Texture Wear Analysis in Textile Floor Coverings by Using Depth Information

S. A. Orjuela Vargas, E. Vansteenkiste, F. Rooms, S. De Meulemeester, R. de Keyser and W.Philips

***Abstract*—Category 4. Considerable industrial and academic interest is addressed to automate the quality inspection of textile floor coverings, mostly using intensity images. Recently, the use of depth information has been explored to better capture the 3D structure of the surface. In this paper, we present a comparison of features extracted from three texture analysis techniques. The evaluation is based on how well the algorithms allow a good linear ranking and a good discriminance of consecutive wear labels. The results show that the use of Local Binary Patterns techniques result in a better ranking of the wear labels as well as in a higher amount of discrimination between features related to consecutive degrees of wear.**

***Palabras Claves*— Automated quality assessment, Wear analysis, texture analysis, Image analysis, texture feature extraction**

I. Introduction

THE change in appearance of textile floor coverings forms the base of a quantitative assessment of their wear. The wear is assessed by first subjecting the carpets to accelerated, intensive mechanical wear. Then an evaluation is performed by human experts using a series of reference containing samples with different degrees of wear. Manufacturers require a more objective assessment because the human assessment is somewhat subjective. Much effort has been devoted to automate this rating process, specifically on techniques extracting texture features from intensity images [1], [2], [3], [4], [5], [6], [7], [8]. However, no automated system for the labelling process has been successfully developed yet.

Practical applications have been limited because of the need to use dedicated algorithms with circumscribed features for specific types of carpets while industry demands generic algorithms fully describing the wear for a wide range of carpet types. Recently, some researchers have been exploring the use of depth information instead of photographs in search of adequately capturing the three dimensional structure of the carpet also evaluated by the experts. As a first attempt researchers used a scanner for digitizing 3D objects, resulting in extracted features which resulted in a poor ranking according to the wear labels [9], [10], [11]. The reasons for the poor ranking were first the poorly suited scanner resulting in a sometimes very sparse (especially for darker, poorly reflecing carpets) unstructured point clouds as input data and second the low amount of useful features that were found as output data to extract from these poor quality input data.

Therefore, a novel 3D scanner based on structured light was developed specifically for scanning carpets [12]. 3D data, termed range data, are obtained by video capturing with a camera the reflection of a uniform laser line on the surface of the carpet. Then, the depth information is calculated from the highest position of the brightest reflection on the columns of each frame. This system offers better linear and linear-rank correlations between wear labels and texture features computed from depth data. Experiments suggest that depth and color information are complementary to generalize the description on several carpets.

To optimize the feature extraction process a methodology based on experimental design has been proposed [13]. The methodology assumes that for a correct description the features must not only change monotonically according to the wear labels but also must be highly discriminative between consecutive wear labels. This methodology has been tested extracting Local Binary Pattern statistics on references from different standards [14], [15]. In this approach we use this methodology for comparing the performance of the features proposed in [13] against features using the Haralick [16], [17] and the Laws' texture energy [18], [19] descriptors.

The optimal features obtained in this approach are used together with features from intensity images in [20] for assigning wear labels on the worn carpets by using linear regression models. As a result a correct assignment of labels in steps of 1 could be achieved for six types of carpets. The correct assessment could be expanded to seven carpets by constructing the depth images using edge detection based on multiresolution analysis [21].

The paper is organized as follows. In Section 2 we describe the elements used to develop this approach. In Section 3 we describe the methods to extract the features and the the methodology to compare them. In Section 4 we report the results of the comparison. Finally, in Sections 5 findings are discussed and conclusions are drawn.

