grading scale for each category [4]. The three categories of the standard pictures are shown in ***Figure 1***, with each category depending on the pill size, yarn count, and fabric structural density. In each of these categories the pilling is evaluated by giving a number between 1 and 5, where the former refers to severe pilling and the later to no pilling. To allow better space for the operator's evaluation, the EMPA standard merges every two pilling ranks in one picture which gives four standard pictures (that represent 1-2, 2-3, 3-4 & 4-5 ranking). ***Figure 1*** shows rank 1-2 in each knitted fabric's pilling category.

The standard photographs of knitted were digitised by scanning to a computer with the resolution of 600 × 600 dpi. As these standard pictures are unique for each level, only twelve pictures (3 categories × 4

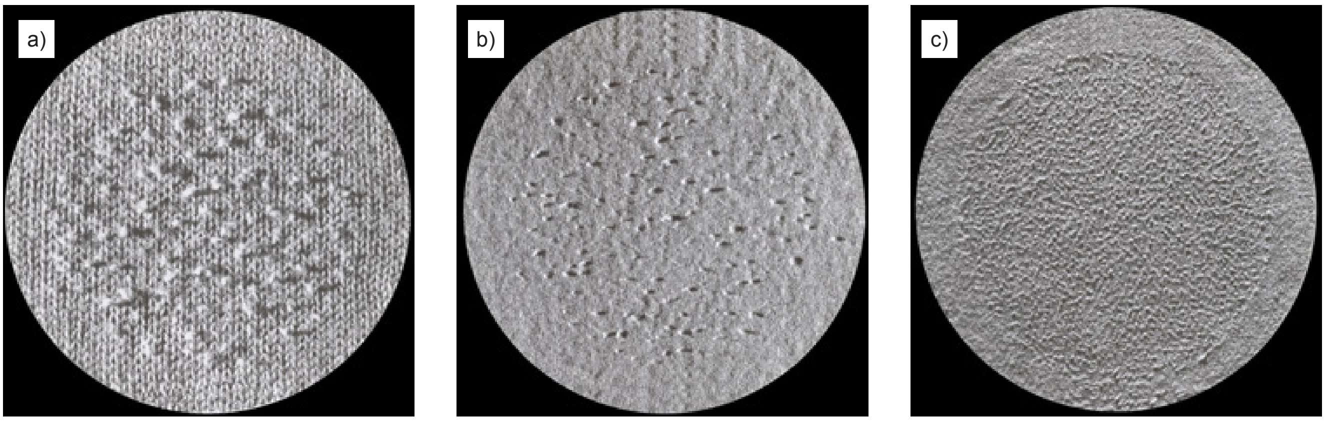

Figure 1. *Pilling pictures of the three EMPA standard categories (all pictures represent the level 1-2 pilling of each category); a) Standard category K1, b) Standard category K2, c) Standard category K3.*

