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MEASUREMENT OF ENZYMATIC TREATMENT EFFECT ON TEXTILE USING DIGITAL IMAGE ANALYSIS

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Abstract

The effect of enzymatic treatment on textiles has been investigated using standard texture algorithms. An extensive study in both the Fourier domain and the spatial domain has revealed the nature of the changes and resulted in one single feature that measures these changes in a fast and robust way.

1 Background

This project started when the R&D group in the detergent enzyme division of Novo Nordisk (a world-leading manufacturer of detergent enzymes) expressed the wish to quantify the effects of enzymatic treatment of textiles using digital image analysis. Until now this quantification has been done qualitatively using microscopic inspection and quantitatively using panel tests and light measurements (Hunter coordinates). There was a need for a new objective, robust, fast and relatively inexpensive method.

The image acquisition is carried out using an RGB high-resolution slow-scan camera. Subsequently we will only show results derived from the green band since the textiles used in this experiment are black and gray and thus contains very little or no color information. The size of the textiles in this study is 15x10cm.

The study regards the enzymatic treatment effect for a single type. We want to assess the effect at different pH values and for different doses. To assess the day-to-day variation the textiles were washed on different days for each pH-level. Thus we have three factors that we want to investigate.

- pH: 3 levels, 1 2 3 (for pH values 7.0, 8.0 and 9.0)
- dose: 8 levels, 0 10 25 40 50 75 100 200
- day(pH): 3 levels, 1 2 3

We have two repetitions for each combination, thus we end up with 144 images. In figure 1 we see 8 textiles representing the 8 doses for pH 1, day 1 and repetition 1.

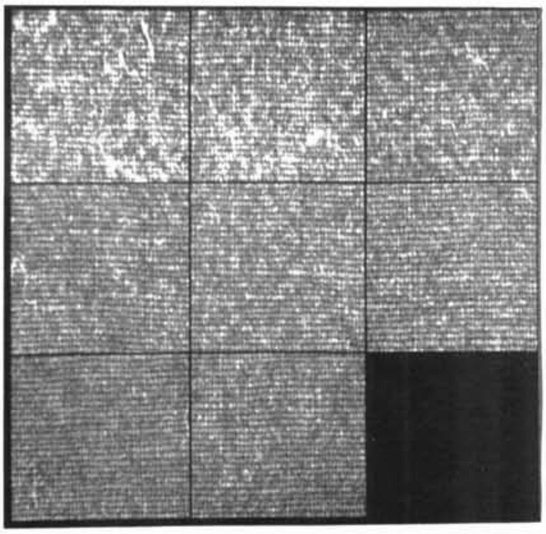

Figure 1: *8 textiles representing the 8 doses for pH 1, day 1.*

2 Description of visual properties

The object of the digital image analysis is to compute one feature that quantifies a given visual property from the image array. In this case the visual property is the human perception of wear. The feature has to correlate well with panel tests. For enzymatic treatment with known effects this means that the feature has to show improvement as a function of dose and show best results for pH values close to the pH with highest enzyme activity (between 7.0 and 8.0 in our case).

Obviously many different features can be computed from the image. A simple feature is the average intensity, *lightness*. This has a strong resemblance to what is measured by the Hunter coordinates. Probably this lightness feature also has a strong influence on a panel test. Figure 2 shows the average intensity as a function of dose for pH level 1. We see that lightness only has discriminative capability for small doses.

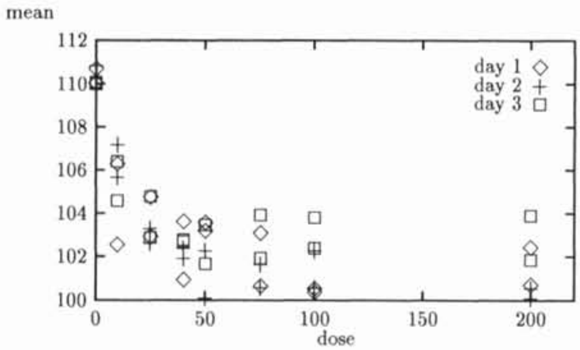

Figure 2: *Average intensity as a function of dose for pH level 1.*

Another aspect of enzymatic effect on the textiles estimated by the panel test is the *distinctness* of the regular textile pattern. This distinctness should increase as a result of the enzymatic treatment. The regular pattern in the investigated textiles resembles a rectangular grid structure. The well defined period of this grid makes it appropriate to look at the textiles in the Fourier domain. This is done in the next section.