II. Materials

In this approach we use eight types of reference sets provided from the EN1471 standard. Each reference contains

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a collection of samples of a particular textile floor covering priorly subjected to different revolutions on the Vettermann tester [22]. This tester is composed of a drum with free-running circular brush inside. To perform the test, a carpet sample is located inside the drum, and the free-running circular brush lightly contacts the surface of the carpet sample when the drum rotates. Loose fibers are extracted by using a vacuum cleaner. We collected samples from carpet types loop, cut/loop, woven cut pile, frisé and shaggy. Each reference includes eight samples that have been have been subjected to the mechanical wearing in order to compose samples with transitional degrees of wear. For this, three experts supervised the wear output for each sample until the required label was achieved. The sets do not include label 5 and the labels vary from 4.5 to 1, with steps of half point. Label 4.5 represents a minor change in appearance and label 1 a severe change.

A database of depth images was composed by scanning samples with a scanner based on structured light designed by Orjuela *et al.* [12]. A photograph of the scanner is shown in Figure 1.

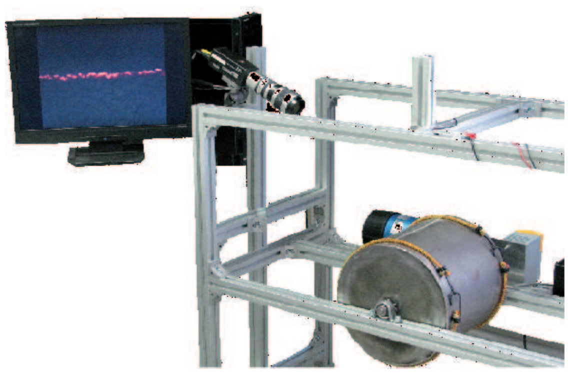

Fig. 1. Scanner used to capture the depth of the surface from the textile floor covering samples.

The samples were scanned one at a time by holding them upon an inox-drum with a diameter of 25 cm with elastic bands. The scanning process consisted of projecting a uniform line on the surface of the sample. This line was generated by a line laser generator located $20\ cm$ above the drum, which produced a bright, crisp laser line of uniform intensity with a length of $20\ cm$, a thickness of 0.5 mm and a fan angle of 60^o. The reflection of this line, representing the depth information, was captured with a Sony camera fixed at a distance of $30\ cm$ from the line to the objective lens. In order to cover the entire surface of the sample with the projected line, the drum was moved using a motor with gear box. This allowed us to control the distance between captured lines around $0.24\ mm$ by adjusting the speed of the motor using an AC inverter drive speed controller.

This system allowed us to extract the depth information provided by the reflected light in a frame and save it into an array. This information was converted to a scale from 0 to 1 for practical purposes, though most information was contained in the interval from 0.1 to 0.3. The applied treshold was dependent on the carpet type. The interval from 0.1 to 0.3 was discretized into 10 equal steps from 1 to 10 (values outside of the interval were fixed to 0) in order to obtain a reliable description of the depth, independent on the type of carpet. Then the depth was considered to be represented by the highest position of the highest value in each column of the frame. An array was constructed using this single depth value per column from the frame. A matrix representation of the depth information was subsequently constructed by adding the arrays when the drum is rotating. To obtain a gray image, the depth values of the matrix were converted to gray scale values from 1 to 255. Two depth image examples obtained with his scanner are shown in Figure 2.

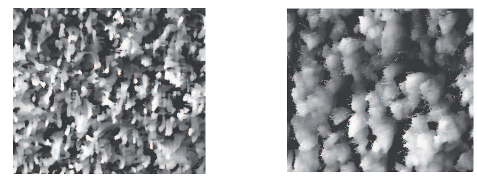

Fig. 2. Surface of depth image samples.

A 3D perspective of a digitized carpet is shown in Figure 3.

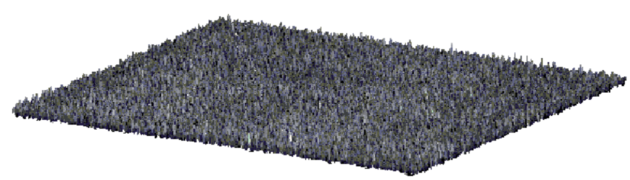

Fig. 3. 3D perspective of a depth image.