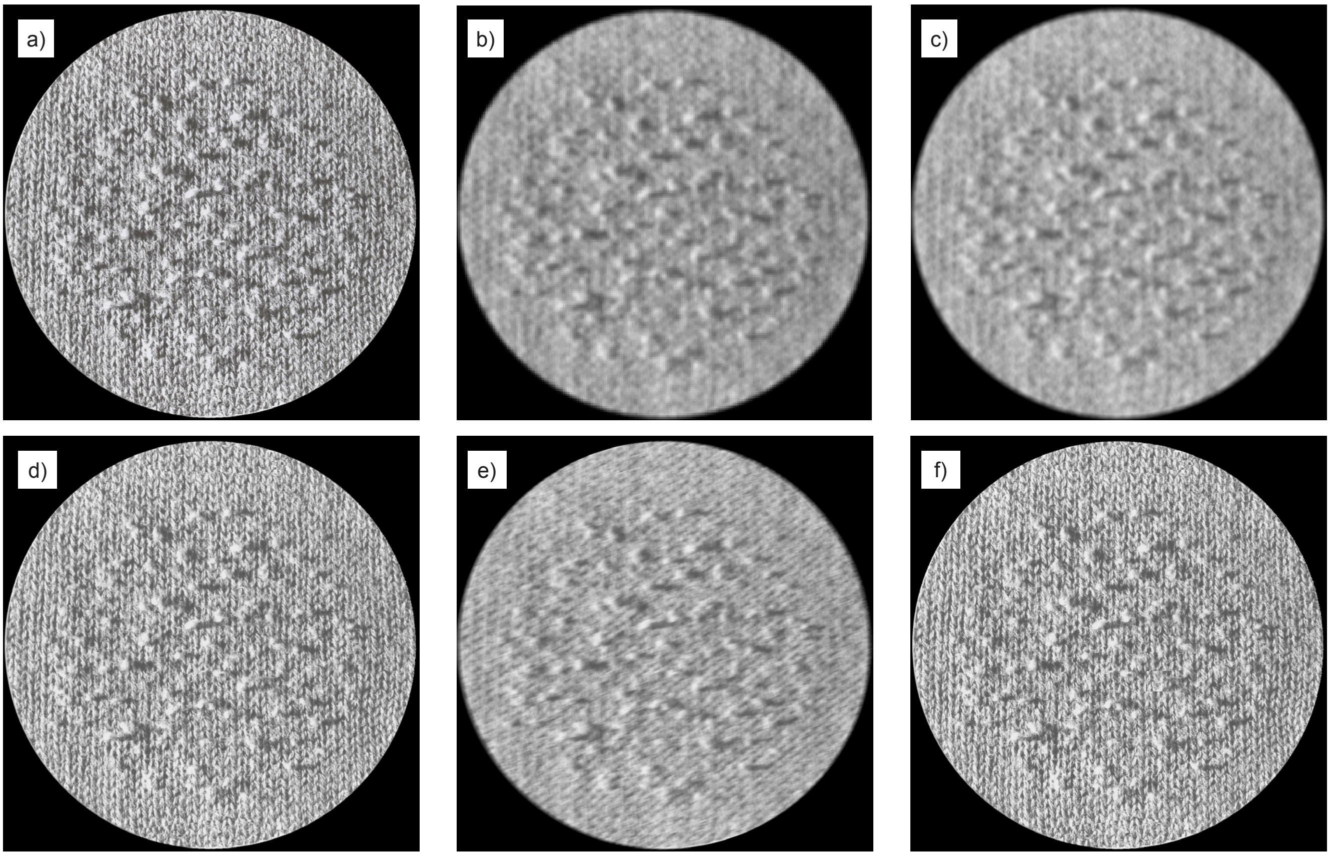

Figure 2. *Examples for different shapes of the same fabric sample after applying random filters; a) Original sample, b) Average filter, c) Disk filter, d) Gaussian filter, e) Motion filter, f) Partial rearrangement.*

rating images/category) can be scanned. On the other hand, the intelligent classification systems need many samples for training and testing. Some researchers have dealt with this problem by scanning the same standard images four times to enlarge the size of their dataset [23]. However, this technique may not be efficient in comparison with actual samples of wide varieties of structures and colours. Our method suggests simulation of the real situation where the actual fabric samples (after their rendering to remove the structure and colour effects) are distorted and there are noised images of the standard sample (after similar processing). Therefore the current method suggests adding random noise to the standard images to allow system robustness in detecting pills of the actual samples. It also enables to generate a dataset that is sufficient for the artificial intelligent classifier training and testing.

To add random noise to the standard pictures, different filter kernels were created with random parameters and each filter was convoluted with the standard image to create a "noised" or "blurred" image. Five different modifications were applied with the use of "averaging", "disk", "Gaussian", and "motion" filters, as well as "partial spatial rearrangement". Each filter and modification was applied with random parameters three times on the standard picture, which creates 15 different duplicates from the same standard photograph. "Partial spatial rearrangement" modification was applied by randomly selecting a sub-image from the original picture and placing it randomly in a different position of the image to create a partial rearrangement of the picture's elements. A representation of the original image and samples from the resulting image after the application of noised filters is shown in ***Figure 2***.

