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**Improving image quality in multi-channel printing
– multilevel halftoning, color separation and graininess
characterization**

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Abstract

Color printing is traditionally achieved by separating an input image into four channels (CMYK) and binarizing them using halftoning algorithms, in order to designate the locations of ink droplet placement. Multi-channel printing means a reproduction that employs additional inks other than these four in order to augment the color gamut (scope of reproducible colors) and reduce undesirable ink droplet visibility, so-called graininess.

One aim of this dissertation has been to characterize a print setup in which both the primary inks CMYK and their light versions are used. The presented approach groups the inks, forming subsets, each representing a channel that is reproduced with multiple inks. To halftone the separated channels in the present methodology, a specific multilevel halftoning algorithm is employed, halftoning each channel to multiple levels. This algorithm performs the binarization from the ink subsets to each separate colorant. Consequently, the print characterization complexity remains unaltered when employing the light inks, avoiding the normal increase in computational complexity, the one-to-many mapping problem and the increase in the number of training samples. The results show that the reproduction is visually improved in terms of graininess and detail enhancement.

The secondary color inks RGB are added in multi-channel printing to increase the color gamut. Utilizing them, however, potentially increases

the perceived graininess. Moreover, employing the primary, secondary and light inks means a color separation from a three-channel CIELAB space into a multi-channel colorant space, resulting in colorimetric redundancy in which multiple ink combinations can reproduce the same target color. To address this, a proposed cost function is incorporated in the color separation approach, weighting selected factors that influence the reproduced image quality, i.e. graininess and color accuracy, in order to select the optimal ink combination. The perceived graininess is modeled by employing S-CIELAB, a spatial low-pass filtering mimicking the human visual system. By applying the filtering to a large dataset, a generalized prediction that quantifies the perceived graininess is carried out and incorporated as a criterion in the color separation.

Consequently, the presented research increases the understanding of color reproduction and image quality in multi-channel printing, provides concrete solutions to challenges in the practical implementation, and rises the possibilities to fully utilize the potential in multi-channel printing for superior image quality.

Populärvetenskaplig sammanfattning

Traditionellt har färgåtergivning i tryck åstadkommits genom att blanda tryckfärgerna cyan, magenta, gult och svart. För att skapa olika proportioner av tryckfärgerna används rastring, en process som delar upp tryckfärgerna i rasterpunkter, som varierar i storlek eller frekvens. På normalt betraktavstånd är de tryckta rasterpunkterna knappt synliga och man kan med traditionellt fyrfärgstryck reproducera ett stort antal kulörer.

Med ny teknik har flerkanalstryck introducerats, dvs. trycktekniker som använder fler än de traditionella fyra tryckfärgerna. Genom att addera ljusare tryckfärger av samma nyans, t.ex. grått som komplement till svart, kan ljusa partier återges med högre kvalitet. Då ljusa partier reproduceras med de traditionella tryckfärgerna finns risken att rasterpunkterna inte blir helt osynliga, och att trycket inte upplevs som homogent. Detta är ett oönskat fenomen som sänker upplevd bildkvalitet, ofta refererat till som grynighet. Användandet av ljusare tryckfärg minskar kontrasten mot papperssubstratet, vilket minskar den upplevda grynigheten och bidrar till högre tryckkvalitet. Man kan i flerkanalstryck även addera komplementfärgerna, dvs. röd, grön och blå tryckfärg, vilket ger en utökad färgrymd med klarare och mer mättade kulörer.

För att till fullo kunna utnyttja potentialen hos flerkanalstryck finns en rad problem och utmaningar som först måste lösas. De extra färgkanalerna

bidrar till en betydande ökning i komplexiteten hos karakteriseringen av tryckprocessen, vilket krävs för en korrekt återgivning. Fler tryckfärger kräver en noggrann kontroll över hur rasterpunkterna placeras, för att undvika att fler färger än vad papperssubstratet kan hantera placeras i någon punkt. Färgseparationen, processen som bestämmer korrekta proportioner av tryckfärger, måste vidare hantera den redundans som uppstår med flera tryckfärger, då en mängd olika kombinationer existerar för att reproducera en given kulör.

Denna avhandling adresserar flera av de tekniska utmaningarna för att till fullo kunna utnyttja potentialen hos flerkanalstryck. För att effektivare utnyttja de ljusare tryckfärgerna implementeras en metod för flernivå-rastrering, där tryckfärger av samma nyans grupperas i separata kanaler. Inom varje kanal placeras rasterpunkterna optimalt, helt utan överlapp, vilket minimerar den upplevda grynigheten och säkerställer att den totala färgmängden i varje punkt kontrolleras. Genom att de ljusare tryckfärgerna hanteras inom steget för flernivå-rastrering, reduceras komplexiteten i färgseparationen till att motsvara traditionellt fyrfärgstryck, och metoden kan därför implementeras även i befintliga flöden. Vidare utreds hur färgseparationen kan påverka tryckkvalitet, i form av upplevd grynighet, då de tre komplementfärgerna används. Genom att använda modeller för synsinnet har metoder för att prediktera upplevd grynighet tagits fram. Denna omfattande karakterisering av grynighet används som ett av flera kriterier i en ny modell för optimal färgseparation i flerkanalstryck, där användaren själv tillåts vikta kriterierna grynighet, kulörexakthet och tryckfärgsbesparing. Sammantaget medför de introducerade metoderna och modellerna både en ökad förståelse av färgåtergivning och bildkvalitet i flerkanalstryck, lösningar på praktiska implementationsutmaningar, och ökade möjligheter att till fullo utnyttja potentialen i flerkanalstryck för ett mycket högkvalitativt tryckresultat.

