Available online at www.sciencedirect.com

ScienceDirect

Engineering Applications of Artificial Intelligence 21 (2008) 907–918

Engineering Applications of ARTIFICIAL INTELLIGENCE

www.elsevier.com/locate/engappai

Classifying carpets based on laser scanner data

Willem Waegeman[a,*,1], Johannes Cottyn[c], Bart Wyns[a], Luc Boullart[a], Bernard De Baets[b], Lieva Van Langenhove[d], Jan Detand[c]

[a]*Department of Electrical Energy, Systems and Automation, Ghent University, Technologiepark 913, B-9052 Ghent, Belgium*
[b]*Department of Applied Mathematics, Biometrics and Process Control, Ghent University, Coupure links 653, B-9000 Ghent, Belgium*
[c]*Department PIH, University College of West-Flanders, Graaf Karel de Goedelaan 5, B-8500 Kortrijk, Belgium*
[d]*Department of Textiles, Ghent University, Technologiepark 907, B-9052 Ghent, Belgium*

Received 18 September 2006; received in revised form 18 July 2007; accepted 20 July 2007
Available online 29 October 2007

Abstract

Nowadays the quality of carpets is in industry still determined through visual assessment by human experts, although this procedure suffers from a number of drawbacks. Existing computer models for automatic assessment of carpet wear are at this moment not capable of matching the human expertise. Therefore, we present a completely new approach to tackle this problem. A three-dimensional laser scanner is used to obtain a digital copy of the carpet. Due to the specific characteristics of the laser scanner data, new algorithms are developed to extract relevant information from the raw data. These features are used as input to a classifier system that defines a partial ranking over the objects. To this end, ordinal regression and multi-class classification models are applied. Experiments demonstrate that our approach gives rise to promising results with correlations up to 0.77 between extracted features and quality labels. The performance obtained with nested cross-validation, including a C-index of more than 0.95, an accuracy of 76% and only 3% serious errors of a full point, gives rise to a substantial improvement compared to other approaches mentioned in the literature.

Keywords: Quality control of carpets; Assessment of carpet wear; Pattern recognition; Laser scanner data processing; Feature extraction; Machine learning; Ordinal regression; Kernel methods

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. To receive big orders (e.g. for blocks of flats, office buildings, etc.) carpet companies need a certificate which proves the superb quality of their carpet types. These certificates are handed out by authorized laboratories with the help of human experts.

The laboratories employ a standardized procedure to evaluate carpets, in which the assignment of quality labels is primarily based on the change of appearance during wear. Wear is simulated in most cases by applying an intensive mechanical friction to the carpet. Subsequently, human experts evaluate the carpet's wear behavior by visual comparison with a set of reference samples in standard conditions. At the beginning of quality control in textiles, five main quality levels were considered (ranging from class 1: maximum wear to 5: no wear). The scale was later extended with two additional sublevels 2.5 and 3.5 in order to further distinguish the most frequently occurring classes 3 and 4. Hence, the experts nowadays determine the quality of a carpet on a 7-value ordinal scale.[2] The ongoing

*Corresponding author. Tel.: + 32 9 2645586; fax: + 32 9 2645839.
E-mail address: Willem.Waegeman@UGent.be (W. Waegeman).

[1]Willem Waegeman is supported by a grant of the "Institute for the Promotion of Innovation through Science and Technology in Flanders (IWT-Vlaanderen)".

[2]Although there is no metric defined on the scale, textile engineers consider a main level and a neighboring sublevel "closer" than two neighboring main levels. See Section 4 for further discussion.

0952-1976/$ - see front matter
doi:10.1016/j.engappai.2007.07.010

evaluation procedure by human experts has important disadvantages (Sette et al., 1995):

- Visual assessment is not objective and requires a certain expertise. In most of the laboratories there is a lack of experienced people.
- Visual assessment is subject to discussion. Some carpet producers believe that certain laboratories are less conservative than others in their judgements.
- Human experts frequently disagree in their judgement. Labels are therefore often assigned by majority voting of at least three experts. Nowadays one allows deviations of 0.5 point for individual experts.
- Consequently, the procedure is also slow as at least three people are involved.
- A limited number of reference sample sets has been established for the evaluation of an almost infinite number of carpet qualities.