Pills segmentation

There are different pill detection and segmentation techniques, as summarised in the introduction of this paper. Simple, fast, and efficient algorithms were selected from these techniques to be applied in the system suggested. Digital images are enhanced by applying a morphological opening that includes erosion and dilation algorithms on the grayscale image. The morphological opening algorithm enhances the image and reduces the background noise by removing elements below a certain size. The algorithm uses a structuring element in a disk shape with a diameter proportionate to the fabric standard category. As the standard samples have three categories with different ranges of pill sizes, yarn counts and fabric density, a disk element with a small diameter was used for the category of fine yarn count and dense fabric. The image produced from the previous algorithm with low background noise is then subjected to binarisation with a specific threshold that results in a number of objects that represent the pills' fabric. ***Figure 3*** demonstrates the segmentation algorithm and ***Figure 3.a*** shows a fabric image with a certain *region of analysis,* circled in the figure. The region of analysis can be changed by the user, introduced for two reasons: first to focus the analysis on the region of the sample that goes under abrasion during Martindale testing. Second to allow system independency from the sample picture's size and resolution. ***Figure 3.b*** shows a binary image of the fabric with segmented pills. To demonstrate the efficacy of the algorithm applied, ***Figure 3.c*** shows superimposed images of the original fabric highlighted with the segmented pills.

Pill quantisation

It is necessary in any objective evaluation to quantise the property under investigation. This quantisation process applies

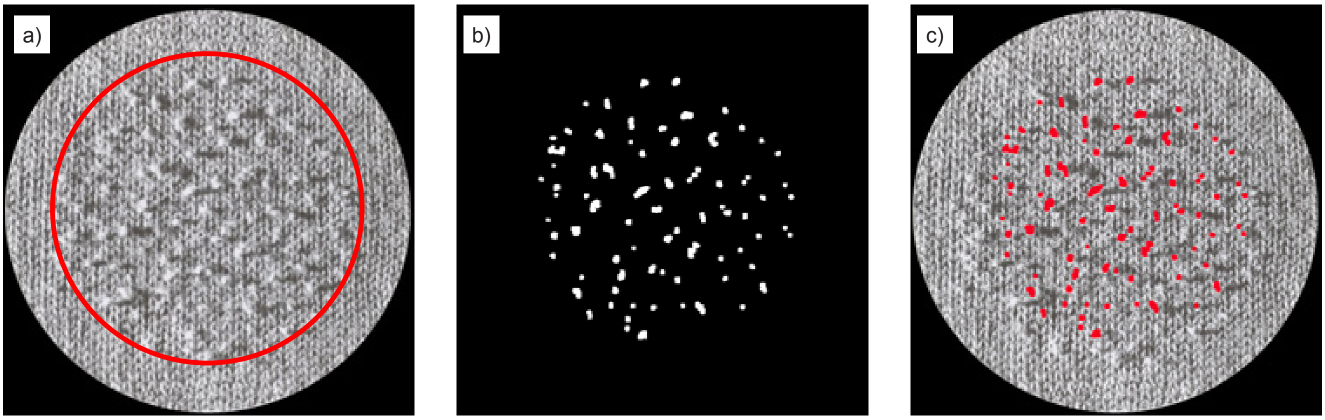

Figure 3. *Knitted fabric image with its preparation steps to detect its pilling; a) Original fabric image with the "region of analysis" circled in red, b) Binary image, c) Combined image.*

many techniques, as demonstrated earlier. Among the most common characteristic features, the following were extracted from the segmented images:

Number of pills

The number of pills is used as a characteristic feature because it shows the severity of deterioration on the fabric surface due to abrasion. To calculate the number of pills, the labelled pixels of the binary image were used to test the connectivity of pixels and therefore find the objects in the image. Pixels may be neighbours but are not connected as long as their values are different and the connectivity of neighboring pixels can be determined in 4 or 8 directions, which thus affects the number of objects obtained. In the current fabric images, a pixel connectivity of 8 was used and the number of objects detected (*N*) was considered as a representation of the number of pills on the fabric surface.