The scanning process resulted in gray images with size of 720×1250 pixels representing a surface sample with size of $17.28 \times 30\ cm^2$. Images with size of 720×576 pixels were however preferred in order to be able to compare depth images with intensity images in different research not covered in this paper. For this purpose, a window was moved along the height of the depth images obtaining five images with size of 720×576 pixels corresponding with a surface sample of $17.28 \times 13.82\ cm^2$. By consequence, each pixel represented a surface sample with size of $(0.24\ mm)^2$ of a textile floor covering sample. The final result was a database composed of 320 gray images representing depth images. Each set contained eight types of reference fatigued specimens, Each reference with samples of eight label scales and each scale represented with five images.

III. Methods

We extract features from the depth images using texture analysis techniques namely features from Local Binary Patterns, coocurrence matrices and Laws' texture measures techniques. These features represent transitional changes in appearance of the worn carpet samples.

We compute features from 32 image variations for each image in the database. These variations have been introduced to add reliability and robustness to the results. The variations consist in random combinations of complement, rotations of 0, 90, 180, 270 degrees and mirrored up-down and left-right. The methods to extract the features are explained in the following.

A. **Features from Local Binary Patterns.** These features are computed by using a symmetrized adaptation of the Kullback-Leibler (SKL) divergence between distributions of patterns from an extension named LBPRMC [13] of the rotational Local Binary Pattern techniques [23], [24], known as LBPROT. The LBPRMC technique is computed as the LPPROT by codifying into a pattern for each pixel its relations with points in a circle around it. In the LBPROT rotational versions of patterns are grouped by using a look up table while in the LBPRMC technique mirror and complement versions are also grouped. This is because a carpet reflected in a mirror or with the colours inverted must be assigned the same rating by human assessors. We compute for this approach LBPRMC patterns using 8 and 12 circular neighbours and using a radius of 1 and $\sqrt{2}$ respectively [13].
   To compute the symmetric Kullback-Leibler divergence the distribution of the LBPRMC patterns corresponding to wear labels should be compared with a distribution reference to quantify the change in texture. To do this, since there are no samples of original appearance in the database, its LBPRMC patterns distribution is estimated by using a simple linear regression model from the histograms of wear labels 1.0 to 4.5. This is justified as patterns changes monotonically from labels 1.0 to 5.0 [13]. The differences in texture between worn and original carpet have been have been quantified by comparing the corresponding LBP histograms using the symmetric Kullback-Leibler divergence [25] described in [13].
B. **Features from Coocurrence Matrices.** These features are computed using the descriptors proposed by Haralick [16], [17] on a given co-ocurrence matrix. A cooccurrence matrix defines the distribution of co-occurring neighbour values in an image at a given distance x and an angle θ. We compute the 14 Haralick descriptors from a matrix resulting from adding four co-ocurrence matrices using $x = 1$ and $\theta = [0^o, 45^o, 90^o, 135^o]$.
C. **Features from Laws' texture measures.** We compute these features by computing Laws' texture energy measures [18], [19] for major regions of the images in the database.
   To compute the Laws' texture energy, the images are first filtered by using a set of 25 masks. These masks are constructed by mutual multiplying five vectors, each with five elements, describing average gray level, edges, spots, ripples and waves from images, respectively known as $L5$, $E5$, $S5$, $R5$ and $W5$. These vectors are derived from the convolution of three vectors, each with three elements, namely $L3$, $E3$ and $S3$. These three vectors represent averaging, first difference and second difference.
   After the convolution of the image with the 25 masks, the energy measure of the major region is computed for each resulting image by summing together their absolute values. The energy values are divided into the energy value corresponding to the $L5L5$ mask to normalize the values. Afterwards, the energy value corresponding to the $L5L5$ mask is discarded and the other 24 energy values are combined into 14 to achieve rotational invariance.