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Main publications

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Chapter 1

Introduction

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1.1 Background

Traditionally, color printing is achieved with a mixture of four colorants on the media substrate. An input image is firstly separated into four channels, each intended for its respective ink, utilizing a color separation model. Such models account for ink/paper/light interactions, allowing the correct perception of the intended color. The four separated channels are then converted to binary representations using halftoning algorithms. Each halftoned channel is composed of a series of discrete dots, indicating the locations at which ink droplets are placed, thus creating the illusion of lighter or darker shades.

However, printed halftones are potentially detectable by a human observer, possibly resulting in an unpleasant graininess impression. This can be particularly prominent in instances in which the ink is in high contrast with the paper color and in which the droplets forming the coverage are scarce. Moreover, the range of colors that a four ink combination can reproduce is much lower than the range that could be perceived by a human observer.

High-quality reproduction, improving the aforementioned issues, can be accomplished by incorporating additional inks in the printing process, in what is known as multi-channel printing. This type of printing, however, raises several challenges, such as an increase in the color separation complexity, characterization of light/paper/ink interactions and adaptation of halftoning algorithms.

1.2 Research project

The work presented in this dissertation is oriented towards a PhD degree, and has been carried out at Linköping University. The research,

partially funded by the Marie Curie Initial Training Networks (ITN) and partially by Linköping University, is part of the CP7.0 project: Colour Printing 7.0: Next Generation Multi-Channel Printing (www.cp70.org).

The project is executed in a consortium of 6 full partners (Gjøvik University College, Norway, Technische Universität Darmstadt, Germany, Voxvil AB, Sweden, University of the West of England, UK, Océ Print Logic Technologies SA, France and Linköping University, Sweden) and 6 associated partners (METSA Board AB, Sweden, MoRe Research AB, Sweden, Fraunhofer Fokus, Germany, Mid Sweden University, Sweden, The National Gallery, UK and Clariant Produkte, Germany), congregating 7 PhDs and 2 Post-Doc researchers working in the field of expansion of conventional printing to multi-channel inkjet printing. The key research areas within the project are spectral modeling of the printer/paper/ink combination, spectral gamut prediction and gamut mapping, paper's optical and surface properties, 2.5 D printing, and halftoning algorithms and tonal reproduction.

1.3 Goals and challenges of the presented research

Multi-channel printing employs additional inks with the goal of enhancing the image quality reproduction. As the implementation is not straightforward, any input target needs to be processed in a way so that the benefits of the added inks can be fully utilized. Such processing methods should either be adapted or developed to be suitable for this type of printing.

The research addressed in this dissertation deals with the image quality in multi-channel inkjet printing, namely employing color separation models and halftoning algorithms. Color separation models, transforming a

target color image to the channels utilized, rise in computational time and complexity in multi-channel printing, thus prompting the need to address the one-to-many mapping problem in which several ink combinations can reproduce the same target color. In addition, the ink placement should be controlled in order to avoid over-inking.

Color separation methods and halftoning algorithms, suitable for an increased number of colorants in multi-channel printing, are research questions addressed in this dissertation. Moreover, since the added colorants aim to improve the perceived quality of the reproduction, the possibility of addressing perceived graininess and augmenting the scope of reproducible colors should be investigated.

The goal of the research presented in this dissertation is developing or adapting color separation models and halftoning algorithms that increase the perceived image quality in multi-channel printing.

1.4 Structure of this dissertation

This dissertation has been written as a monograph, and is based on the research that has been published as part of the PhD studies. A list of published papers is given on page xiii. Choosing to write a monograph has provided the opportunity to exceed the imposed publication's page limitations, complement the published research with additional work and ideas, and has permitted the opportunity to shape the research with added flow between the published papers.

This dissertation begins with the background and theory chapters, explaining terms and concepts used in the research presented. After this introduction, Chapter 2: *Color theory and reproduction* explains the principles of color vision and color reproduction, providing an overview of the models and metrics available to quantify and compare colors. Chapter 3:

Halftoning algorithms and color reproduction models explains the nature and the need for halftoning algorithms, providing the general ramification and the details of the algorithms significant for this research. In addition, the light/paper/ink interaction effect on the reproduced color and several models that predict this behavior are explained.

Chapter 4: *Halftone quality evaluation* explains print quality concepts and investigates different evaluation methods to qualitatively assess a reproduction. The chapter also explores different image quality metrics, presenting results with the goal of selecting the appropriate ones for the research presented in the following chapters.

