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MEASUREMENT AS INFORMATION CHANNEL WITH AN APPLICATION TO PRINTABILITY

Marja Mettänen, *Risto Ritala*

Tampere University of Technology, Department of Automation Science and Engineering
P.O. Box 692, 33101 Tampere, Finland, e-mail: firstname.lastname@tut.fi

Abstract – Printability of paper is a multidimensional concept consisting of runnability and print quality. The lack of definition for print quality makes printability rather ambiguous. In this paper we discuss the measurability of the high-level printability and print quality and present an interpretation of the measurements of low-level print quality related characteristics as information channels about high-level concepts. This enables the construction of a layered model in which the information provided by measurements is propagated to infer about higher level concepts of quality, eventually supporting decision making. As an example, we present a case study of low-level print quality defects caused by the small-scale measurable properties of the paper, and consider the meaning of this process from the viewpoint of print quality analysis.

Keywords: printability, print quality, Bayesian network

1. INTRODUCTION

The concept of printability of paper is ambiguous yet of high practical importance in paper trade, and in product and process development. Printability refers to the quality potential of the paper as a substrate in a specified printing process [1]. Runnability, i.e., the maximum speed of a printing machine without encountering problems, can also be regarded as a part of printability. A paper of good printability thus does not jam or break in the printing press, withstands post-press operations without ink smearing or papers sticking together, and has a high print quality. The topic of main emphasis in this paper, print quality, is high-dimensional by definition and does not have absolute terms. Thus there exists no generally accepted or formulated way of measuring the overall printability.

Laboratory printing tests can provide useful information about printability [1]. Early research in printability focused on identifying paper property measurements that are related to print quality. Measurement methods that deliver one single value to characterize paper structural aspects were applied; examples are PPS roughness, air leakage porosity or a formation index. These studies (e.g. [2,3]) searched for the interrelations between coarse-scale paper properties and print quality, also integrating parameters related to ink properties and the printing process. The measured paper properties were correlated with parameters describing printability, such as ink demand, print-through and evenness of the reflectance of printed area [4].

In more recent work 2D measurements of local paper properties have been increasingly employed. Analyzing the microstructure of the paper through the multi-channel 2D measurements is justified by the fact that the microstructure and its inhomogeneity are associated with printability and with the quality of the final printed product. Statistically significant correlation has been established between spatially aligned 2D measurements of paper surface topography, formation and print quality [5,6].

Printability has also been approached from the human assessment point of view. Recently, the attributes that the jury members have used when assessing the quality of printed images, have been systematically analyzed to determine the perceptually relevant quality dimensions [7]. Some relations have been successfully established between physical measures and subjective assessments, for instance within the unevenness of print [8].

As shown above, various measurements are being made on characteristics that are certainly related to printability. However, compared to the strict definition of measurability, as defined by e.g. Ferris [9], Finkelstein [10] and Campbell [11], printability intrinsically is not a measurable characteristic, and neither is print quality; they are not objective.

This paper discusses how the different approaches can be integrated into a unified one and how such measurement approach should be considered from the measurement theory point of view.

We will address this problem in the present paper with the following structure. Section 2 will discuss the basic philosophy of measuring and measurability, and describe generalized measurements as information channels. In Section 3 we will use this formulation and consider the measurement information with regard to assessing print quality. This approach will lead to a natural presentation of information in the form of conditional probabilities that propagate in a network model and support the inference about high-level concepts - and thus also decision making based on measurement information. In Section 4, we will demonstrate a Bayesian network model as a tool for implementing the information flow. We will also present an example of inferring about print quality defects through the examination of small-scale surface topography measurement of paper. Conclusions, both concerning practical printability assessment and the generalizability of the approach to other areas where human assessment is to be linked with measurement data, will be drawn in Section 5.

2. MEASURABILITY AND INFORMATION CHANNEL

What should the object of examination be like in order to be definable as a *measurable* quantity? As reviewed in [12], Campbell [11] has proposed in 1920: Measurability may be established by, first, "proving that the characteristic under investigation involves an empirical *order relation*", and second, by either (a) "finding a physical *addition* operation that allows the construction of a reference measurement scale and then performing measurement by comparison with it", or (b) "finding some *physical law* that allows the measure to be expressed as a function of other quantities". According to [12], at the time of Campbell's theory, sensation intensities could not be considered measurable quantities because it was impossible to define an addition operation for them. Later the requirement of additivity has been relieved by, e.g., accepting the equality of *ratios* to form the reference scale, and by utilizing representational theory largely developed among behavioral scientists. However, the requirement of *objectivity* remains in the definitions of measurement (e.g. [9], [10]). It means that, as numbers are assigned to properties in the measurement process, the numbers must be independent of the observer within the error limits. Our target of interest, high-level printability (or the affiliated perceived print quality), is not objective and hence we consider it non-measurable.

