Carpet Wear Classification based on Support Vector Machine Pattern Recognition Approach

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Outline

- Introduction
- Features extraction
- PCA (Principal Component Analysis)
- Features classification
- Results
- Conclusion
Objective

- Visual assessment by human expert (compared with standard)

- Mechanical wear
  - 5000 loops
  - 10000 loops
  - 15000 loops
  - 20000 loops
  - 25000 loops

- Carpet sample

- 3D Laser Scanner

- Co-occurrence matrix

- Computer classification

- Computer LABEL

Automated classifier

Introduction
Data Acquisition

Fig 1. Digital image

Fig 2. Laser image
Co-occurrence matrix composed

\[ C_d(g(i, j), g(i + k, j + l)) = C_d(g(i, j), g(i + k, j + l)) + 1 \]

Where: \( d = \sqrt{k^2 + l^2} \)
Features extraction

Haralick’s Features

- Energy
- Sum Entropy
- Entropy
- Sum Variance
- Inertia
- Difference Variance
- Homogeneity
- Difference Entropy
- Contrast
- Informational Measures of Correlation
- Correlation
- Maximal Correlation Coefficient
- Sum Average

Theoretical representation
Features Validation

Table of human expert

<table>
<thead>
<tr>
<th>Name of carpet</th>
<th>Human expert classification</th>
</tr>
</thead>
<tbody>
<tr>
<td>20 kl 517</td>
<td>BMW</td>
</tr>
<tr>
<td>20 kl 517 – 2</td>
<td>2.5</td>
</tr>
<tr>
<td>20 kl 517 – 4</td>
<td>2.5</td>
</tr>
<tr>
<td>20 kl 517 – 6</td>
<td>2.5</td>
</tr>
<tr>
<td>20 kl 517 – 8</td>
<td>2</td>
</tr>
<tr>
<td>20 kl 517 – 10</td>
<td>2</td>
</tr>
<tr>
<td>20 kl 517 – 12</td>
<td>2</td>
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</table>

Haralick feature - Energy
Principal Component Analysis is a useful technique used to reduce the dimensionality of large data sets, such as those from micro array analysis;

When there are more than three variables, it is more difficult to visualize graphically their relationships.
PCA Results

2D Plotting of first tow PC

3D Plotting of first third PC
Binary SVM

A separated hyperplane:

\[ w^T x + b = 0 \]

\[ w^T x + b > 0 \quad \text{if} \quad y = 1 \]
\[ w^T x + b < 0 \quad \text{if} \quad y = -1 \]

Where
- \( x \) is training data
- \( y \) is indicator vector

\[ w^T x + b = \begin{bmatrix} +1 \\ 0 \\ -1 \end{bmatrix} \]
Nonlinear - SVM

The separable plane will be:

\[ k(x_i, x_j)w^T + b = 0 \]

- polynomial kernel

\[ k(x_i, x_j) = (x_i x_j + 1)^p \]

- Gaussian kernel

\[ k(x_i, x_j) = e^{-||x - y||^2 / 2\sigma^2} \]
Multi-class SVM

- One-Against-All decomposition

![Features classification graph]
For every carpet are used:

- 4 points for training
- 1 point for testing

<table>
<thead>
<tr>
<th>Type of carpet</th>
<th>Polynomial kernel %</th>
<th>Gaussian kernel %</th>
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<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>
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<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>
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<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>
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<tr>
<td>LA 9</td>
<td>72</td>
<td>100</td>
</tr>
<tr>
<td>20 KL 803</td>
<td>100</td>
<td>100</td>
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<tr>
<td><strong>Over all</strong></td>
<td><strong>89.56</strong></td>
<td><strong>95.48</strong></td>
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</table>

Table of percentage classification
SVM Classification

Classification for carpet KL-517

Results
Automated carpet classification can be achieved using co-occurrence matrix, PCA and SVM

- Polynomial kernel gives 88.32% over all classification
- Gaussian kernel gives 94.24% over all classification
THANK YOU!