

Image analytical monitoring of paper quality – a feasibility study

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ABSTRACT: We evaluated 14 selected paper quality parameters using new image analytical techniques for characterization and monitoring of paper quality (multivariate AMT regression). We tested the technique on six major paper types. Of the parameters tested, 13 could be modeled with only minor optimization of the initial experimental image recording parameters. Although this analysis was performed in the laboratory with static sheets of paper, this new “remote sensing” image technique shows promising application potential for on-line product monitoring of the specified physical qualities.

Application: The research presented here should lead to an on-line method for evaluating paper quality during production.

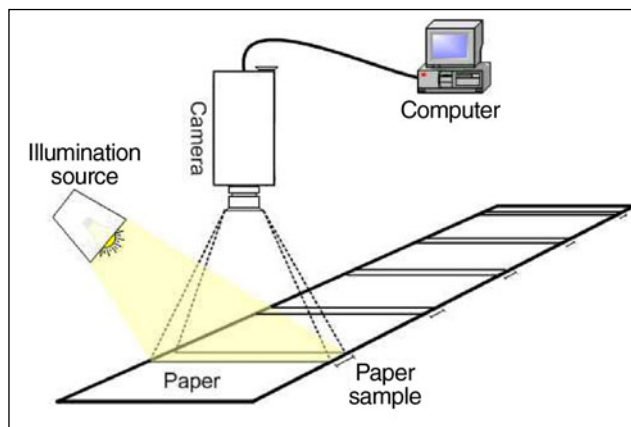
Off-line testing (lab testing) of finished sheet characteristics is still the most common practice to ensure that process and quality specifications are being met. These methods are often too slow for on-line process control strategies, and also have an inherent sampling problem: physical samples are usually cut only from the end part of a master roll.

Commercial technologies for on-line measurement of finished paper characteristics have proven to be limited in both speed and range of tests. Image analytical techniques could become a very useful tool for on-line measurement of paper properties. Image processing technology is used in the industry today, but it cannot be used to control all quality parameters alone and must often be combined with other methods. The complexity of integrating these other methods into the image analysis puts high demands on the reliability and standardization of information, both of which are necessary to develop robust process and product control systems.

An alternative approach, combining all necessary characterization methods into one, may some day come into existence, presumably based on optical (visual [VIS] and near-infrared [NIR]) and physical-radiometric (neutron activation analysis [NAA]) techniques, amalgamated into one.

This paper investigates how far optical paper quality characterization can reach on its own merits. The technique used is a combination of digital image acquisition, followed by the angle measure technique (AMT) [1-3,6-11,13]. We designed an image analytical system to simulate automatic monitoring of as large a set of paper quality parameters as possible. The system relies on problem-dependent oblique unilateral illumination together with multivariate calibration of transformed images.

In this study, isotropic images of low-angle oblique illumination enhanced paper surface texture are transformed into so-called AMT complexity spectra [3,7,8], which are subjected to multivariate calibration using partial least squares (PLS) regression [4,12].



1. Typical image analytical system setup.

IMAGING

Figure 1 shows a proposed on-line (on-machine) image system setup. Recorded images of the paper surface provide information about its texture and other physical properties. The critical vision system parameters include the camera performance specifications, which should be adequate for the task required (though not detailed in this study), and the illumination conditions. It is often also important to carry out problem-dependent image processing, which in the present case included enhancement of selected surface features (i.e., texture). By using low- to very low-angle (oblique) unilateral illumination, complex shadows are created, which in turn enhance the feature extraction function of the AMT. With the paper lane suitably illuminated, images are acquired automatically with a camera connected directly to a computer by FireWire or similar fast computer interface connection. A fast connection is needed to capture high resolution, high quality, real-time images of the moving paper. Although the paper speed may exceed 1000 meters/min., only a small fraction of the total lot (length) of

paper needs to be sampled (strip-imaged) and analyzed, typically using a sampling rate of 1:100 or less.

Image analysis can be used for both quantitative and qualitative measurement. The images of the virtual paper strips “cut out” by the camera system should be representative of the entire paper master roll. Two key issues must be addressed for this to be valid:

1. The sampling rate must be adequate along the longitudinal length-dimension of the master roll (the total width of the paper lane is supposedly captured).
2. The degree to which the upper surface of the paper lane will function in relation to the properties present throughout the total thickness of the paper.

