**Automatic Carpet Wear Classification Based on Support Vector Machine and Haralick Descriptors**

**Cosmin Copot, Robin De Keysér, Syam Syafie, Sergio Vargas, Lieva Van Langenhove** and *Corneliu Lazar*

**Abstract.** The Flemish carpet industry starts to look for a quality label to attest the resistance-to-wear of their product. Currently, this quality label is determined through visual assessment by human experts. However, this approach has some disadvantages, mainly related to problems generated by the subjectivity of human evaluators. The idea of using computers for automatic quality labelling is not new, but until now most results were not satisfying; the human expert still seems to be the best choice. This paper presents an approach to this problem using 3D lasers for scanning the carpets. Resampling the 3D data on different grid sizes, a 2D image is obtained and then a technique based on Haralick descriptors is applied to detect the carpet features. These features represent the inputs to a classifier system which is based on support vector machine (SVM). The performance of our proposed technique gives an average of about 92% correct labelling.

**Key words:** machine learning algorithm, automatic labeling, carpet wear, optimal hyperplane, co-occurrence matrix.

**2000 Mathematics Subject Classification:** 53B25, 53C15.

1. **Introduction**

In manufacturing and engineering, the quality of products or services is in many cases determined by humans, because no automated procedure capable of matching the human expertise exists. Carpets are a kind of products that are nowadays still evaluated with the help of human experts. The automated evaluation of carpet wear has been a topic of study of several institutes during the last three decades. Amongst others, the carpet quality is defined by the carpet wear. Hence, the quality evaluation demanded in carpet industry should
have a reliable, accurate and objective assessment of the carpet under examination.

The most important parameter in carpet quality evaluation is a common wear evaluation. The label is assigned by using Carpet and Rug Institute (CRI)’s Performance Standards. The standards take only into account the appearance changed due to matting and crushing that might occur from stepping and walking on. Time of the wearing is not associated with the ratings, however, the number of frictions is the most important influence parameters. This wearing can be simulated using a mechanical treatment in an accelerated movement such as “Tetrapod Walker Tester”, “Hexapod Drum Tester” and “Vettermann Drum Tester” [1].

Several instrumental methods have been studied including microscopy, photography, densitometry, colorimetry, photogrammetry, glass bead filling and pile mapping [2], [3], [4]. Extensive research has been conducted in this field using many different image analysis algorithms with the intention to quantify tuft definition, tuft geometry, periodicity and texture [5]. Some algorithms which have been used successfully on a limited set of carpet samples are gray value histogram analysis, local intensity variation filters, edge detection, template matching and classifier systems [3].

The idea of using a computer for automated labelling is not new but until now all the results were not satisfying and the human experts are still the best choice. We present a new approach to this problem using lasers for scanning the carpets and obtaining a three dimensional image of the carpet. Due to the specific characteristic of three dimensional images new algorithms are needed to extract and process information from the digital copy of the carpet.

This paper proposes a study for analyzing and classifying the texture of the weared carpet surface. It starts from a 3D image, where the 3D image is produced by a 3D laser scanner. These 3D image data are then resampled based on different grid sizes to obtain a 2D image. The features are extracted based on Haralick descriptors [6], [7] of generated co-occurrence matrix, here 14 features are extracted. It means that these 14 features would give 14 dimensional spaces in the input for classification. The Principal Component Analysis (PCA) is applied to reduce the dimension [8], and at the same time to simplify the problem in classification.

Finally, the features are classified by use of a support vector machine. In order to train the machine, the three first principal components from the chosen combinations, 1 replica for testing and 4 replicas for training are used. In total, 10 different type carpets were tested. To obtain separable input feature data, kernel functions (polynomial, Gaussian) are used. The proposed classification in this paper based on support vector machine (SVM) gives 89.56% classification by using polynomial kernel function and 95.48% classification using Gaussian kernel function.
2. Data Preprocessing and Features Extraction

The main objective of the paper is to develop a classification algorithm for automated label of the carpet quality. There are five standard carpet levels which range from class 1: maximum wear to 5: no wear. Till nowadays, the level of the carpet is classified by human experts based on visual comparison. At least 3 human experts are involved for classification. Each of them could give his own level depending on visual inspection and comparison of the examined carpet with the standard one, Fig. 1. Therefore, the level scales are extended from integer levels to half levels as: 1, 1.5, 2, 2.5, 3, 3.5, 4, 4.5, 5.