The research carried out to date is presented in Chapters 5, 6 and 7. Chapter 5: *Multilevel halftoning – implementation and analysis* presents the implementation of a multilevel halftoning algorithm suitable for multi-channel printing purposes, resolving several challenges encountered. This research has been published in Žitinski Elías et al. (2014), Žitinski Elías (2014) and Žitinski Elías et al. (2015). Chapter 6: *Print characterization employing multilevel halftoning* describes the research presented in Žitinski Elías, Gooran and Nyström (2016) of the incorporation of the multilevel halftoning algorithm in the color separation and color prediction models. Chapter 7: *Color separation for improved image quality* expands the work of the previous chapters by introducing the challenge of additional colorants in the print setup, resulting in a proposed color separation approach that takes into account the reproduction quality in terms of graininess. This research also contains the work performed in the incorporation of a method for graininess prediction. The research presented in this chapter was published in Žitinski Elías, Nyström and Gooran (2016) and Nyström et al. (2017).

Finally, Chapter 8: *Conclusions and future work* concludes the research presented, discussing several future research possibilities.

Chapter 2

Color theory and reproduction

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2.1 Introduction

This chapter aims to explain concepts related to the perception and reproduction of colors, giving an overview of the way humans perceive colors. It also explains how to define, measure, and quantify colors, with notions such as color spaces and color difference formulae. These concepts are crucial for understanding the research presented in the following chapters.

2.2 Colorimetry

Colorimetry is the science and technology used to quantify and physically describe the human color perception (Ohno, 2000). The principles of the human visual system are investigated with the goal of understanding, quantifying and representing colors.

2.2.1 Human visual system

The human visual system (HVS), responsible for the notion of sight, consists of photoreceptors located in the eye's retina that are susceptible to illumination stimuli. There are two kinds of photoreceptors: rods and cones. Rods are useful for vision under low light levels and do not contribute to color. When the light levels are higher, the rods become saturated and do not contribute to vision. The cones are the ones that become active under normal light levels, and are responsible for color vision.

There are three types of cones with different light susceptibility, peaking at short (420-440 nm), medium (530-540 nm), and long (560-580 nm) wavelengths of visible light (Sharma, 2002). These cone types divide

the visible light spectrum into three bands, accounting for the human trichromatic color vision (Stockman et al., 1993). Any light susceptible by the cones evokes stimuli that are translated in the brain as a color sensation. These stimulus combinations account for the colors perceived by the HVS.

2.2.2 CIE color spaces

A color space is a mathematical tuple of three or four primary color components (primaries). According to Tkalčić and Tašić (2003), a color space can be described as a precise notation by which colors are specified. Several color spaces and subdivisions exist, e.g. RGB, CMYK, CIELAB and CIEXYZ.

The International Commission on Illumination (The Commission Internationale de l'Eclairage, CIE) is the primary organization responsible for standardization of color metrics and terminology (Sharma, 2002). In 1931, they experimentally found the three color matching functions, $r(\lambda)$, $g(\lambda)$ and $b(\lambda)$, that best represent the sensitivity functions of the HVS. For some wavelengths this experiment resulted in negative sensitivity values, meaning that the stimuli at those wavelengths could not be obtained by any physically achievable primary (Sharma, 2002). Therefore, the $r(\lambda)$, $g(\lambda)$ and $b(\lambda)$ color matching functions were translated by a matrix multiplication into $\bar{x}(\lambda)$, $\bar{y}(\lambda)$ and $\bar{z}(\lambda)$ color matching functions (Figure 2.1).

The viewing condition is an important factor in CIE color spaces. The illumination is one aspect of the viewing condition and CIE denominates different light illumination sources as standard illuminants – A, B, C, and a series of D sources. Among the D standard illuminants, the light source D50 corresponds to daylight at a temperature of 5003 K and is widely used in graphic industry, while D65 corresponds to 6504 K and is used in

Figure 2.1: CIE $\bar{x}$ $\bar{y}$ $\bar{z}$ color matching functions.

paper industry (Fairchild, 2013). Another aspect of the viewing condition is the observer, since the color matching functions are dependent on the observer's field of view. In standard colorimetry, an observer's field of view that subtended 2° was firstly used in 1931, followed in 1964 by a supplementary standard colorimetric observer of 10° (Fairchild, 2013).

2.2.2.1 CIEXYZ color space

The CIEXYZ color space was created in 1931 to approximate human vision, thus containing the whole range of perceivable colors of the HVS (Smith and Guild, 1931). The tristimulus XYZ values are derived from the $\bar{x}(\lambda)$, $\bar{y}(\lambda)$ and $\bar{z}(\lambda)$ color matching functions by:

$$\begin{aligned} X &= k \int_l^u I(\lambda) R(\lambda) \bar{x}(\lambda) d\lambda \\ Y &= k \int_l^u I(\lambda) R(\lambda) \bar{y}(\lambda) d\lambda \\ Z &= k \int_l^u I(\lambda) R(\lambda) \bar{z}(\lambda) d\lambda \end{aligned} \tag{2.1}$$

where $I(\lambda)$ is the spectral power distribution of the light source, $R(\lambda)$ is the spectral surface reflectance of the object, and l and u are the lower and upper limits of the visible wavelengths, approximately 380 and 780 nm. k is the normalization constant set so that a perfect diffuse surface $R(\lambda) \equiv 1$ always gives $Y = 100$:

$$k = \frac{100}{\int_l^u I(\lambda) \bar{y}(\lambda) d\lambda} \tag{2.2}$$

CIE XYZ is a device-independent color space, which means that the color representation is independent of the reproduction medium or technology of the device. The XYZ values correspond to linear transformations of the physical primaries, chosen to eliminate their negative values, and normalized to yield equal tristimulus values for the equi-energy spectrum. Furthermore, $\bar{y}(\lambda)$ is chosen to coincide with the luminous efficiency function, i.e. the tristimulus value Y represents the perceived luminance (Sharma, 2002). A drawback of CIE XYZ is that it is perceptually non-uniform, meaning that the Euclidean distance between colors coordinates does not correspond to the perceived color difference (Sharma, 2002), impeding a quantitative comparison between colors.