Pills' average area

The area of each pill (object) A_i obtained is calculated by summing up the number of pixels in each object. The average pill size ($A_{avg.}$) is then calculated according to the relation:

$$A_{avg.} = \frac{\sum_{i=1}^{N} A_i}{N} \quad (1)$$

Pills' area ratio

Unlike the ASTM pilling definition mentioned in the introduction, the "Textile Institute Textile Terms and Definitions" includes the density of pills that should be great enough for light not to pass through them to the fabric surface and cause a shadow to be cast on the surface [12]. Therefore the extent of pills on the fabric surface is considered using two characteristic features, which are the area ratio ($A_{rat.}$) and density (ρ_{pills}). The area ratio is defined as the ratio of the area of all pills that cover the surface to the area of the region of analysis ($A_{analysis}$) within the fabric image. The area ratio ($A_{rat.}$) is calculated as:

$$A_{rat.} = \frac{\sum_{i=1}^{N} A_i}{A_{analysis}} \quad (2)$$

Pill density

The pills' areal density (ρ_{pills}) can be expressed as the number of pills per unit area of the region of analysis in the fabric image. It can be expressed mathematically as:

$$\rho_{pills} = \frac{N}{A_{analysis}} \quad (3)$$

Pilling classification

After generating a library of standard images and their derivatives, the pictures were processed and analysed to generate a featur dataset according to the procedures described in the previous sections. The features dataset consists of the features extracted from the noised images as well as those obtained from the original picture. However; to avoid system bias, the noised samples represented 30% of the size of the dataset and the remaining percentage represented the original standard picture (that is 15 pictures for noised samples and 35 repeated pictures of the original standard). The final feature dataset consisted of 600 readings where each one of the three standard categories (K1, K2, and K3) form a third of the readings. The feature dataset was then split randomly into a training dataset that represents 80% and one that represents the remaining 20% of the data. The training dataset (of the four pilling features and standard category number) was fed to a pattern recognition artificial neural network (ANN). The ANN is shown in ***Figure 4*** and consists of a one hidden layer with 15 neurons and an output layer where all neurons have sigmoid transfer functions. The output of the ANN is a single number that represents the rating of the fabric sample with the features introduced.

Statistical analysis

Spearman's coefficient of rank correlation (r_s) was used to measure the association between the two sets of observations by human operators and the computer pilling evaluation, expressed on an ordinal scale. Spearman's coefficient can be formulated as:

$$r_s = 1 - \frac{6 \sum d^2}{n(n^2-1)} \quad (4)$$

Where *d* is the difference between the observations in the two groups and *n* the number of samples in comparison.

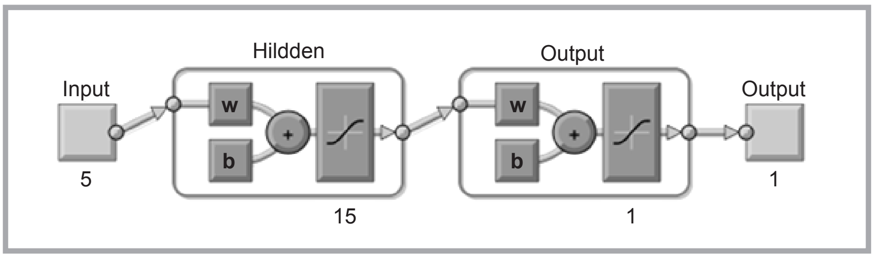

Figure 4. *Architecture of the ANN used for pilling classification.*

Table 2. Pilling level in the actual samples obtained subjectively from 5 operators and objectively obtained using the ANN classifier.

Symbol	Operator					Operators' evaluation	ANN evaluation
	1	2	3	4	5		
K1	2	2	2	3	2	2	1
K2	3	3	2	3	5	3	4
K3	2	2	1	2	2	2	1
K4	2	1	2	2	2	2	2
K5	1	1	1	2	1	1	1

Experimental setup

Five knitted fabrics with different structures and colours are specified as listed in ***Table 1***. To test the system's ability to detect fabric pilling regardless of the colour shade, test samples were selected to have different colours. The samples were tested on a Martindale instrument for their fabric pilling resistance, where two circular specimens of 140 mm diameter from each sample were placed on the machine head. The lower specimen's face is up and a specimen is placed on the top of a standard felt of 140 mm diameter. The upper specimen is mounted on a holder of 90 mm diameter with a standard felt of the same size and fixed to the holder with an elastic ring. The upper holder is installed on the machine where the faces of the upper and lower specimens are in contact with each other. The samples were tested under 2.5 cN/cm^2 pressure for 10,000 cycles of Lissajous figure with a 24 mm stroke.