How should we mathematically define the concept of measuring? Rossi [13] presents both deterministic and probabilistic models for the measurement process. We apply the probabilistic approach. Let the random variable Y denote the target property that is being measured and let the random variable X denote the observations of Y. We shall allow X and Y to be vector-valued or scalars and the value space of their components may be real numbers, or discrete finite or infinite sets. In the probabilistic definition, the measurement of the target value $Y = y$ is described as

$$f_{X|y}(x|y). \tag{1}$$

The measurement description is thus equivalent to the probability density (or probability for discrete measurement value space) of the observations, given the target $Y = y$. Thus measurement is an information channel, described as a conditional probability density. The channel carries information about the property that is being measured. Using the Bayes formula, the information about the target, given that measurement value $X = x$ has been obtained, is

$$f_{Y|x}(y|x) = \frac{f_{X|y}(x|y) f_Y(y)}{\int_{domain(Y)} f_{X|y}(x|y) f_Y(y)\, dy}, \tag{2}$$

where $f_Y(y)$ is the a priori information about the target. This can be assumed uniform, maximum entropy, if no information about the target is available prior to making the measurement. The information carried by the probability densities (1) and (2) is valuable when used in decisions on, say, product development. The estimate of Y is commonly taken as the value with the highest posterior probability density. The uncertainty is described by the second order terms of Taylor expansion of the logarithm of posterior probability density around the estimate of Y.

The Bayes formula (2) can be generalized also to cases where X or Y or both take discrete values. However, reducing the full measurement information of posterior probabilities to a single estimate value is questionable in this case. The most straightforward approach is to use the entire measurement information, the posterior probability, rather than estimates, in decision making. Many measurement concepts generalize quite naturally to such interpretation. For instance, the sensitivity of a measurement generalizes to comparing the measurement information through Kullback-Leibler distances [14] between the posterior distributions resulting from different measurement values.

Moreover, in practice it makes no difference for the decision maker whether the information comes from a *measurement* in a strict sense, or from an information channel. Namely, in the strict definition of measurement, the uncertainty of the estimate should affect the decisions; also when providing the entire measurement information for the decision maker, she/he must have a specified attitude towards uncertainties. Providing the estimate and its uncertainty as a covariance matrix corresponds to approximating the measurement with a Gaussian probability density.

In summary, all measurements can be thought as information channels, but not every information channel is a measurement in the strict sense.

3. MEASUREMENT INFORMATION ON PRINT QUALITY

We aim at assessing the quality of the print, using instrumental measurements of the paper and the print. The perceptual print quality, as judged by a group of human observers, is the reference data against which the instrumentally measurable properties are compared. This is necessary for identifying the measurement description (1). Now the question addressed is: assuming such perception of a group of observers is consistent enough to specify the reference information, which are the physical features to be measured, and how are the measurement results related to the actual print quality, or to the reality concerning the target? We propose to model these interrelationships as a network with conditional probabilistic connections between the nodes, i.e. a Bayesian network. The data of instrumental measurement in this model/channel propagates through interconnected conditional joint probability densities.

To outline the structure of the model, we start from the subjectively assessed high-level print quality. The jury provides a discrete probability distribution over the predefined discrete scale of qualities. The result from the jury is thus a probability density on classification rather than an estimate of quality. The jury may assess the overall print quality using lower level quality concepts such as naturalness and clarity of details (usefulness) that are also on a discrete scale. The essential difference between the high-level and low-level quality concepts is that the former is expected to be context dependent while the latter are not. Still, the level of abstractness and subjectiveness is high and the quality concepts are multidimensional. Evidence of both the context - and content - dependence and the multidimensionality of the quality perception can be found, for instance, in [15], where Leisti et al. analyze the data from a subjective paired comparison test augmented by an interview of each observer. The interview data reveals that the evaluators change their criteria for preference when the comparison conditions are changed [15]. The test images of an image quality assessment should therefore be selected very carefully to obtain consistent reference data from the jury.