2.2.2.2 CIELAB color space

The color space CIELAB was derived from CIE XYZ, as shown in Equation 2.3, with the goal of constructing a perceptually uniform color space.

The L^* coordinate denotes lightness, where $L^* = 100$ is white stimulus and $L^* = 0$ means black stimulus, a^* is the red-green axis where positive values indicate red and negative values are green, and b^* yellow-blue axis where positive values mean yellow and negative ones are blue.

$$\begin{aligned}
 L^* &= \begin{cases} 116 \left(\frac{Y}{Y_n} \right)^{\frac{1}{3}} - 16, & \frac{Y}{Y_n} > 0.008856 \\ 903.3 \left(\frac{Y}{Y_n} \right), & \frac{Y}{Y_n} \leq 0.008856 \end{cases} \\
 a^* &= 500 \left(f \left(\frac{X}{X_n} \right) - f \left(\frac{Y}{Y_n} \right) \right) \\
 b^* &= 200 \left(f \left(\frac{Y}{Y_n} \right) - f \left(\frac{Z}{Z_n} \right) \right),
 \end{aligned} \tag{2.3}$$

where

$$f(x) = \begin{cases} x^{\frac{1}{3}}, & x > 0.008856 \\ 7.787x + \frac{16}{116}, & x \leq 0.008856 \end{cases} \tag{2.4}$$

X_n , Y_n and Z_n are the CIE XYZ values for the white point of the chosen light source.

A spatial extension of CIELAB, called Spatial-CIELAB or S-CIELAB, was proposed in Zhang and Wandell (1997), in which spatial filtering is applied to an image in order to simulate the spatial blurring of the HVS. The implementation and application S-CIELAB is discussed in Section 4.4.

2.2.2.3 Color difference

Although CIELAB was created to serve as a perceptually uniform color space, in which the distance between colors could serve as a metric of their perceived difference, it has been found that large perceptual non-linearities exist, specially around the blue area and low-chroma regions

2. Color theory and reproduction

(Luo et al., 2001). Therefore, several color difference formulae exist, ranging from simpler to more computationally challenging ones, the latter offering improved accuracy.

The CIE 1976 color difference ΔE_{ab} is the formula characterized by its calculation simplicity, measuring the Euclidian distance between the coordinates of two colors:

$$\Delta E_{ab} = \sqrt{(L_2^* - L_1^*)^2 + (a_2^* - a_1^*)^2 + (b_2^* - b_1^*)^2} \quad (2.5)$$

More complex color difference formulae have been proposed, such as the CIE 1994 and 2000, which weight the lightness ΔL^* , chroma ΔC_{ab}^* and hue ΔH_{ab}^* to account for CIELAB's non-linearities.

The CIE 1994, ΔE_{94} , is calculated as:

$$\begin{aligned} \Delta E_{94} &= \sqrt{\left(\frac{\Delta L^*}{k_L S_L}\right)^2 + \left(\frac{\Delta C_{ab}^*}{k_C S_C}\right)^2 + \left(\frac{\Delta H_{ab}^*}{k_H S_H}\right)^2} \\ \Delta C_{ab}^* &= \sqrt{\Delta a^{*2} + \Delta b^{*2}} \\ \Delta H_{ab}^* &= \sqrt{\Delta E_{ab}^{*2} - \Delta L^{*2} - \Delta C_{ab}^{*2}} = \sqrt{\Delta a^{*2} + \Delta b^{*2} - \Delta C_{ab}^{*2}} \end{aligned} \quad (2.6)$$

Here, S_L , S_C and S_H are the weighting functions, defined as:

$$\begin{aligned} S_L &= 1 \\ S_C &= 1 + K_1 C_1^* \\ S_H &= 1 + K_2 C_1^* \end{aligned} \quad (2.7)$$

K_1 and K_2 are fixed numbers, dependent on the application to graphic arts or textiles, and C_1^* is the chroma of the reference color. k_L , k_C and k_H are parametric factors, and are included so that adjustments can be made in the equation in case of deviation of viewing conditions. If no

deviations from the model are made, the parametric factors are set to 1 (McDonald and Smith, 2008). This formula has been predominately used in the research presented in Chapters 4 – 7.

The color difference CIE 2000 formula, ΔE_{00} , is considerably more sophisticated, with a non-trivial implementation that could be significant in particularly precise applications, such as industry (Sharma et al., 2005). The implementation details, together with the codes, are available in the original article (Sharma et al., 2005).