The Theory of Sampling (TOS) [6,17,18] is a comprehensive theory for obtaining structurally correct samples (samples that represent the average composition of the lot material). TOS (1-dimensional sampling) uses variogram analysis [6,15,16] methodology to ensure that the fractions (strip areas) sampled by the camera are representative of the whole 1-dimensional production lot or paper master roll, with a specified sampling error. This technique can be used for sampling on-line measurements and is well described by Petersen et. al. [17]. Variographic techniques and PLS-regression have recently been used to study pulp bleaching processes [7,8].

The sample strip longitudinal dimension will be determined on a problem-dependent application basis. Because non-physical, remote sensing (imaging) is being used, we can analyze as many and as large samples as the variogram analysis demands. Only in the calibration process of the prediction model is it necessary to extract the physical samples from which the reference values for the paper quality parameters are determined. The sampled strip-images are then subjected to feature extraction by the AMT transform. This results in a “complexity-spectra,” x , which can be subjected to multivariate calibration using PLS-regression with paper quality parameters, y .

PLS-REGRESSION

PLS-regression is a bilinear projection method, where samples expressed in the x -space (defined by the original x -variables) are projected onto new axes (termed PLS-components), which define a new space constituted by a few latent variables only. The projected locations of the samples in this PLS-component space are termed scores. These PLS-projections are dynamically inter-correlated with the y -space (one or more y -variables, see further below), in such a fashion that the y -space data structure is used actively to find only the relevant information in x (i.e., the most correlated). This optimizes the covariance between the two spaces and often leads to very simple models consisting only of a few latent PLS-components in each space (often as low as 2, 3, or 4).

Two different versions of PLS exist: PLS1 and PLS2. In PLS1, one y -variable is modelled only. PLS2 models on all y -variables simultaneously. PLS1 is optimal for predicting a single y -vari-

able, while PLS2 is used for overview modelling only, because of the advantage of modelling all correlations between all x - and y -variables simultaneously. Predictions are always based on PLS1 exclusively. PLS-regression can generally be schematized in the following way:

$$X = \sum_A T \cdot P^T + E$$

$$Y = \sum_A U \cdot Q^T + F$$

T: x -scores
U: y -scores
P: x -loadings; W: x -loading weights (“effective” loadings, see [4,12])
Q: y -loadings
E: Error matrix for the x -space
F: Error matrix for the y -space
A: The number of PLS components
T: Transpose operator

Both the x - and y -space are modelled by summarized product of scores (T/U) and loadings (P/Q) and error matrices (E/F). The product of the scores and loadings (loadings are the coordinates of the new axes in the original space, which is a reflection of how well each variable is taken into account by the PLS-components) can then be seen as a compact model of the covariance data-structure, while the error matrices contain the remaining, noncorrelated information.

MATERIALS

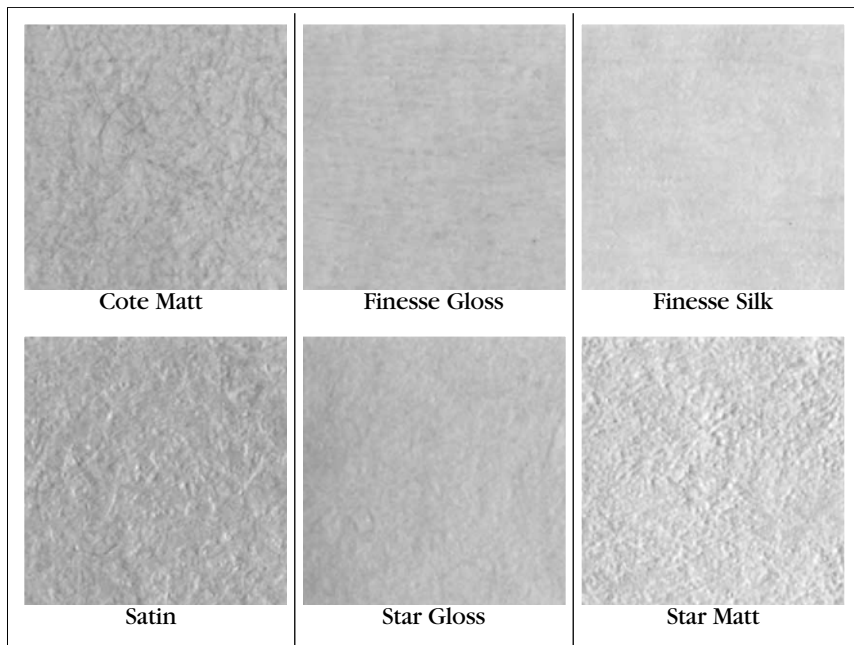
Six different paper types from UPM-Kymmene Corporation (Finland) were studied (**Fig. 2**). Each represents a printing grade with different degrees of finish. The Cote matte grade represents a coated sheet, which must have characteristics of functionality, consistency, and good print results on both gloss and matte surfaces (Cote matte paper is imaged in this study). The Finesse grade is a wood-free, high brightness and opacity sheet, with differing finishes, from gloss to matte (silk). The different finishes provide a good basis for image and text reproduction. The Satin sheet allows print to stand out on both matte and glossy surfaces (only matte was imaged). Star paper is double-coated and used for high-quality print reproduction. It exhibits high brightness, gloss, and smoothness. Both matte and gloss finish were sampled.