The samples measured were evaluated visually by five different operators against the photographs of the EMPA Standards (SN 198525). The samples measured were then digitised using the setup schematically shown in ***Figure 5*** and processed using the software algorithm developed to obtain the pilling classes. The image acquisition system consists of a digital CCD camera equipped with a macro lenses to capture sample surface details. An image resolution of 300 dpi was captured and the image dimensions were 2048 × 1536 pixels. Lighting is critical for the imaging system, therefore two light sources that equally distribute light on the surface of the fabric were applied. The sample was tilted at a slight angle to the horizontal plane to allow to contrast the pills with their shadow.

Results and discussion

Photographs of the EMPA Standards (SN 198525) were acquired and a library of training images constructed after application of the filters with random parameters. Images were then processed for pilling segmentation and the quantisation process was performed to create a feature dataset. After training the ANN classifier, the performance was tested using the remaining 120 readings (that form the testing dataset), the results of which are presented in ***Figure 6***. The performance of the ANN developed is 87.5%, as expressed in terms of the correct classification rate (CCR), where the sample pilling class predicted matches with the pilling level targeted.

Pilling Classification (PC) software was developed to handle digital images of the fabrics tested. The graphical user interface (GUI) of the program is shown in ***Figure 7***, where the user can read the image, specify the standard comparison category, and determine the region of analysis for the fabric image. Once the user hits "Apply the modification algorithm" the modified fabric image will appear on the program's window with two controllers for the threshold and eroding diameter. Adjusting the eroding allows the removal of background noise in the main fabric structure and tuning the threshold level determines the pilling size and density detected. The results of changing any value will interactively appear in the fabric's image. After reaching a suitable detection level for the pills on the fabric surface, the user can classify them by pressing the "Classify" button and the program will recall the ANN classifier trained for predicting the sample pilling. The program produces the pilling level as well as characteristic pilling features in the program's window. The user can save the pill's segmented image or the superimposed image, as well as numerical results. All fabric sample images can be treated in a similar manner.