The interpretation of the acceptability of color difference values is subjective and dependent on the application. For instance, Kang (1997) states that the common just noticeable difference (JND) value is $\Delta E_{ab} = 1$, while Mahy et al. (1994) note it as $\Delta E_{ab} = 2.3$. Hardeberg (1999) classifies a rule of thumb in which color differences $\Delta E_{ab} \leq 3$ are hardly perceptible, $3 < \Delta E_{ab} \leq 6$ are perceptible but acceptable, and $\Delta E_{ab} > 6$ are not acceptable. Meanwhile, Abrardo et al. (1996) interpret the color difference for the evaluation of scanners as follows: $\Delta E_{ab} \leq 1$ as limit of perception, $1 < \Delta E_{ab} \leq 3$ as very good quality, $3 < \Delta E_{ab} \leq 6$ as good quality, $6 < \Delta E_{ab} \leq 10$ as sufficient, and $\Delta E_{ab} > 10$ as insufficient.

2.3 Color reproduction

As opposed to device-independent CIE color spaces (Section 2.2.2), device-dependent color spaces (e.g. RGB, CMYK) are employed to represent colors for reproduction. Depending on the reproduction type, there is a differentiation between additive and subtractive color mixing.

2.3.1 Additive color mixing

The idea of reproducing the full range of colors by mixing three lights with different color bands lead to the principles of some of today's color reproduction systems. The three colored lights were chosen so that their wavelengths closely matched the light susceptibility wavelengths of the three different types of cones. The additive mixture of these three lights at their maxima – red (R), green (G) and blue (B) – renders white, labeling it additive color mixing (Figure 2.2 – left). In additive color mixing, the color sensation is achieved by photon emission from a light source. The applicability is to any device that emits photons of energy to display colors, like monitors or projectors.

Figure 2.2: Additive (left) and subtractive (right) color mixing.

2.3.2 Subtractive color mixing

Contrary to photon emittance, color sensation could also originate from photons reflected from an object that is illuminated by a light source, e.g. when mixing ink pigments in printing reproduction. A different color mixing model is then used to reproduce colors, employing red's, green's

and blue's complementary colors – cyan (C), magenta (M) and yellow (Y) – as primaries. Contrary to additive color mixing, the lack of the three primary colors creates the sensation of white (assuming a white background) and this model is thus called subtractive color mixing. The amount of cyan pigment applied to the paper will control the amount of red in the white light that will be absorbed by the ink. By applying 100% cyan coverage, in theory no red will be reflected. By applying 100% ink coverage of cyan, 100% magenta and 100% yellow, in theory, all light will be absorbed and thus the sensation of black will be achieved (Figure 2.2 – right). However, in printing technologies, black (K) is added as a fourth ink, due to the imperfection of ink pigments and paper substrate that results in inhomogeneous surface coverage. Since each primary in this color space can be referred to as a channel, CMYK printing is also called four-channel printing.

2.3.3 Multi-channel printing

Certain undesirable printing aspects may lower the perceived reproduction quality. For instance, the perception of shades is achieved by placing ink droplets onto the paper surface (further explained in Chapter 3). The primary ink droplets thus pose a likelihood of being detected against the white paper substrate at areas where ink dots are scarce. This phenomenon is called graininess. In addition, subtractive color mixing causes a lightness decrease in overlapping inks, causing certain shades reproduced by a mixture of two primaries hard to achieve (Boll, 1994). Examples would be light shades of red (magenta + yellow), green (cyan + yellow) and blue (cyan + magenta). In the interest of improving print quality, additional channels other than CMYK are introduced (Boll, 1994, Jang et al., 2006b). This is then referred to as multi-channel printing.

To address the graininess problem, light versions of the primary inks -

light cyan, light magenta and gray inks - can be added. The light inks closely resemble the hue of the main inks (Gooran and Žitinski Elías, 2015), and are differentiated mainly by their lower contrast against the paper, thus reducing graininess. The secondary color inks, i.e. red, green and blue, can also be added, with the goal of increasing the printer's gamut, i.e. the scope of printable colors. Introducing additional channels thus helps achieving higher quality prints.

The additional inks in multi-channel printing increase the necessity of controlling the ink overlap in order to avoid over-inking, i.e. exceeding the maximum amount of ink that the paper substrate can absorb, possibly causing ink bleeding and color inaccuracy problems (Zeng, 2000). In addition, when more than three inks are used, determining the ink combination that should be used to reproduce a specific 3-channel CIELAB color imposes a one-to-many mapping problem. The number of ink combinations that can reproduce the same target color increases in multi-channel printing, leading to a higher extent of colorimetric redundancy.

Control over the multi-channel reproduction opens a research area that is addressed in this dissertation in Chapters 5 – 7.

2.4 Summary

The purpose of this chapter was to explain the basics of colorimetry and to acquaint the reader with the concepts used in the research described in the following chapters. In addition, an attempt was made to explain the basics of color reproduction and the need to extend the conventional four-channel to multi-channel printing, along with the associated issues of control over the reproduction.

A deeper understanding of the print process, including halftoning algorithms and paper/light/ink interaction, is needed to predict the print result,

which is further discussed in Chapter 3.