We measured 72 paper quality parameters for each paper type. A PLS2 model [4,12] was developed between these parameters and the AMT-spectra to observe relationships (**Fig. 3**).

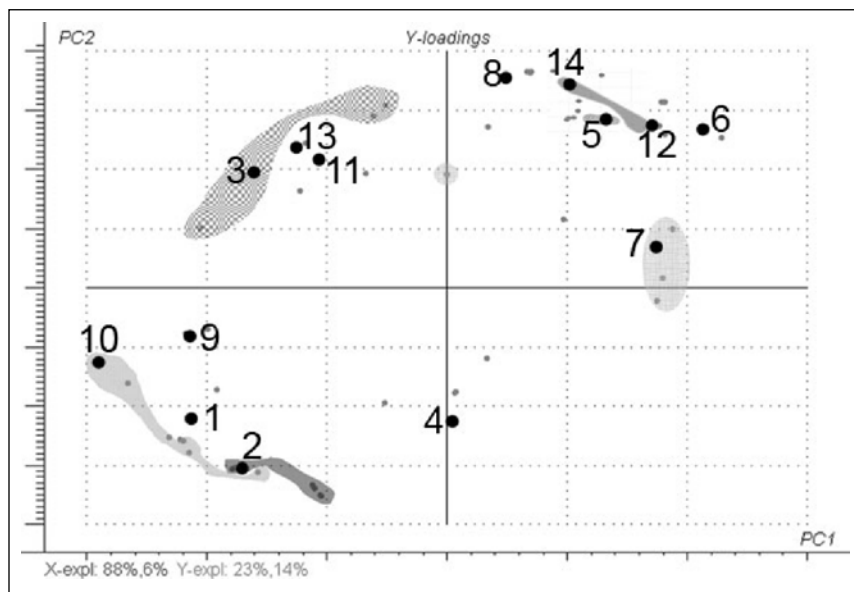
The y -loadings (Q) for the first PLS component are plotted against the y -loadings for the second PLS component. Similarly behaving variables are grouped tightly, which indicates a strong internal correlation [4,12]. For example, six different measures for brightness have been measured and modeled and these are grouped as contiguous gray-shaded area number 5 in Fig. 3.

The 14 y -variables numbered in Fig. 3 and named in **Table I** that span the depicted loading space were selected for further individual analysis with PLS1. This reduced set represents key variables important to paper quality. Also, the vari-

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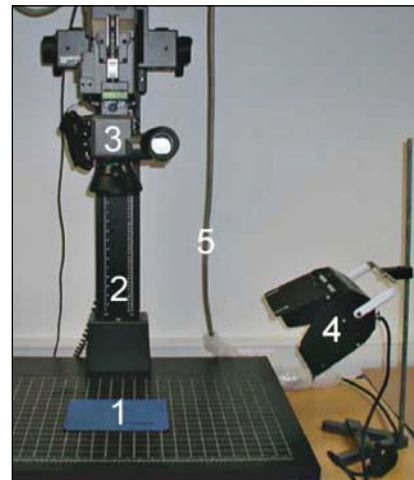
2. Visual appearance of the six imaged paper types.



3. PLS analysis graph (PLS2 loading weights) showing groupings of correlated variables (see Table I for variable groups). The two PLS-components (plotted as the x- and y-axis, respectively) use $88 + 6 = 94\%$ of the x-variance to explain $23 + 14 = 37\%$ of the y-variance.