Studies with ink-jet printing [7] and laser printing [15] have arrived in quite similar lists of attributes that the jury members have typically used when assessing the quality of printed images. These findings are valuable when selecting the relevant attributes to the nodes of the Bayesian network. The attributes fall into several hierarchical levels in the perception of quality. For instance, the frequently mentioned sharpness and brightness represent a lower level than naturalness. To facilitate the construction of a model of the whole information channel, we assume that the lowest perception level consists of special concepts called perceptual quality elements (PQEs). They are assumed to be the attributes of the image that the humans can directly assess and that their assessments - despite the non-physical nature - are objective. Hence a jury would largely have consistent opinions about them. Instrumental measurements of print quality lie on the bottom of the hierarchy together with the measurements of paper quality properties.

We also assume that because of objectiveness all the instrumental measurements are defined as conditional probabilities in which PQEs are to be considered as measurement targets, see (1). The instrumental measurements thus provide information about the reality concerning the PQEs. Eerola et al. have presented an extensive study about the instrumental (or computational) measures of paper and print characteristics and their correspondence with human visual rankings of print quality [16]. Their findings within inkjet printing support the selection of, e.g., paper gloss and brightness, as well as print contrast, mottling and color properties to the model of print quality.

4. BAYESIAN NETWORK AND 2D PROPERTY MAPS

A simplified graphical presentation of the proposed print quality model is shown in Fig. 1. It is a five-layered Bayesian network that realizes the hierarchy discussed in Section 3. The directed edges of the network, i.e. the arrows, describe the probabilistic relations between the nodes. The edges can be identified from a data set that contains parallel observations of the states of all nodes. For instance, identifying the edges between the instrumentally measurable print property layer and the PQE layer requires that both the instrumental measurements and jury's opinions about PQEs have been acquired from the same set of samples. As described in [17], the edges can be identified using e.g.

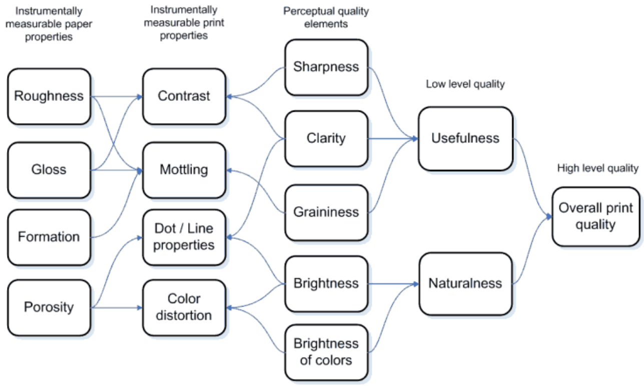

Fig. 1. An example configuration of the Bayesian network for the modelling of print quality.

correlation or mutual information (MI) as a similarity measure between the attributes in the identification data set. Pearson's correlation describes the linear dependence while MI also applies when the relations are nonlinear. The edges are identified as conditional state probability distributions at all combinations of states of the parent nodes.

It must be noted that the positions of the arrows in Fig. 1 are indicative and several other structures of the network are also possible. The data available so far does not support the simultaneous identification of all the edges between the nodes. However, the feasibility of a probabilistic network model in high-level quality assessment has already been shown by, e.g., Pulla et al. [17] who have successfully identified and analyzed a smaller Bayesian network structure in a case study of visual image quality on a laptop display. In the current study, we augment the setup by taking account of the paper and the printing process, and hence introducing the layer of instrumentally measurable paper properties. We present an example of inferring about the occurrence of print defects based on the detection of defects in the paper surface before printing. This example illustrates the use of measurement information under uncertainty.

We examine the relationship between the small-scale 2D measurements of the reflectance[1] of printed paper and the surface topography of unprinted paper. The interpretation is that high values of printed reflectance denote insufficient or missing printing ink. The analysis of the aligned topography and reflectance measurements reveals the degree to which the surface topography has affected the occurrence of such print defects. While earlier studies in the analysis of the aligned 2D maps of paper and print properties (e.g., [5,6]) have focused on identifying deterministic relationships between local paper properties and local print characteristics, we recognize the non-deterministic nature of the dependences and apply the conditional probability distributions as models of measurements and information channels.

The measurement data consists of surface topography maps and reflectance maps acquired from 16 newspaper samples before and after printing by a sheet-fed offset press. All the measurements are camera based and the pixel size is

[1] This is not a true reflectance measurement (as described in [18] but rather a photographic image of the paper surface.