![Fig. 1 − Carpet samples.](image)

The virtual image created by the 3D laser scanner is used to extract information about the carpet. For every carpet, our dataset contains the following information: the carpet number, the carpet type, the laser data, the wear quantity. The wear is quantified by a number representing the number of loops used by the wearing device to wear the carpet. After scanning a four dimensional point cloud is returned to the system, the first three coordinates of each point correspond to the X, Y, and Z position of the point on the carpet surface [9]. The fourth dimension matches the fraction of the laser light captured by scanner on a seven level ordinal scale and it gives an indication of the light reflection for each individual point. A number of carpets are submitted to the mechanical wear process and for each of them a 3D virtual image is created using a laser scanner and a standardized procedure, as in Fig. 2. This technique allows a more direct analysis of the carpet texture with less stringent side conditions. The laser scanner is generating every time the same results for the same carpet because the process of acquiring the data is less sensitive to the position of the carpet in the scanning moment. The solution consists in a three-step approach and, in the end, machine-learning methods are used for classification.
Because the carpet is not perfectly flat, pieces of wood are put on it to keep the carpet flat. During the scanning, these pieces are also scanned and need to be removed from the dataset. Therefore, 21 random carpets are analysed to define two thresholds to separate the pieces of wood from the carpet: scanned carpets are typically between these thresholds, but the scanned wood is not [9].

The data produced by the 3D laser scanner represent a measurement on a random grid, so to construct 2D images these 3D data need to be resampled into a regular grid. To find an optimal, the resample technique is tested for 3 different resampling sizes. In this paper, we test the next 3 sample schemes of $10 \times 10$ cells, $5 \times 5$ cells and $2 \times 2$ cells per cm$^2$ (Fig. 3). A sampling of $5 \times 5$ cells per square centimetres is optimally based on analysis of variance [9]. In this case, the number of cells containing sample points is on average 30% of the total number of cells.

Two resampling techniques are applied: the first estimates the data in each cell by using the samples in the cells and its 8 neighbours; the second one using only the sample points in the cell itself, as in Fig. 4. We have 4 values for each data cell provided from the scanner: the first two represent the statistical mean or median of the $z$ value noted with Z-mean and Z-median, for the both cases the sample is taking over $3 \times 3$ neighbourhood or just the points from the cell. The third value is the median intensity value, noted with “Q”, and the last
one is the density “D”, which represents the total number of points in a $3 \times 3$ neighbourhood (first resampling method) or the number of points either per cell (second resampling method).

![With Neighbours](image1.png) ![Without Neighbours](image2.png)

Fig. 4 – The types of resample technique.

As a result, there are 24 representative images for each carpet to analyse; for each 4 measurement values both resampling techniques are applied and that for all 3 different resampling sizes ($2 \times 2$, $5 \times 5$ and $10 \times 10$ cells per cm$^2$). Analysis of variance is applied to see the difference between the filling method and also the difference of measurements. After some tests, we notice that from all 4 measurements, the optimal is Z-median and the filling method without neighbours, so the optimal solution is Z-median, without neighbours and resampling size $5 \times 5$ cells. Fig. 5 presents a 2D image after which the resampling method was applied.

![2D image](image3.png)

Fig. 5 – An example for a 2D image after what resampling method was applied.

The characteristics of the scanner approve that the sample points have a bigger concentration in the middle of the scan band than in the borders. The carpets are wearing in the middle of the X-axis and the amount of wear can be written as a function of the Y-direction. So, as an input for machine classifier, we will use the scan line as a replica. It will be explained how these replicas are used for classification. How the scan line is represented will be explained next.

The holes are removed with morphological operators, and after that, we extract the regions around the scanned lines. Each scan line is divided into 48 equal regions and co-occurrence matrices are computed for each combination
(Resample, Filling and Measurement). Subsequently, a window of 5 co-occurrence matrices is defined and moved along the X-axis [9]. Then, 14 Haralick descriptors [6], [7], [10] for each combination are computed for each window location resulting in a set of $24 \times 14 \times 44$ descriptors per scan line (Fig. 6). Finally, the curvature obtained from plotting each of the $24 \times 14$ descriptors is computed integrating over all 44 window location.