Since most of the changes due to wear appear in the tips of the pile yarns tufts and their size depends of the type of carpet, the images in the database are evaluated at different resolutions. Scale resolutions within the range from 0.6 to 1 in steps of 0.1 are considered because the optimal resolution are found to always lie in this interval [13].

In total, a collection of 30 features for each scale factor have been computed, 2 from the LBPRMC technique, 14 from the co-ocurrence matrix and 14 from the Laws' texture energy.

The features for the 8 wear labels are characterized following the methodology described in [13]. This methodology is based on the assumption that the features are expected to change monotonically with the wear labels. In that case, the features must be highly discriminant between consecutive wear labels. To evaluate this, the following two characteristics, termed response variables, are quantified.

1. **The monotonicity, termed ρ.** We desire to obtain features that change monotonically with the wear labels. For such features, the resulting relationship between features of consecutive wear labels should be linear-ranked. The linear ranking can be evaluated by computing the Spearman rank correlation between the wear labels and the mean values of the associated features. This is done by first ordering the mean values from small to large and then calculating the difference between the assigned rank and the expected rank. Finally, a significance of the correspondence is assigned between -1 to 1, with 1 indicating a perfect rank correlation. The formal computation of the Spearman rank correlation is described in the following equation
$$\rho = 1 - \frac{6}{(L(L^2-1))} \sum_{l=1}^{L} {d_l}^2 \qquad (1)$$
   with $L = 8$ the number of wear labels and d_l the difference between the assigned rank and the expected rank for the mean value l (with l from 1 to L).
2. **The number of consecutive wear labels that can be statistically distinguished, termed τ.** This number is quantified by counting the number of times the difference between consecutive means exceeds the threshold for a statistic significance. The statistic significance is computed based on the Tukey test which allows pairwise comparisons. The Tukey test requires an equal number of features values per wear label. The significance is computed by the equation below:
$$\varsigma = \frac{q_{(\alpha,L,SL-L)}}{\sqrt{(SL-L)S}} \sqrt{\sum_{l=1}^{L}\sum_{s=1}^{S}(F_{ls}-\mu_l)^2} \qquad (2)$$
   F_{ls} refers to a given feature for wear label l and variation of the image s. $q_{(\alpha,L,SL-L)}$ is obtained from the studentized range distribution at $100(1-\alpha)$ of confidence. $S = 32$ is the number of image variations, $L = 8$ is the number of wear labels and μ_l is the mean value of

the features associated with the wear label l. τ is finally computed as the number of times that the difference of features between consecutive wear labels is bigger than ς.

The techniques are compared using an ANalysis Of VAriance test (ANOVA) [26] on the optimal response variables for each carpet type. For this, for each technique the highest response variables for each carpet type are chosen. ANOVA results are probabilities, termed p-values, where a p-value less than a given α means that there is at least one significant difference with $100(1-\alpha)\%$ of confidence. ANOVA does not specify the differences when more than two classes are compared. In that case, a test for multiple comparisons must be performed. We choose for this the Scheff test [26], in which significant differences are also detected when p-values are less than a given α.

IV. Results

The ANOVA results show that features from the LBPRMC technique performs better than features from the co-ocurrence matrix and the Laws' texture for both characteristics, the monotonicity and the number of consecutive wear labels that can be statistically distinguished.

To obtain these results, we tested for significant differences in the response variables computed from the images on the database applying the three techniques. The analysis has been performed on the optimal response variables for each carpet type. In the following, we will describe the ANOVA results in detail.

A. *Evaluation of the Spearman correlation.*

ρ values are identified to be significantly different (p-value $= 0.029 < 0.05$) among the techniques. The Sheeffé test show significant differences between features from the co-ocurrence matrix technique and features from the LBPRMC technique (p-value < 0.05). No significant differences have been identified between features from the co-ocurrence matrix technique and features from the Laws' texture measures technique (p-value > 0.05). Likewise, no significant differences have been identified between features from the Laws' texture measures technique and features from the LBPRMC technique (p-value > 0.05). Although no significant difference were detected between the Laws' texture energy and the LBPRMC technique, the fact that the Laws' texture energy is not clearly distinguishable from the co-occurrence technique makes the LBPRMC technique the optimal from the three for describing more monotonically the transitional changes due to wear.