Chapter 3

Halftoning algorithms and color reproduction models

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3.5 Summary 43

3.1 Introduction

Print reproduction utilizes the subtractive mixing color space, i.e. CMYK (Section 2.3.2). An input image, if represented in another color space, is thus transformed into the CMYK color space, in which mixed ratios of ink primaries reproduce different colors. However, achieving different ink ratios is not a straightforward operation, since there exists only the binary choice of either placing or not placing an ink droplet. Thus, before the channel can be printed with its respective ink, it needs to be transformed into a binary channel (bitmap). This is achieved by applying a halftoning algorithm, resulting in a halftoned image. Such an image consists of a series of dots, varying in size and/or frequency, yet small enough to remain unnoticed by the human eye, thus achieving the impression of lighter and darker shades (Figure 3.1). Literature reveals a large number of halftoning algorithms (Baqai et al., 2005), some of which are explained in Section 3.2.

Figure 3.1: A halftoned image.

When ink is deposited onto the paper, certain light, paper and ink interactions occur that influence the perception of the printed output. Thus, understanding and characterizing these interactions is necessary in or-

der to predict the print result. One such phenomenon is the tone value increase resulting from ink droplet placement on the paper surface. This is also called dot gain, and it originates from a physical spreading of ink and an optical effect caused by light scattering in the substrate. Dot gain is the cause of a differentiation between the input coverage (dot size sent to the printer) and the output coverage (dot size once printed). This will be further elaborated in Section 3.3. A number of halftone color reproduction models exist (Wyble and Berns, 2000) that account for dot gain, thus predicting the output of halftone prints. Some of the most common ones are explained in Section 3.4.

3.2 Halftoning algorithms

Halftoning algorithms transform the continuous-tone channels of the input image into binary (halftoned) channels, each of which being a guide of ink and no ink placement. When viewed from a certain distance, the halftoned image is ideally analogous to the continuous-tone input image. In other words, the idea behind halftoning is an equivalent average value of an area of microdots (called halftone cell) as that of the corresponding tone value of the input, continuous-tone, image. Two halftoning specifications are of importance, screen frequency (lines per inch, lpi) denoting the number of halftone cells per inch, and print resolution (dots per inch, dpi), representing the number of microdots per inch. Examples of halftone cells with different dpi are illustrated in Figure 3.2. The left one is a 3×3 halftone cell and a halftone dot representing the gray level of $5/9$, the middle one is an 8×8 halftone cell with a halftone dot representing the gray level of $44/64$, and the right one is a 10×10 halftone cell with a dot representing the gray level of $72/100$.

The lpi and dpi values are dependent on the printing technology and printing device, media, etc. Higher lpi and dpi values mean smaller and

Figure 3.2: Halftone cells with different dpi.

visually less noticeable halftone cells and microdots. The number of levels presented in a halftoned image is dependent on the dpi/lpi ratio as in the following equation:

$$\text{Number of levels} = \left(\frac{\text{dpi}}{\text{lpi}} \right)^2 + 1 \quad (3.1)$$

Figure 3.3 displays an image halftoned with AM halftoning (explained in Section 3.2.1) at 150 dpi with different lpi values, i.e. 20 lpi on the left image and 60 lpi on the right image. The number of levels and the lpi are inversely proportional.

Figure 3.3: AM halftoned image at 20 lpi (left) and 60 lpi (right).

Unless stated otherwise, all the images in this chapter are halftoned at 150 dpi.

3.2.1 AM and FM halftoning

AM and FM halftoning algorithms are the general disambiguation of all halftoning algorithms (Sharma, 2002). In AM halftoning the size of the halftone elements varies according to the gray level to be represented, while the frequency remains constant (Figure 3.3). Contrarily, FM halftoning algorithms vary the frequency of the halftone dots. Meanwhile, their dot size can either remain constant (first generation FM, Figure 3.4) or can also be altered (second generation FM). An example of such dot size variation can be seen in Figure 3.5.

Figure 3.4: First generation FM halftoned image, IMCDP algorithm.

AM halftoning is a technique with good printing stability and low computational requirements (Lau and Arce, 2001), showing less dot gain in mid-tone areas when compared to FM halftoning (Gooran, 2005). Nevertheless, since the dot frequency remains constant, an undesirable optical grid effect, called moiré, can appear when overlaying halftoned channels for color reproduction. In order to avoid moiré, each channel is laid in a

Figure 3.5: Second generation FM halftoned image.

specific angle, thus altering the formation of this optical phenomenon, creating instead a higher frequency pattern called rosette.

FM halftoning algorithms generate the effect of lighter or darker areas by altering the frequency of the microdots, placing them in lower or higher concentration depending on the gray level to be reproduced. Being non-periodic, FM algorithms are not as susceptible to moiré visual artifacts when multiple channels are overlaid. It is usual that the channels are halftoned independently of each other, although alternative methods that halftone the channels dependently exist. For example, in Gooran (2001), the strategy is to use dot-off-dot printing as much as possible to reduce the color noise and ink consumption. Dot-off-dot strategies avoid overlapping dots of colorant channels. The advantage of FM is fine detail reproduction, due to small size halftone elements (Gooran, 2006).

Second generation FM, as mentioned, alters both the size and frequency of the halftone dots in the binarization process. This benefits the repro-

duction in terms of printability improvement and noise reduction, compared to first generation FM (NAMEDANIAN, 2013).

It is possible to combine AM and FM algorithms in what is then called hybrid AM-FM halftoning, benefiting from their specific advantages. For instance, a hybrid halftoning method was proposed in Gooran (2005) to achieve a better reproduction in cases when it is unfeasible to achieve small and precise halftone dots in light areas when employing AM halftoning.