3 Analysis in the Fourier domain

3.1 Frequency based methods.

Figure 3 shows the full resolution power spectra of the textiles in figure 1. The concentric circles are isolines for the spatial frequency. Several high-intensity spots in the power spectrum is showing the periodicity of the weaves. The spots of lower intensity in the high-frequency areas are higher harmonics. We see that the intensity in the low-frequency areas (near the center of the power spectrum) is fading for higher doses of enzyme. To illustrate this effect we computed the average of the power spectrum in the rings between the concentric circles and plotted it versus the radius of the rings. These averages are computed for each of the power spectra in figure 3, and the average corresponding to dose 0 subtracted from the averages of each of the other doses. The plot is shown in figure 4, and it is obvious that the averages in the low-frequency areas are decreasing for higher doses. We also note that all the curves has approximately the same intersection at a frequency corresponding to the frequency of the weaves. Thus having established that the power spectrum actually contains relevant information about the textile wear, we will try to quantify this in a single Fourier feature.

3.2 Spectral texture features.

Texture features derived in the spatial frequency domain have been investigated in e.g. Liu & Jernigan (1990). The features tested in the present context are listed below.

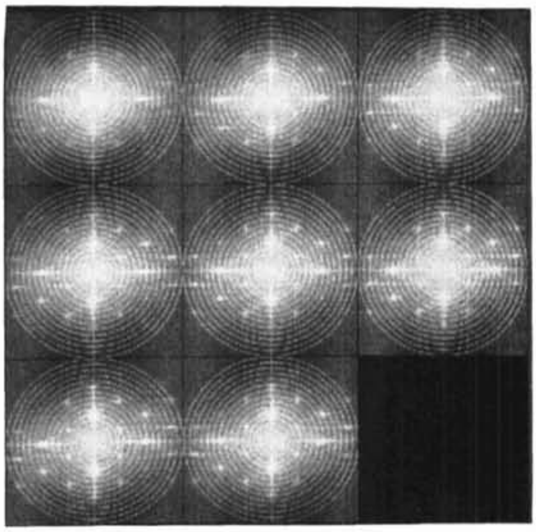

Figure 3: *Power spectra of the textiles in figure 1.*

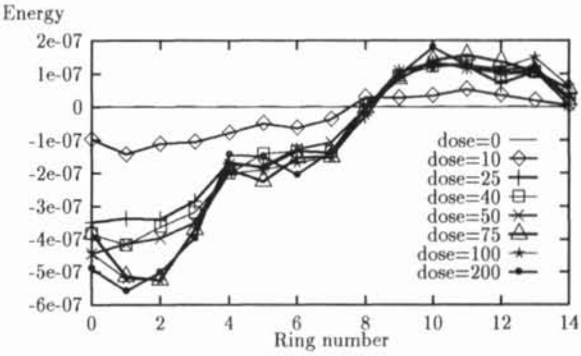

Figure 4: *Average of power spectra rings relative to dose 0 for the spectra in figure 3.*

1. Rings
2. Wedges
3. Inertia
4. Entropy
5. Anisotropy

The features were computed on both the power spectrum and the log-power spectrum. It turned out that the features calculated on the log-power spectrum performed significantly better than the power spectral features. Furthermore we found that inertia and entropy features performed better than the other features. The inertia feature performed generally a little better than the entropy feature, and it seems to be a more natural way summarize the phenomena observed in figure 4.

The inertia feature I and log-power inertia LI is computed as

$$I = \sum_{(u,v)} (u^2 + v^2) \mid F(u,v) \mid^2$$

$$LI = \sum_{(u,v)} (u^2 + v^2) \log(1 + \mid F(u,v) \mid^2)$$

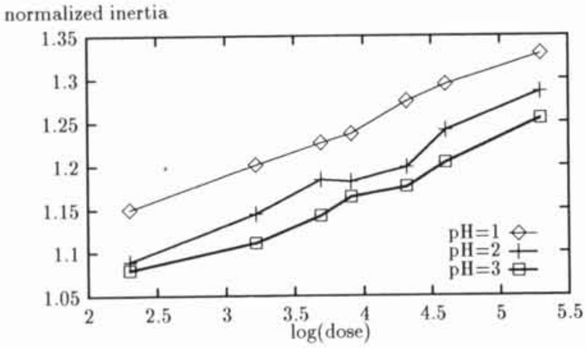

Figure 5: *Normalized log-power inertia versus log(dose). We see that the measure reflects the expected ranking.*

where we are summing over all frequencies. The normalized inertia is the inertia divided by the inertia of the corresponding textile with *dose* = 0. In figure 5 we show the normalized log-power inertia vs. log(dose) for all three values of pH. Thus the measure is averaged over days and repetitions. It can be seen that there is a clear distinction between the performance of the enzymes at the three pH values. In addition there seems to be an approximately linear relation between the inertia and log(dose).

3.3 Discussion of results

The spectral approach has provided us with a useful feature and a lot of insight regarding the nature of this problem. The use of the FFT algorithm however introduces some, somewhat technical, limitations regarding computational speed and the flexibility in removing textile irregularities from the analysis.