1. Ash	5. Brightness	10. Roughness
2. b*C2	6. Density	11. Tear strength
3. Bending resistance	7. Gloss	12. Tensile strength
4. Bending resistance ratio	8. Grammage	13. Thickness
	9. Opacity	14. Whiteness

1. Paper quality parameters in this study.



4. Image analytical setup: 1. paper sample; 2. camera stand (elevator); 3. camera; 4. low angle illumination source; 5. cable to computer.

ables loading space spans a summary of their individual PLS1 modeling and prediction abilities, and as such will provide a condensed, yet reliable view on the current feasibility study objectives.

EXPERIMENTAL SETUP

The optical system was composed of a QImaging black-and-white CCD camera with a Nikkor 120 mm F2.8 macro lens, supporting 12-bit grayscale images with a resolution of 1280 x 1024 pixels, all mounted directly to a Kaiser rePro photo stand (Fig. 4). The entire camera stand was placed in a dark room to eliminate stray external light. This prevented inaccurate color reproduction and extensive natural light variations, which among other variables would negatively affect modeling. Maintaining as constant a light-setting as possible minimizes modeling error in an on-line industrial application.

The paper was placed directly underneath the camera and illuminated with a FalconEyes LHS-500 lamp holder fitted with a 150W bulb. The holder was vertically adjustable to provide low to very-low oblique illumination. We used this combination to enhance the appearance of the sheets' surface features. The recorded images were transferred to a personal computer via a FireWire connection.

We used standard experimental design approaches to optimize the imaging conditions. For the six paper types, surface feature (texture) images were sampled by changing both illumination angle and image size (resolution). Four different experimental setups were selected (series 1-4, **Table II**).

	Paper footprint size: 1.7 x 1.35 cm (low resolution)	Paper footprint size: 1.0 x 0.8 cm (high resolution)
Illumination angle: 21°	1	4
Illumination angle: 17.5°	2	3

II. Experimental overview. The four experimental series are numbered as indicated.

We used illumination angles of 17.5° and 21° to image the same sample of Star matte paper. Significant improvements in the surface roughness and compositional texture definitions were observed in the images using the lower angle (**Fig. 5**).



5. Visual appearance with 17.5° (left) and 21° (right) illumination angles on Star matte paper.

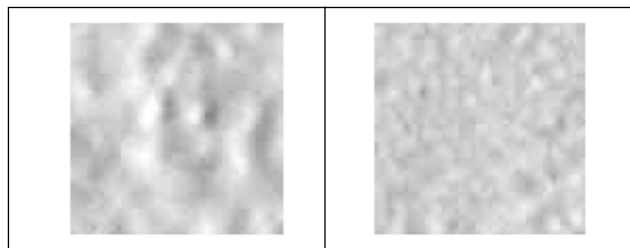
Two footprint sizes (absolute size of the camera field-of-view) were used to determine whether a few large image cutouts or many small(er) samplings would be optimal. Theoretically, and in industrial applications, the entire paper lane cross-section should be imaged to obtain the most representative sample characteristics. This paper investigates only a first estimate of the usable sampling rate relationships needed (see the study by Mortensen and Esbensen [13]).

We investigated footprint sizes of 1.7 x 1.35 cm (low resolution) and 1.0 x 0.8 cm (high resolution). These footprint sizes roughly correspond to a realistic industrial sampling rate. **Figure 6** shows that this difference in size is markedly visible—the texture definition is of course changed as a function of the pixel-size scale resolved.

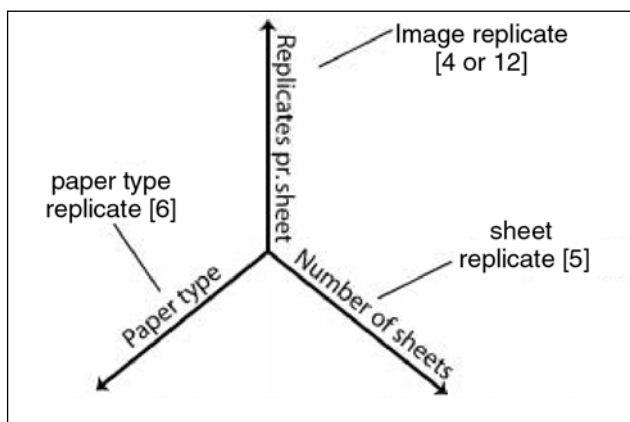
To minimize measurement errors, we used a number of replicates between and within the paper type sheets (**Fig. 7**).