On the other hand, carpet companies insist on a more reliable and more objective evaluation procedure and, consequently, the automated evaluation of carpet wear has been a topic of study by several institutes during the last three decades. To this end, several instrumental methods have been studied (Siew et al., 1988; Xu, 1994) including microscopy, photography, densitometry, colorimetry, photogrammetry, glass bead filling and pile mapping. However, most researchers applied image analysis techniques to classify carpet wear. Extensive research has been conducted in this field using many different image analysis algorithms with the intention to quantify tuft definition, tuft geometry, tuft placement, periodicity, texture, pile-lay orientation and roughness (see for example Wood and Hodgson, 1989; Xu, 1994; Pourdeyhimi et al., 1994; Sette et al., 1995; Van Steenlandt et al., 1996). Some of the algorithms which have been used successfully on a limited set of carpet samples are gray value histogram analysis, local intensity variation filters, statistical measures, edge detection filters, template matching and classifier systems.

Almost all of this research has been conducted using a (very) limited number of carpet samples (most of the aforementioned studies concern less than 50 samples including the wear samples). The acquisition of carpet samples, applying the necessary wear and the corresponding (human) assessment is time consuming and, as a consequence, severely limits the number of samples that a single research institute can generate. Moreover, interest was mostly limited to one or two carpet types due to the great differences, existing, between carpet types. As a result no "global" automated carpet evaluation system has yet been developed.

Another problem in the development of such a global system is the reproducibility of the images (Wood and Hodgson, 1989). Lighting arrangement, camera setup, focusing and level of digitization noise must all be considered with the greatest care to produce accurate (and reproducible) results. Even slight changes (replacement of old lamps, minor change of lighting angle, etc.) can substantially influence the resulting image.

In this paper we present a (partial) solution to the aforementioned problems. Our solution consists of a three step pattern recognition approach, namely data acquisition, feature extraction and model fitting with machine learning methods.

First of all, a laser scanner is used here instead of a camera to obtain a digital copy of the carpet. This technique allows for a more direct analysis of the carpet texture with less stringent side conditions. In essence the measured data for each carpet consists of a three-dimensional model of the carpet surface, represented by a four-dimensional point cloud with variable size. The fourth dimension represents the fraction of the laser light captured by the CCD-camera and gives an indication of the light reflection for individual points in the point cloud. More details about the laser scanning procedure and the characteristics of the obtained data set can be found in Section 2.

The specific nature of this application and of the point cloud data (non-vectorial data) imply that standard algorithms to derive meaningful information from the data cannot be used here. We combine several methods like point cloud segmentation and density estimation algorithms to extract relevant features from the raw data. Details about these methods can be found in Section 3.

In the last phase the data are modeled with different statistical and machine learning methods to explore the quality of the extracted features. For this purpose we have used recently developed kernel ordinal regression methods, which have several advantages compared to older techniques used in previous research, like neural networks and nearest neighbor classifiers (Sette et al., 1995; Van Steenlandt et al., 1996). These models take the ordering of the classes into account resulting in more accurate, less variable and better interpretable models, for which smaller data sets are needed. They also build up a deterministic model leading to better reproducible results. Details of the conducted procedure and the results can be found in Section 4.

2. Data acquisition

For our analysis a data set of 99 carpets of type *frieze* was collected with a large variety in colors and patterns. A list of different colors and patterns is given in Table 1 and pictures of some carpets are displayed in Fig. 1. In particular, 59 carpets had a pattern while 40 carpets were dyed with a single color. All carpets were labeled by human experts following a standardized procedure (except samples of class five) after simulating wear with a friction device, namely a *vettermann drum*. This device creates a worn-out zone in the middle of the rectangular carpet piece, while the edges remain undamaged. In a standard setup the mechanical friction takes a fixed number of loops in the device (5000 or 22 000 loops). For carpets of class one or