![Fig. 6](image)

Fig. 6 – Computation of Haralick descriptors on scan lines.

Principal Component Analysis (PCA) is applied to the features extracted from laser scanned image because the 14 features extracted from the laser scanned image are very difficult to enter directly to train the classifier. It means that these 14 features would give 14 dimensional spaces in the input for classification. Therefore, reducing dimension is to simplify the problem in classification. The way to do this is by applying PCA [8]. Another strategy can be by using one or two features, but it is not a good strategy because working with few features, the important information from each feature of the carpet will be lost.

The output of PCA represents the original data mapped into the new coordinate system defined by the principal components. The new reducing features computed using the PCA method from the original features contained the same information as the original features but having a different repartition of the information through the features.

3. Support Vector Machine

Support Vector Machine (SVM) has been proposed as a new technique for pattern recognition. Support Vector Machine is an approximate implementation of the method of structural risk minimization and is based on statistical learning theory [11], [12]. SVM has been developed in the reverse order to the development of neural networks (NNs). SVM evolved from the sound theory to the implementation and experiments, while the NNs followed a more heuristic path, from applications and extensive experimentation to the theory. It is interesting to note that the very strong theoretical background of SVM did not
make them widely appreciated at the beginning. They were taken seriously only when excellent results on practical learning benchmarks were achieved in numeral recognition, computer vision and text categorization. Today, SVM shows better results than (or comparable outcomes to) NNs and other statistical models on the most popular benchmark problems.

Since SVM is a type of linear classifier dividing the feature space in two subspaces by the hyperplane that is maximum distance from one sample data to other sample data. This separable plane can be called as Optimal Separable Hyperplane (OSH). In real-world, in most of the cases, the input data is not linearly separable. Therefore, using kernel function the input data are mapped into a high-dimensional space where the linear separability may be done. Constructing the OSH in high-dimensional space is corresponding to perform the nonlinear classification in the input space.

In this study, the performances of classification are analyzed using two different kernel functions, polynomial and Gaussian kernels. Because each type of carpet has a different class distribution, the classifier is individually trained for all types of carpets. The input data for training classifier is given by the first three principal components from the randomly chosen combination, 4 replicas (samples) are used for training and a replica for testing, where every class of carpet has 5 replicas.

3.1. Binary Classification

Suppose the case when the classes are linearly separable, the training data are represented by \{x_i,y_i\}, i = 1, 2, ..., N, and \(y_i \in \{-1, 1\}\), where N is the number of training samples. If two classes are linear separable, it means that at least one hyperplane, defined by a vector \(w\) with a bias \(b\), can be found to separate the classes without error [12]. The algorithm of the support vector machine is to find the optimal hyperplane, this can be formulated as follows:

\[
w \cdot x + b = 0 .
\]

To find such a hyperplane, \(w\) and \(b\) should be estimated in a way so that:

\[
w \cdot x_i + b \geq +1, \quad if \quad y_i = +1
\]

\[
w \cdot x_i + b \leq -1, \quad if \quad y_i = -1 .
\]

These two equations can be combined in an inequality:

\[
y_i (w \cdot x_i + b) - 1 \geq 0 .
\]

To find the optimal separable hyperplane, the norm of \(||w|||\) is minimized
under inequality (3) [13]. Using Lagrangian formulation, the problem of finding optimal solution can be translated to:

\[ L_p = \frac{1}{2} \|w\|^2 - \sum_{i=1}^{l} \alpha_i y_i (w \cdot x_i + b) + \sum_{i=1}^{l} \alpha_i , \]

where \( \alpha_i \) are the Lagrange multipliers. Now, minimizing \( L_p \) with respect to \( w \) and \( b \), gives the conditions:

\[ \begin{align*}
  w &= \sum_i \alpha_i y_i x_i \\
  \sum_i \alpha_i y_i &= 0
\end{align*} \]

These conditions can be substituted into equation (4) and gives:

\[ L_d = \sum_i \alpha_i - \frac{1}{2} \sum_{i,j} \alpha_i \alpha_j y_i y_j x_i x_j . \]

Fig. 7 – Principle of Support Vector Machine.