Within each paper sheet, two sets of replicates were used. For the low-resolution settings, four image replicates for each sheet were acquired, while 12 were acquired for the high-resolution settings (**Fig. 8**).

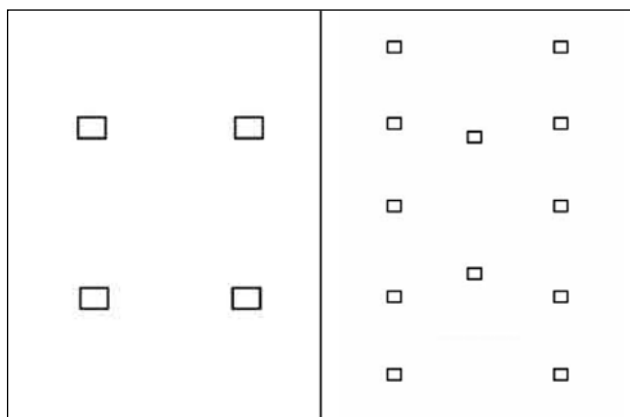
Five sheet replicates of each of the six paper type repli-



6. Resolution alternatives studied. Star paper matte finish, 17.5° illumination, 100 x 100 pixels. Pixel size is 8 x 6 μm (high resolution) (left) and 13 x 10 μm (low resolution) (right).



7. Layout of replicate regimen studied.



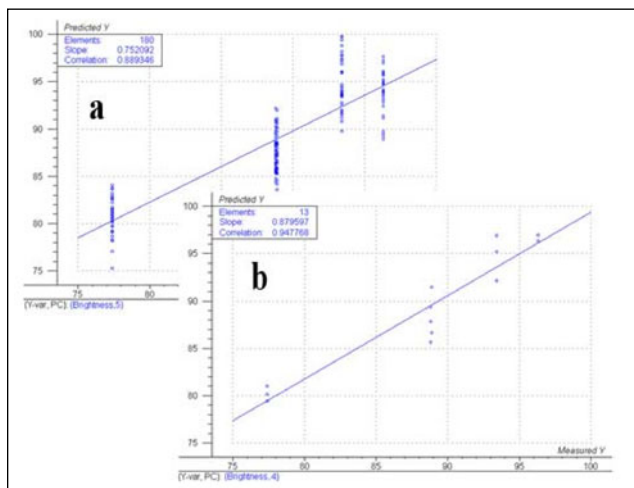
8. Sheet replicate scheme for low-resolution images (experimental series 1 and 2) (left) and high-resolution images (experimental series 3 and 4) (right).

cates were subjected to imaging, resulting in 120 images for the larger, low-resolution image samples and 360 images for the smaller, higher resolution image samples.

Feature extraction of the images using the AMT transform yielded 500 x-variables for each image, of 5000 initial points (pixels), A, which corresponded to approximately 0.5% of the total image size.

The overall sampling error and modeling quality were greatly improved by averaging the individual AMT spectra

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9. Predicted vs. measured plot for brightness, no averaging (a) and averaging within individual sheets (b). (Cote paper was not included in brightness models due to lack of reference values)

within each sheet before performing the multivariate data analysis. This averaging resulted in 30 AMT spectra for multivariate data analysis (five replicates for each of the six paper types) (**Fig. 9**).

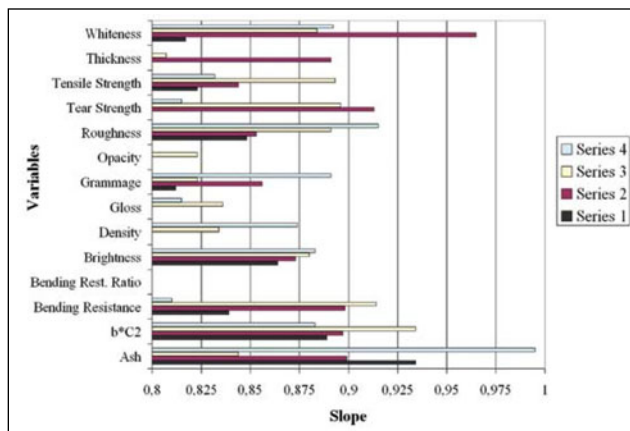
The x - and y -data sets were normalized to zero mean and each of the 14 selected variables was modeled using PLS1 with test set validation.