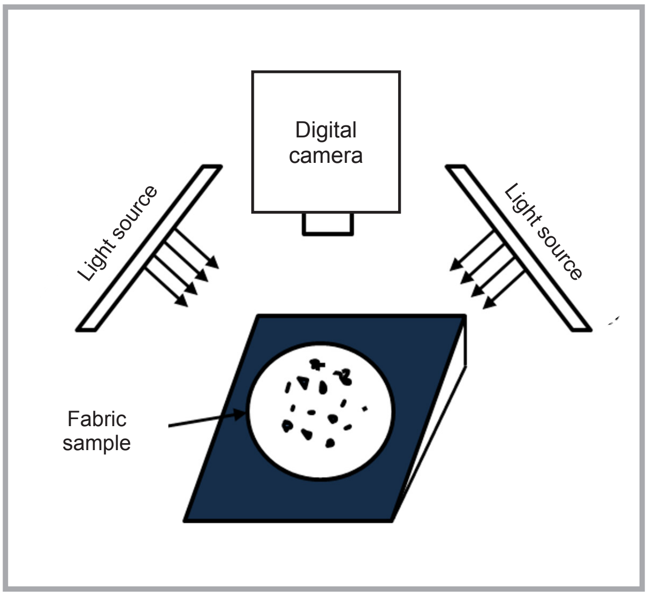

Figure 5. *Schematic representation for the image acquisition setup.*

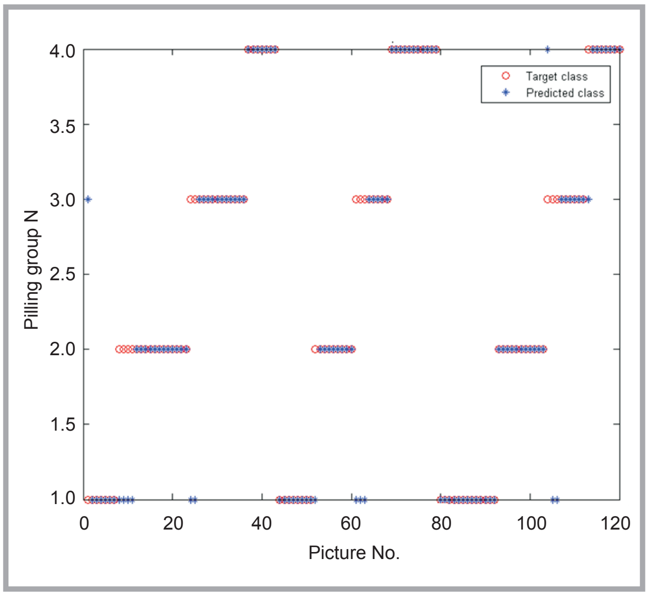

Figure 6. *Performance of the ANN in pilling classification (the CCR is 87.5%).*

The actual knitted fabric samples were tested for their pilling resistance performance on a Martindale tester as described earlier. The samples were then introduced to five operators to rank the pilling level in comparison to the standard images. The samples were also digitised using the setup shown in ***Figure 5*** and then processed on PC software developed for the current method. Results of the human subjective evaluation as well as the ANN classifier's objective evaluation are listed in ***Table 2***. The human operator's evaluation was calculated as the mode of ranking for individual operators. The evaluation of the knitted samples showed that they are distributed mainly between the three ranks of pilling. Spearman's coefficient of rank correlation between the two categories (*i.e.* the last two columns in ***Table 2***) is +0.85, which implies a good agreement between the two sets of results.

The actual samples treated for their pilling classification using the system suggested are shown in ***Figure 8***. It should be noted from the processed images that the region of analysis might differ between the samples because this part will be decided by the operator according to the sample introduced . This difference in the areas of analysis is the reason behind normalising the features according to the area used, which significantly improves the performance of the system as it allows its flexibility to deal with images of different sizes (i.e. regardless of the digitisation method) and different areas of analysis.