3.2.2 Iterative halftoning

Iterative halftoning algorithms take into account the entire image, instead of operating point-by-point or on a neighborhood. This makes the algorithm more computationally challenging, although the result is a high quality halftoned image (Kacker and Allebach, 1998, Gooran, 2001, Bernal et al., 2014, Gooran and Kruse, 2015).

Most iterative algorithms use low-pass filters, representing the human visual system (HVS), to define a quality measure. They find the error by calculating the difference between the low-pass versions of the original and binary images. The aim is to minimize this error by iteratively changing the initial binary image. The process comes to an end when the initial given condition is met, or when no change in the binary image is achieved. In the next subsection, the iterative algorithm used in the work in Chapters 4 – 7 is explained.

3.2.2.1 IMCDP

Iterative Method Controlling the Dot Placement (IMCDP) is an iterative halftoning algorithm described in Gooran (2001). An image halftoned with IMCDP is shown in Figure 3.4. Since it has been developed within

our research group, thus having full control over the algorithm, it has been the halftoning method chosen in the research work done in this dissertation.

The algorithm works as follows. For a $n \times n$ gray tone image, $2^{n \times n}$ possibilities of a binary halftoned image exist. This number can, however, be narrowed down by calculating the number of black dots k the halftoned image must have, k being the closest integer to the sum of the gray values of all the pixels of the original image. In this algorithm the original image is supposed to be normalized to values between 0 and 1, where 0 indicates white and 1 indicates black. Halftoning is now a decision on the placement location of k number of black dots.

The goal of this halftoning algorithm is to minimize the difference e between the original continuous-tone image, g , and the binary image, b . Since the HVS acts like a low-pass filter, the difference between the images can be calculated with the following equation:

$$e = \sum_{i,j} (f_g(i,j) - h_b(i,j))^2, \quad (3.2)$$

where $f_g(i,j)$ and $h_b(i,j)$ are the pixel values at the location (i,j) of the images, and f_g and h_b the filtered versions of the original and binary image, respectively. The experimental results show that the best general choice of the low-pass filter is a Gaussian filter with standard deviation 1.3 truncated to 11×11 pixels. The algorithm workflow is displayed in Figure 3.6.

Firstly the initial image g is filtered with a filter f , resulting in an image f_g . The algorithm finds the position of the largest pixel value (if there are more, choosing the first one found), and places a dot at this same position in the image b . This image is then filtered with a filter h , resulting in h_b . The difference $f_g - h_b$ is calculated (called the feedback process) and the algorithm from then on calculates the position of the next highest

Figure 3.6: IMCDP halftoning algorithm.

pixel value in that image. This process continues until the known number of dots, k , is placed. For additional algorithm details, interested readers are referred to the original paper (Gooran, 2001).

Keeping in mind the high quality of the final halftoned image, two drawbacks of this algorithm exist. First, for images with large uniform areas, the algorithm may result in a highly structured halftoned image. This is, however, avoided by adding a very small amount of noise to f_g (Figure 3.6). Secondly, as any iterative halftoning algorithm, processing time is increased in comparison to algorithms that operate point-by-point or on a neighborhood. This issue has been addressed in Gooran and Kruse (2015), in which a high speed version of the IMCDP algorithm has been developed. It is based on the original algorithm, creating image-independent first or second generation FM threshold matrices, thus achieving a fast binarization. The algorithm allows a modification in the dot size, shape, and alignment, as well as the halftone structure. For additional details, the interested readers are referred to the original article (Gooran and Kruse, 2015).

3.2.3 Multilevel halftoning

The previously discussed halftoning algorithms generate a binary image, consisting of zeros and ones. Consequently, they can be referred to as bilevel algorithms. Multilevel halftoning algorithms, on the other hand, are not limited to a two level output, and could instead consist of several levels. This is useful in several applications related to improved image quality; as a method of embedding binary halftones into higher bit-depth output (Goldschneider et al., 1997) or to lower the quantization noise (Broja et al., 1990). In a similar research, the bilevel algorithm is treated as a multilevel algorithm in order to control the halftone dot distribution (Zhu et al., 2014). In Derhak and Hartley (2002), the input consists of a linearized channel and all the information necessary to execute the halftoning – the number of levels and sublevels, level limits and the translation from sublevel to process values. In their setup, it is possible to limit the use of each of the inks up until a user-defined coverage. As for the halftoning part, several calculations are performed for each pixel, marking the need of an adaptation and/or development of a bilevel halftoning algorithm specific for this multilevel process. The authors give a general comment that various types of halftoning processes can be used, without offering details about necessary adaptations.

The multilevel halftoning algorithm described in Gooran (2006) operates by first separating an image into different regions, then halftoning them simultaneously using a bilevel halftoning algorithm, and finally merging them in the post-processing step. This specific instance of multilevel algorithm is used in the research described in Chapters 5 – 7. From now on, when multilevel halftoning is mentioned, it will refer to this specific type of multilevel halftoning. Figure 3.7 displays an image halftoned with this multilevel algorithm, using IMCDP as the bilevel FM halftoning method. The image displays 4 levels: 0 (no ink), 0.33, 0.66 and 1.

Figure 3.7: Multilevel IMCDP halftoned image.