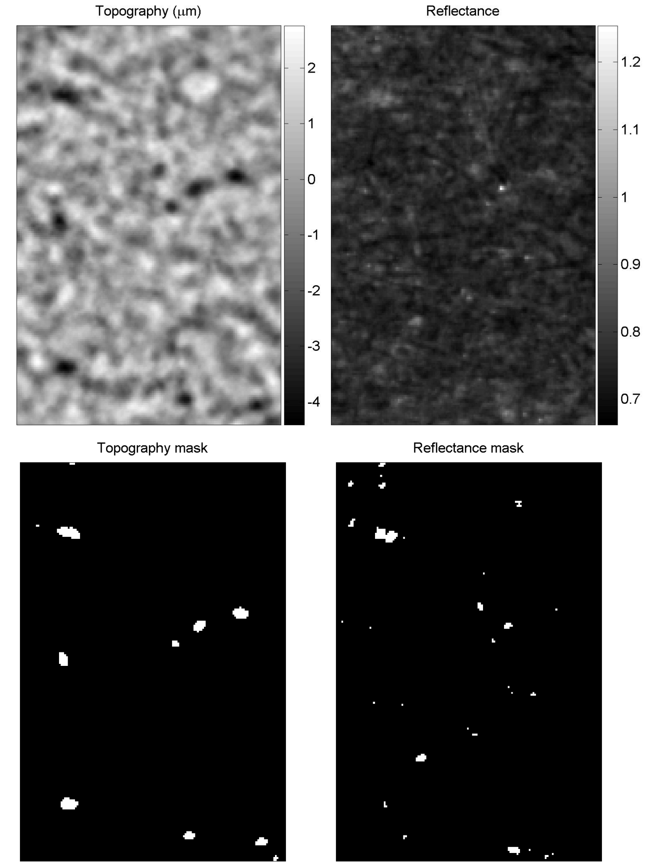

Fig. 2. Aligned measurements (top) and the corresponding anomaly masks on a 1.5 by 2 mm area. Left: unprinted surface topography, right: printed reflectance. The masks indicate 1 % of the lowest topography and 1 % of the highest reflectance points, respectively.

10 µm by 10 µm. The image area is 22.5 mm by 15 mm. The measurements before and after printing have been aligned with subpixel accuracy using a cross-correlation based method [19] and the center area of approximately 2.5 million pixels has been selected for analysis to avoid the geometrically distorted edges. Fig. 2 presents an example of the aligned measurements of unprinted surface topography and printed reflectance, zoomed on a 1.5 mm by 2 mm area to show small details. The lower part of Fig. 2 presents the corresponding anomaly masks that in this case indicate the

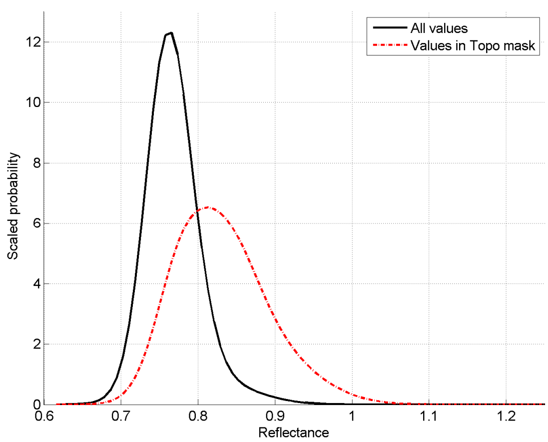

Fig. 3. Marginal (solid black) and conditional (dashed red) probability distributions of printed reflectance values. Both curves have been normalized so that their integrals equal one.

lowest 1 % percentile of the topography map (i.e. the most extreme pits) and the highest 1 % of the reflectance values (i.e. the brightest print defects).

The coincidence of the two masks implies that some of the deep depressions (pits) on the paper surface are responsible for missing printing ink. If there were no dependence between these phenomena, the overlap of the masks would equal the mask percentage, in this case 1 %. In the 16 paper samples analyzed, the average overlap between the 1 % reflectance and topography masks is approximately 15 %. The statistical dependence between surface topography and printed reflectance is also depicted in Fig. 3 by the conditional probability distribution of the reflectance values on condition that the topography value has been classified (by the 1 % mask) as exceptionally low. The conditional distribution predicts clearly higher printed reflectance values compared to the general behavior of the reflectance that is described by the marginal probability distribution. The paper sample used in the illustrations of Fig. 2 and Fig. 3 represents the sample set very well.

The probability distribution approach presented in the above example naturally connects to the Bayesian network idea of analyzing the print quality. Similarly as the detection of paper surface defects leads into information about potential print defects, the low level measurement information in general propagates and interconnects with the other information channels. The nodes of the network will be determined by the quality evaluation task in question and thereby according to the measurement information available. It is expected that the context of the print quality evaluation task will, to a large degree, determine the information that is relevant to be gathered [7, 15, 20].