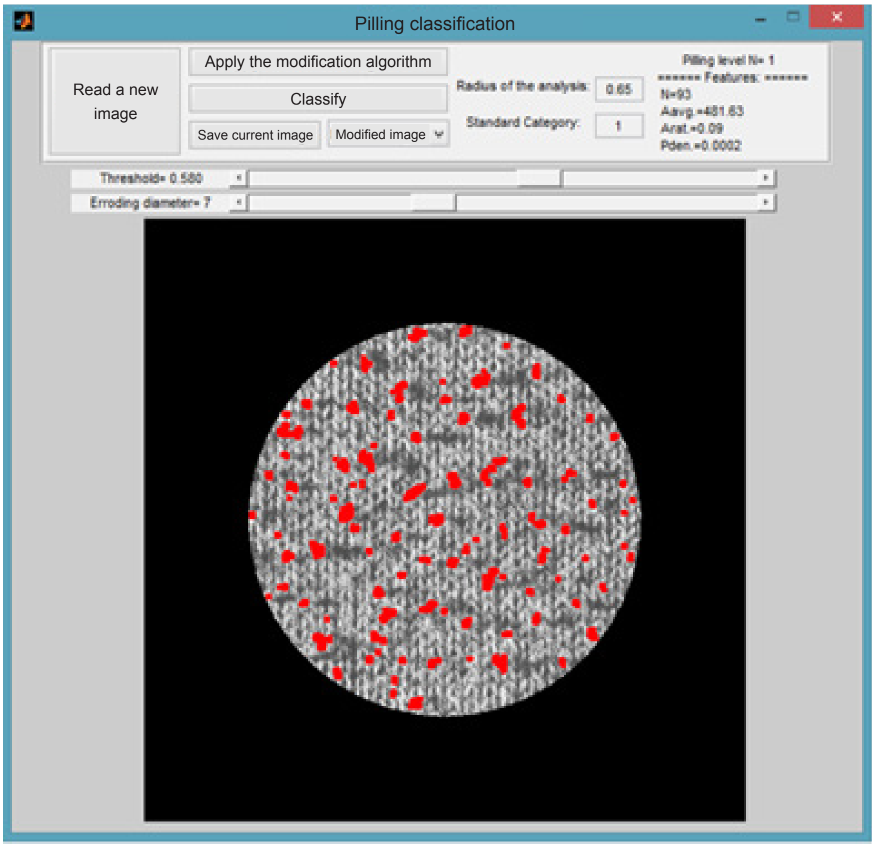

Figure 7. *Interface of pilling classification software developed.*

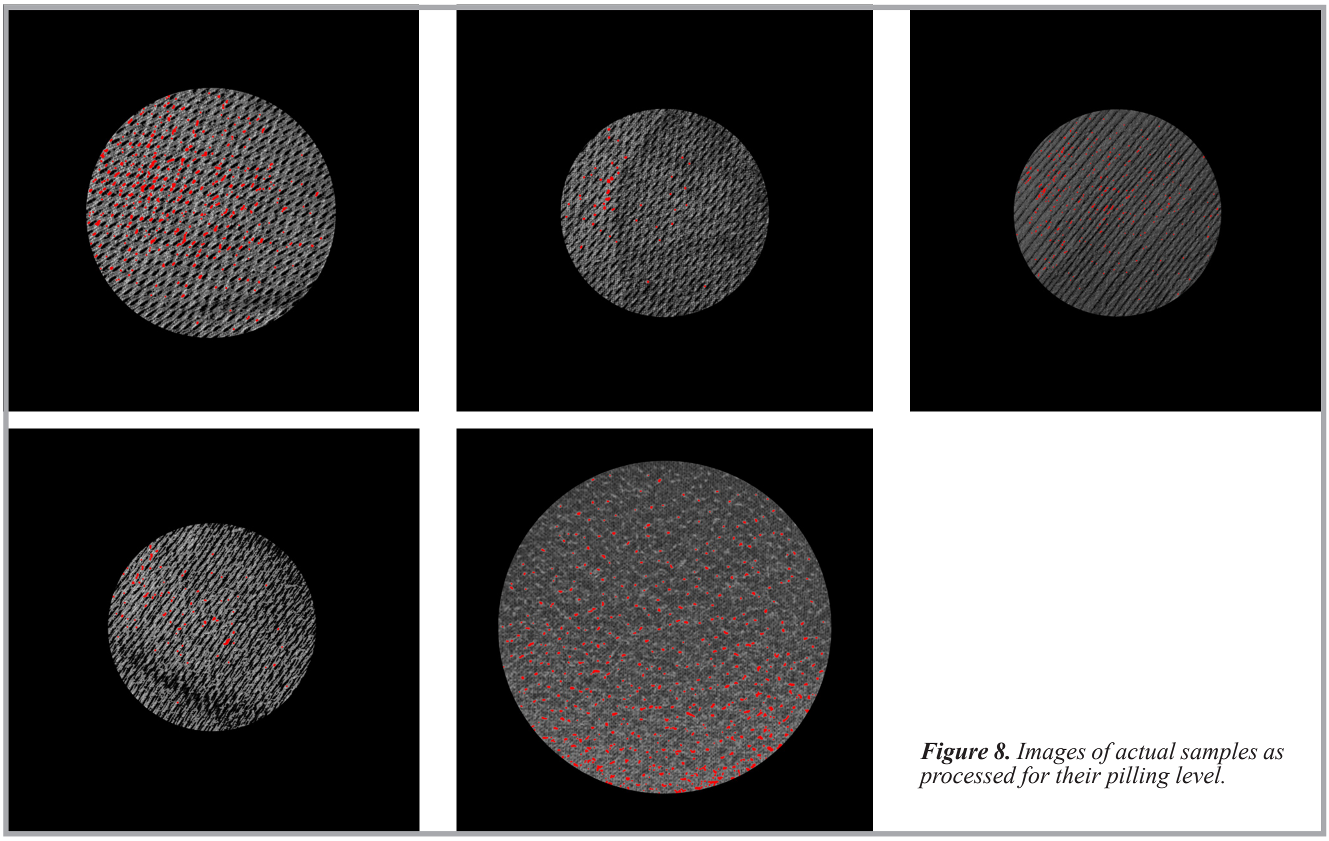

Figure 8. *Images of actual samples as processed for their pilling level.*

Conclusion

An integrated system for objective evaluation of the pilling of knitted fabric was introduced. The system utilises simple and effective techniques from those commonly available in the literature to integrate the four main stages of the evaluation process. This work introduced a new method that simulates real evaluation situations to generate an image library based on EMPA standard photographs. The images generated were processed and a feature dataset produced with a sufficient number of data for training and testing the artificial neural network classifier. The ANN classifier shows robustness in handling actual fabric samples with different structures and colours. The system introduced is user friendly and does not depend on human experience of the process, which enables standardised evaluation for the pilling resistance of knitted fabrics.

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