PREDICTION OF PAPER QUALITY FUNCTIONAL PROPERTIES

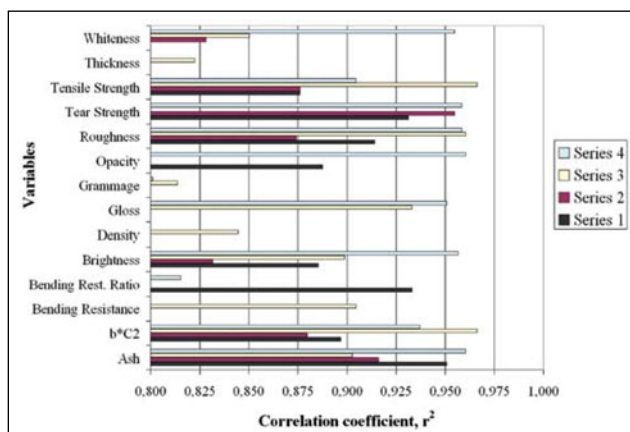
The 14 parameters were modeled using PLS. Either two or three of the five paper sheet replicates (for each paper type) were randomly chosen for testing the prediction models (test set definition). The fitted slope (accuracy) and the r^2 correlation coefficient (precision) were used to describe the quality of the established multivariate prediction models for the paper quality parameters (**Figs. 10** and **11**).

Results show that series 3 and 4 (smallest footprint areas, highest resolution) yielded the best prediction quality statistic (r^2), indicating that the physical area being imaged (or the pixel size in μm) is important in determining the precision of this image analytical method. However, the optimal experimental settings do vary, as evident in the parameters thickness, tensile strength, and density.

All 14 paper quality parameters cannot accurately be predicted with only one of the four experimental settings. However, 13 of them could be modeled reasonably well using the third experimental settings. The bending resistance ratio failed to model well with any of the four series. We do not yet fully understand why this physical material characteristic was not predicted and other physical tests were. Even though series 3 was able to predict most parameters, series 2 gave the best models for whiteness and tear strength. With



10. Prediction model slopes, reflecting overall accuracy of prediction.



11. Prediction model correlation coefficient indicating overall precision of prediction.

all 14 slopes (but one) and all correlation coefficients higher than 0.80, the potential for image analytical prediction in these grades of paper are quite promising.

DISCUSSION

In this study we investigated whether paper quality can be predicted from image analysis. The results show that this image analytical technique is capable of predicting many key paper quality parameters. To apply the off-line techniques discussed here into an on-line application, a faster imaging system with sufficient processing speed is needed.

To process the large amounts of data that are collected on-line, modifications must be made to the current algorithms for AMT, which are the limiting factor today. Optimized algorithms are in development [11]. The computational system requirements (and algorithms) are highly dependent upon the image size and image sampling frequency. The computational requirements are even greater if any image preprocessing is to be performed.

To obtain acceptable prediction models, it might be nec-

essary to optimize the system settings both before and after imaging. In this study, a set of illumination angles and camera resolution settings were varied to achieve optimum correlation to sheet properties. Additional experimentation with different illumination angles and sample sizes, or the use of a different problem-dependent illumination source may improve results even further. Existing knowledge on light sources versus AMT performance may also assist in making the optimal equipment, imaging, and data analysis selections [14]. Finally, the set of ideal system parameters may need to be established by trying them under a series of realistic on-line conditions and comparing the results with the use of the techniques discussed in this paper.

Prediction performance may be further improved by preprocessing the raw images with various image analytical filters before data analysis. Small changes in contrast or brightness can greatly affect image features. A previous study [2] showed that some variables could not be modeled at all without preprocessing, while much more satisfactory mod-

els were obtained with preprocessing.

All paper quality parameters can roughly be divided into two groups: optical (surface relevant properties) and physical (mechanical). It should be possible to describe almost all optical parameters using the present imaging technique. Some physical parameters, such as bending resistance ratio, appear more difficult to predict, while those correlating with paper texture such as thickness and density, are more accurately modeled. However, correlations might be reduced for paper grades that do not focus on surface properties (such as tissue, linerboard, corrugated medias, etc.), especially if the relevant parameters are not correlated with surface properties.