B. *Evaluation of the number of Consecutive Wear labels that can be Statistically Discriminated.*

τ values are identified to be significantly different (p-value $= 0.003 < 0.05$) among the techniques. The Sheeffé test show significant differences between features from the co-ocurrence matrix technique and features from the LBPRMC technique (p-value < 0.05). Significant difference are identified among the three techniques, with the LBPRMC distinguishing a bigger number of consecutive wear labels.

Figure 4 summarize the ANOVA results. Mean values, at the bottom of the boxes, and standard deviations, represented with $\leftrightarrow$ at the top of the boxes, are shown.

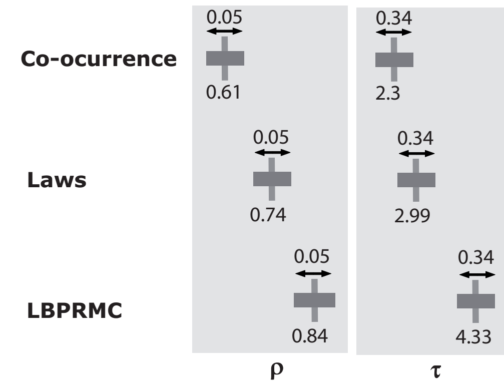

Fig. 4. Comparison of response variables response for the three texture techniques.

TABLE I
Optimal representation chosen for the 8 types of carpets.

	Optimal Representation		Quantified Characteristics		
Carpet Type	Type of Image	Scale Factor	ρ	τ	r
Shaggy1	Depth	0.7	0.93	4.00	0.92
	Intensity	0.7	0.93	4.60	0.75
Cut/loop	Depth	0.7	0.53	4.00	0.48
	Intensity	0.9	0.49	5.20	0.49
Shaggy2	Depth	0.9	0.77	4.00	0.80
	Intensity	1.0	0.92	5.60	0.87
High/Low loop	Depth	0.6	0.88	4.00	0.93
	Intensity	0.9	0.99	6.40	0.97
Frisé	Depth	0.9	0.97	5.40	0.97
	Intensity	1.0	0.89	5.20	0.82
Cut	Depth	0.9	0.95	3.60	0.93
	Intensity	1.0	0.99	6.00	0.96
Loop	Depth	0.8	1.00	6.60	0.94
	Intensity	0.9	0.98	6.20	0.97
Cut Design	Depth	1.0	0.72	2.80	0.67
	Intensity	0.9	0.87	4.20	0.81

V. Discussions and Conclusions

In this paper a comparison between three texture analysis techniques for describing the wear in carpets from depth images has been presented. We have compared the performance of features extracted from the Co-ocurrence matrix, the Laws' texture measures and an extension of the Local Binary Pattern Technique. The depth images were obtained from samples of eight types of carpets provided from the EN1471 standard. The samples represent eight transitional changes of wear in steps of 0.5 that were achieved under the supervision of human experts on the Vetterman Test. It has been previously demonstrated that the LBPRMC extension performs better than common LBP techniques on these types of images. The results of this approach show that the LBPRMC technique performs better than the other two, the co-ocurrence matrix and the Laws' texture measures. This has been demonstrated because the LBPRMC technique describes more monotonically the transitional changes due to wear as well as distinguishes a bigger number of consecutive wear labels.

We believe that the algorithm to reconstruct the surface from the scanner data must be improved to obtain more reliable description of the wear. Moreover, further study of combinations between texture features from depth images and features obtained from intensity images is required before an automated and universal carpet-labeling system can be developed. The extracted features can be used in generate linear models to assign the wear label of a sample. Further, we would also like to extend the application area of our scanner to digitize surfaces of general textiles and other materials, and to analyze the roughness of bendable materials.

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