In most cases, in real-life application, classes are not linearly separable, but support vector machines can be extended to handle nonlinear separation data using a feature function \( \Phi(x) \) [14]. This extension of SVM is based on mapping the input space into a feature space of a higher dimension and then to solve the problem in this feature space. A simple example (Fig. 7) should exemplify the idea of a nonlinear mapping to higher dimensional space and how it happens that the data became linearly separable in the feature space.

To generate a mapping in a high dimensional feature space, a method based on kernel:
was developed. If $K$ is a symmetric positive definite function, which satisfies the Mercer’s conditions:

$$K(x_i, x_j) = \sum_{m=1}^{\infty} \alpha_m \Phi(x_i) \Phi(x_j), \quad \alpha_m \geq 0$$

then the kernel represents an inner product in the feature space. The dual optimization problem can now be written as:

$$L(\alpha) = \sum_{i=1}^{n} \alpha_i - \frac{1}{2} \sum_{i=1}^{n} \sum_{j=1}^{n} \alpha_i \alpha_j y_i y_j K(x_i, x_j),$$

subject to $\sum_{i=1}^{n} \alpha_i y_i = 0$ and $\alpha_i \geq 0$, $i=1, \ldots, n$.

In this paper, two different kernels, polynomial and respectively Gaussian kernel are used:

$$K(x,y) = (x \cdot y + 1)^d,$$

$$K(x,y) = \exp(-\frac{\|x - y\|^2}{2\sigma^2}).$$

### 3.2. Multi-class Classification

The SVM method was developed to be applied only for two classes. There are two types of SVM approaches to solve the multi-classification problems. One is the “all the classes at once”, which solves this problem by considering all the instances from all the classes in a unique optimization formulation, the other one is the “decomposition-reconstruction” architecture approach using binary SVM [15]. More usual multi-classification SVM are “one against one” and “one against all”, in both cases, a first decomposition phase generates several learning machines in parallel and a reconstruction scheme allows obtaining the overall output by merging outputs from the
decomposition phase. In this study *one-against-all* (OAA) method is used for multi-class classification.

![Multi-class Classifier](image)

**Fig. 8** – Multi-class classification.

OAA decomposition transforms the multiclass problem into a series of binary subtasks that can be trained by the binary SVM (Fig. 8). OAA classification scheme splits the training set into two classes, one containing samples in the currently considered class, the other holding the samples of all other classes [15].

### 4. Experimental Results

These algorithms presented above are implemented and evaluated to observe the performance of the classification. The algorithm is applied for different types of carpets. In this experiment was used a set of 10 different carpets types: A8-501, A8-701, BIG4, 20 KL 803 Beige, LA7, PR 84, BIG8, 517, BIG8, LA9, 20 KL 803 Dark to analyze the performance. The laser image data for this experiment are provided by Textile Department at Ghent University. The performance of the system classifier depends on the image data (corresponding to the type of carpet) and on which type of kernel function is used (Table 1). To see the qualities of carpet, some simulations with different number of loops are applied, the level of wear is 98% correlated with the number of loops. The three first principal components from the chosen combination are used for the training input.
A training SVM is plotted in Fig. 9 for type of carpet LA9. This type of carpet has 4 classes based on human expert classification, so the SVM classifier has training data just for these classes. For different classes, the data are plotted in different colours. To test the classifier for each class of the carpet 1 left replica data are used. Classes 3.5 and 4 have more training data compared to classes 4.5 and 5. Class 3.5 has 8 training data and 2 for testing points; class 4 has 12 training data and leaves 3 data for testing. For classes 4.5 and 5, each has 4 training data and 1 for testing.

Fig. 10 – Classifier for type of carpet 701 with Gaussian kernel.
In Fig. 10, it is plotted a training SVM for carpet A8-701, where the training data is represented by a star, the testing data by a circle and the SVM by a black square. This carpet has 5 classes. The SVM classifier is built with these 5 classes data for training. The machine classified gives 84.4% using polynomial kernel, and 100% of testing data using Gaussian kernel (Table 1).

The classifiers are developed for both kernels. From the available laser scanned image, the performance of the classification can be improved significantly by the kernel function chosen in the mapping data from input space to higher dimensional space.