4 Spatial domain features

The distinctness property and other textural properties can also be measured by textural features in the spatial domain. Siew, Hodgson, & Wood (1988) used features based on different texture matrices for carpet wear assessment. The conclusion of the paper was, that features based on texture matrices (e.g. GLCM) can be used to characterize the appearance of carpets and changes, they undergo during wear. The problem of carpet wear assessment is similar to measuring effects of enzymatic treatment, and therefore we included GLCM features in our study.

4.1 Spatial features

The spatial domain features included in this study were a set of first-order statistics :

1. Mean
2. Variance
3. Skewness
4. Kurtosis
5. median
6. entropy

and the following 15 GLCM features (Haralick, Shanmugam, & Dinstein, 1973; Laws, 1980; Conners, Trivedi, & Harlow, 1984; Parkkinen, Selkäinaho, & Oja, 1990) :

1. Energy
2. Entropy
3. Maximum probability
4. Correlation
5. Diagonal correlation
6. Kappa
7. Difference energy
8. Difference entropy
9. Inertia
10. Local homogeneity
11. Sum energy
12. Sum entropy
13. Sum variance
14. Cluster shade
15. Cluster prominence.

The features were computed for several numbers of gray levels and at several resolutions. Attempts to make the features robust have included correction for inhomogeneous lighting and automatic removal of textile irregularities.

4.2 The operational feature

Many of the tested features performed well on subsets of the images, but only a few features gave an overall good and robust measurement.

It was possible to find a relatively simple feature with an overall good and robust performance. This feature is computed as follows. The image is transformed to a resolution where the regular textile pattern has just disappeared (in our case the images were lowpass-filtered and subsampled to 1/16 size). Then the variance of this image is computed. The variances are normalized (divided) by the variance of the corresponding textile with dose=0. The average over days and repetitions of this feature is shown in figure 6 in a log-log plot. It ranks the textiles just as expected and it seems that a linear fit is appropriate for each pH level. This feature shall subsequently be called the *coarse-scale normalized variance (csnv) feature*. The csnv feature can be compared to the the Fourier inertia feature in the Fourier domain. The low-

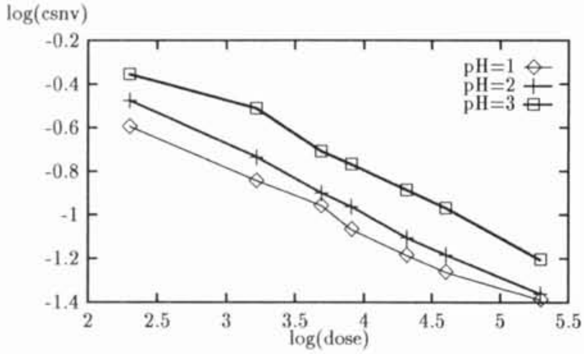

Figure 6: *Plot of (log) coarse-scale normalized variance versus log(dose). We see that the measure reflects the expected ranking.*

pass filter we used correspond approximately to a multiplication with a Gaussian weighting function centered at (0,0) in the Fourier domain. For the Fourier inertia feature the weighting function is $(u^2 + v^2)$. Thus the csnv feature measures the energy in the low frequencies and the inertia feature measures the energy in the high frequencies. Since the measures are normalized they will actually measure similar properties, but as the textile wear seems to be best described in the low frequencies, the inertia feature is not as robust as the csnv feature.

Fitting a general linear model with the SAS GLM-procedure:

```
proc glm;
  class ph day;
  model logvar = logdose ph day(ph)
   ph*logdose logdose*day(ph) ;
  lsmeans ph;
  random day(ph);
```

gives an R-Square of 0.956079, i.e. 95.6% of the variation is described by the model.

The type III sun of squares give

Source	DF	F Value	Pr > F
LD	1	1944.35	0.0001
PH	2	11.99	0.0001
D(PH)	6	2.12	0.0565
LD*PH	2	1.22	0.2999
LD*D(PH)	6	2.06	0.0637

where LD=LOGDOSE and D(PH)=DAY(PH). It follows that the amount of variability explained by pH and dose are orders of magnitude greater than the remaining effects, inclusive the day-to-day variability. Thus the conclusive model will only include the pH and dose effects. The least square means for the three pH levels show the expected ranking:

PH	LSMEAN
1	-1.04568416
2	-0.96280088
3	-0.77615044

5 Conclusion

We have obtained a single feature from digital image analysis to describe the effect of enzymatic treatment of textiles. This feature is also fast to compute and seems to be robust. Other features measuring the variation in the textile that is coarser than the regular textile pattern can possibly describe the same textile properties, but the coarse-scale normalized variance seems to be the feature that has the overall best performance of the features considered. The feature may also be useful in e.g. carpet wear assessment.

Acknowledgements

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