5. CONCLUSIONS

Typically the printability of paper is understood as the print quality resulting from the interaction between the paper properties and printing parameters. A challenging problem stems from the basic philosophy of measuring as such when applied to paper printability. We have proposed to interpret the technical measurements and the subjective quality classifications as information channels, to be linked together by a Bayesian network model. This is a feasible way to connect the information of various abstraction levels and to support the evaluation of ambiguous - often subjective - characteristics that in the strict sense may not be measurable.

REFERENCES

[1] [1] J.-E. Levlin and L. Söderhjelm, *Pulp and Paper Testing*, in Papermaking Science and Technology, Fapet Oy. Jyväskylä, Finland, 1999.

[2] J. M. Fetsko and A. C. Zettlemoyer, “Factors affecting print gloss and uniformity”, *Tappi*, vol. 45, n°. 8, pp. 667-681, Aug. 1962.

[3] J. R. Parker, “Fundamental paper properties in relation to printability”, *Trans. of the 5th Fund. Res. Symp.*, (ed. F. Bolam), pp. 517-543, BPBIF, London, UK, 1976.

[4] B. Lyne, “Machine-calendering: implications for surface structure and printing properties”, *Tappi J.*, vol. 59, n°. 8, pp. 101-106, Aug. 1976.

[5] G. G. Barros. *Influence of substrate topography on ink distribution in flexography*, PhD Thesis, Karlstad University, Sweden, 2006.

[6] I. M. Kajanto, “Pointwise dependence between local grammage and local print density”, *Paper and Timber*, vol. 73, n°. 4, pp. 338-345, 1991.

[7] P. Oittinen, R. Halonen, A. Kokkonen, T. Leisti, G. Nyman, et al., ”Framework for modeling visual printed image quality from the paper perspective”, *SPIE/IS&T Electronic Imaging 2008, Image Qual. and System Perform. V*, San Jose, USA, Jan. 2008.

[8] P. J. Mangin and M. Dubé, “Fundamental questions on print quality”, *SPIE/IS&T Electronic Imaging 2006, Image Qual. and System Perform. III*, San Jose, USA, Jan. 2006.

[9] T. L. J. Ferris, “A new definition of measurement”, *Measurement*, vol. 36, nº. 1, pp. 101-109, July 2004.

[10] L. Finkelstein, "Widely, strongly and weakly defined measurement", *Measurement*, vol. 34, nº. 1, pp. 39-48, July 2003.

[11] N. R. Campbell, *Physics - The Elements*, (1920), reprinted as *Foundations of Science*, Dover, New York, 1957.

[12] G. B. Rossi, “Measurability”, *Measurement*, vol. 40, nº. 6, pp. 545-562, July 2007.

[13] G. B. Rossi, “A probabilistic model for measurement processes”, *Measurement*, vol.34, nº.2, pp. 85-99, Sep. 2003.

[14] C. M. Bishop, *Pattern Recognition and Machine Learning*, Springer, Singapore, 2006.

[15] T. Leisti, R. Halonen, A. Kokkonen, H. Weckman, M. Mettänen, et al., ”Process perspective on image quality evaluation”, *SPIE/IS&T Electronic Imaging 2008, Image Qual. and System Perform. V*, San Jose, USA, Jan. 2008.

[16] T. Eerola, J.-K. Kamarainen, T. Leisti, R. Halonen, L. Lensu, et al., ”Finding best measurable quantities for predicting human visual quality experience”, *IEEE Int. Conf. on Systems, Man and Cybernetics*, pp. 733-738, Oct. 2008.

[17] J. Pulla, M. Mettänen, K. Konkarikoski and R. Ritala, ”Bayesian network model as an overall image quality measurement system”, *12th IMEKO TC1&TC7 Symp. on Man Science & Measurement*, Annecy, France, Sep. 2008.

[18] H. F. Rance (ed.), *Handbook of Paper Science*, Elsevier, Amsterdam, 1982.

[19] M. Lähdekorpi, H. Ihalainen, and R. Ritala, "Using image registration and alignment to compare alternative 2D measurements", *XVIII IMEKO World Congress*, Rio de Janeiro, Brazil, Sep. 2006.

[20] G. Nyman, J. Radun, T. Leisti, J. Oja, H. Ojanen, et al., ”What do users really perceive - probing the subjective image quality”, *SPIE/IS&T Electronic Imaging 2006, Image Qual. and System Perform. III*, San Jose, USA, Jan. 2006.