<table>
<thead>
<tr>
<th>Type of carpet</th>
<th>Polynomial kernel, [%]</th>
<th>Gaussian kernel, [%]</th>
</tr>
</thead>
<tbody>
<tr>
<td>A8 – 501</td>
<td>84.4</td>
<td>84.4</td>
</tr>
<tr>
<td>A8 – 701</td>
<td>84.4</td>
<td>100</td>
</tr>
<tr>
<td>Big 4</td>
<td>100</td>
<td>100</td>
</tr>
<tr>
<td>20 KL 803 Beige</td>
<td>84.4</td>
<td>84.4</td>
</tr>
<tr>
<td>LA 7</td>
<td>84.4</td>
<td>100</td>
</tr>
<tr>
<td>Pr 84</td>
<td>100</td>
<td>100</td>
</tr>
<tr>
<td>20 KL 517</td>
<td>100</td>
<td>100</td>
</tr>
<tr>
<td>Big 8</td>
<td>86</td>
<td>86</td>
</tr>
<tr>
<td>LA 9</td>
<td>72</td>
<td>100</td>
</tr>
<tr>
<td>20 KL 803 Dark</td>
<td>100</td>
<td>100</td>
</tr>
<tr>
<td><strong>Over all</strong></td>
<td><strong>89.56</strong></td>
<td><strong>95.48</strong></td>
</tr>
</tbody>
</table>

The polynomial kernel and Gaussian kernel are used to improve the performance, polynomial kernel gives 72% classification, and Gaussian kernel gives 100% correct classification for carpet LA9 (Table 1). This two kernels function does not improve the classifier performance for the same cases (A8 501, 20 KL 803, and Big 8) because the distribution data in classes are too complex to have an optimal hyperplane. Mapping the data from input space to feature space, using the polynomial kernel, the classifier gives 89.56% correctness and by using Gaussian kernel, SVM classifier improves to 95.48% correct classification.

5. Conclusions

In this paper, automatic quality assessment for carpet wear has been approached following the next three phases. In the first phase, a 3D laser scanner is used to extract the data from the carpets; in the second phase Haralick descriptors are used to extract the features; in the last phase a machine learning algorithm based on SVM (Support Vector Machine) is applied to classify the data.

Overall, the machine classifies 89% correctly using a polynomial kernel and 95% using a Gaussian kernel. This new technique represents an important
improvement in automated classification of carpets. Further research is going-
on in order to produce an automated classifier system for carpet wear evaluation
which should be highly applicable in industry.

A c k n o w l e d g e m e n t s. This paper has been realized during an Erasmus
grant at Ghent University supported by Socrates National Agency from Romania.

Received: September 12, 2009

**Gheorghe Asachi** Technical University of Iaşi,
Department of Automatic Control
and Applied Informatics
e-mails: ccopot@ac.tuiasi.ro
claraz@ac.tuiasi.ro
Ghent University, Belgium
**Department of Electrical energy,
Systems and Automation
***Telin Department
****Textile Department

R E F E R E N C E S

Clasificarea carpetelor folosind Suport Vector Machine și descriptorii Haralick

(Rezumat)

În această lucrare este descrisă o metodă de clasificare a carpetelor folosind Suport Vector Machine și descriptorii Haralick. În prezent, în industria carpetelor, analiza calității se realizează cu ajutorul experților umani deoarece nu există un algoritm de evaluare automatizată capabil să urmărească rezultatele expertizei umane. Această lucrare propune o nouă strategie pentru analiza și clasificarea texturii unei carpete folosind imagini 3D. Aceste imagini 3D sunt obținute cu ajutorul unui laser 3D. Trăsăturile extrase sunt bazate pe descriptorii Haralick generate din matricea de co-ocurență. Aceste trăsături sunt folosite ca intrare în sistemul de clasificare, sistem ce se bazează pe Support Vector Machine (SVM). Datele de intrare aparțin mai multor clase, de aceea este necesară introducerea unui sistem de clasificare multi-class bazat pe SVM. Separarea claselor nelineare s-a realizat cu ajutorul a două funcții kernel (Gaussian și polinomială). Clasificarea bazată pe SVM propusă în această lucrare oferă o rată de clasificare de 89,56%, utilizând funcția polinomială și o rată de 95,48% utilizând kernelul Gaussian.