The current system only investigated a small fraction of the image area, but it provided quite satisfactory first-order models. Larger images (composite images from well-sampled increments over the entire paper lane width) will undoubtedly improve the models [5]. This strategy for improvement in real-world implementations corresponds to increasing the number of sheet replicates (five in the present investigation).

This study investigated 14 different quality variables, although 72 different parameters are often used in the quality control of the paper grades investigated. In Fig. 3, all 72 parameters are modeled simultaneously using PLS2. Most functional groups were modeled and a large part of the variable space was covered by the 14 paper parameters selected here. Most of the remaining variables can most likely be modeled with individual PLS1 models similar to those used here.

CONCLUSION

Two different illumination angles and two different resolutions (image sizes) were tested within a relevant parameter space. The combination of 17.5° angle illumination and high resolution images could predict most parameters. The only variable that was not modeled with acceptable accuracy was the bending resistance ratio.

The following paper quality parameters were modeled successfully with only minor optimization of the initial experimental parameters: ash, b*C2, bending resistance, brightness, density,

INSIGHTS FROM THE AUTHORS

A former research project was the forerunner for this project and hence woke my interest to dig deeper into the possibilities of combining image analytical sampling with monitoring of paper and bulk quality.

This work supports previous work done in cooperation with a Finnish paper mill, but it also differs from previous research projects regarding the application of this new imaging technique.

The most difficult aspect of this work was to find a set of relevant parameters, which potentially could characterize 72 process parameters. However, a large PLS2 model did successfully find 13 parameters, which spanned the whole measurement space.

It was expected that the surface images could be correlated to the surface properties such as brightness. However, it was surprising that it was possibly to correlate the surface images with the mechanical bulk properties, such as paper thickness.

Because this cheap technique can be applied to on-line monitoring of paper and bulk quality parameters



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it can definitely be beneficial to the paper industry.

The next step in developing this technique would be to perform a mill trial.

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gloss, grammage, opacity, roughness, tear strength, tensile strength, thickness, and whiteness.

The present image analytical AMT/PLS technique has shown a promising application potential for monitoring paper quality by being able to model those 13 representative key quality parameters by remote optical sensing.

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LITERATURE CITED

1. Dahl, C.K., Petersen, L., and Esbensen, K.H., "Automated image analytical characterization of powder agglomeration by AMT-regression," Powder Tech., submitted.
2. Dahl, C.K. and Esbensen, K.H., "Image analytical determination of particle size distribution for natural and industrial bulk solids aggregates," Chemomem. Intell. Lab Syst., submitted.
3. Esbensen, K.H., Hjelmén, K.H., and Kvaal, K., J. Chemom., 10(5-6): 569(1996).
4. Esbensen, K.H., The Introducer Package: Multivariate Data Analysis In Practice, 5th edn., CAMO AS, Oslo, Norway, 2002.
5. Gy, P., Sampling for analytical purposes, John Wiley and Sons, New York, New York, USA, 1998.
6. Huang, J. and Esbensen, K.H., Chemom. Intell. Lab. Syst., 54(1): 1(2000).
7. Huang, J., "Developments in applied chemometrics-AMT, acoustic chemometrics and N-way analysis," Ph.D. thesis, Høgskolen i Telemark, Norway, 2001.
8. Huang, J. and Esbensen, K.H., Chemom. Intell. Lab. Syst., 57(1): 37(2001).
9. Huang, J., Ose, S., de Silva, S., and Esbensen, K.H., Powder Tech., 129(1-3): 1(2003).
10. Huang, J., Wium, H., Qvist, K.B., and Esbensen, K.H., Chemom. Intell. Lab. Syst., 66(2): 141(2003).
11. Johansen, S.B., Laugesen, J., Frøst, M.B., et al., Angle measure technique-proposal of new algorithm and systematic examination of method performances, in prep.
12. Martens, H. and Næs, T., Multivariate Calibration, John Wiley and Sons, New York, 1989.
13. Mortensen, P.P. and Esbensen, K.H., Chemom. Intell. Lab. Syst., 75 (2): 219 (2005).
14. Zuech, N. and Miller, R.K., Machine Vision, Kluwer Academic Publishers, Dordrecht, The Netherlands, 1989.

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