As discussed in Section 2.3.3, multi-channel printers use additional inks other than the traditional four. Nevertheless, a paper substrate can absorb only a certain amount of ink. The way to ensure the ink limits are not exceeded is by controlling the placement of the halftone dots. In the multilevel halftoning algorithm described in Gooran (2006) it is possible to halftone an image in a way that is printed using multiple inks of same (similar) hue with no ink overlap. The specific details of this halftoning algorithm are described in Chapter 5, together with the implementation results.

3.3 Dot gain

Dot gain or tone value increase is the result of the interaction between the ink and media substrate (e.g. paper). The ink droplets expand in contact with the paper, spreading through the substrate and penetrating

it. In addition, incoming light scatters within the paper, visually enlarging the printed ink drops. As each halftone dot is enlarged, the overall result is a darker image than the original one. A representation of the dot gain effect is shown in Figure 3.8. A side-effect could be information loss in the darkest regions.

Figure 3.8: An image (left) and the simulated dot gain effect (right).

Dot gain caused by ink spreading and ink penetration in contact with paper is called physical or mechanical dot gain, while the result of light scattering and light absorption is referred to as optical dot gain. When the photons of light enter the paper through the ink layer of the image, they can, for instance, scatter within the paper and get absorbed in it, or exit the paper at a further point. This is illustrated in Figure 3.9, where the dashed lines represent the photon paths where light exchange between different chromatic areas occurs, causing optical dot gain.

Because of the enlarged dot size, two types of area coverage values are differentiated - nominal a_{nom} and effective a_{eff} area coverages. Nominal area coverages are the coverage values that are sent to the printer. These coverages, increased once printed due to dot gain, are then referred to as effective area coverage values. Effective area coverage is the measured value of the printed ink coverage, while the dot gain is the difference between effective and nominal area coverage. A dot gain curve, such as the one seen in Figure 3.10, is a way of displaying the

Figure 3.9: Possible paths a photon may take in a paper/ink medium.

relationship between nominal area coverage and dot gain, where (on the x-axis) 0 means no ink coverage and 100 means fulltone coverage.

Research has been carried out to characterize dot gain (Arney et al., 1996, Rogers, 1997, Gustavson, 1997, Nyström, 2008, Nyström and Yang, 2009, Namedanian, 2013) in order to understand and account for it. It has been found that dot gain is dependent on the type of substrate, inks, printing technology, type of halftoning algorithm (AM/FM), screen frequency, print resolution, halftone dot shape, etc. It is logical to notice that the paper properties will have an effect on the dot gain, as different papers absorb ink and scatter light differently (Namedanian et al., 2014). In addition, the shape of the halftone affects dot gain too; the larger the perimeter of the halftone elements, the larger the physical (Nyström, 2008, Nyström and Yang, 2009) and optical (Namedanian et al., 2013) dot gain are.

Control over the printed output evidently includes accounting for the dot gain effect, i.e. adjusting the nominal ink coverages in order to render the desired effective coverages. Halftone reproduction models – explaining the relationship between the two – help predict the output.

Figure 3.10: Plot of the effective area coverage and dot gain versus nominal area coverage.

3.4 Halftone reproduction models

Wyble and Berns (2000) describe several relatively simple and reasonably accurate halftone reproduction models, with the goal of predicting the outcome of the printing process. An overview of the well-known reproduction models that are also used in the research explained in Chapters 5 – 7 is given below. Some of them predict the halftone reflectance of only single monochrome channels, while others calculate the reflectance of overlapping ink combinations. In addition, some models consider the influence of the optical dot gain, while others disregard it in their calculations.

The common attribute of the halftone reproduction models is that they predict colorimetric or spectral values of the printed halftone, given the

nominal ink coverages of the involved ink(s). These are called forward models or color reproduction models. In contrast, inverse color models (or color separation models) determine the ink combinations that should be used to reproduce a specific target color.

The color separation calculation is commonly used in a print workflow. As mentioned in this section's introduction, an image needs to be transformed to the CMYK color space in order to be printed. The image, often represented in RGB or with colorimetric values, is converted to the CMYK ink coverages using a color separation approach. This will be further discussed in Chapters 6 and 7.

3.4.1 Murray-Davies model

The first reproduction model of a monochrome halftone print is presented in Murray (1936). The formula, known as the Murray-Davies model, predicts the reflectance by a weighted linear interpolation between the full-tone and the substrate reflectances:

$$R_\lambda = a_i R_{\lambda,i} + (1 - a_i) R_{\lambda,s} \quad (3.3)$$

where R_λ is the predicted spectral reflectance of the halftone, a_i the fractional ink area coverage, $R_{\lambda,i}$ the spectral reflectance of the full coverage ink, and $R_{\lambda,s}$ the substrate's reflectance. The fractional ink area coverage refers to the printed ink coverage. This model is a single-ink prediction model and it has served as the base for extensions and improvements.

One of the drawbacks of this model is that it neglects dot gain, equalizing nominal and effective area coverage. The other one is that it only explains single-channel interactions.

3.4.2 Neugebauer model

An extension of the Murray-Davies model to account for multiple channels was made by Neugebauer (1937). Neugebauer approximated the reflectance of a multi-colorant printing system by calculating the sum of the joined spectral reflectances at full area coverage:

$$R_\lambda = \sum_i a_i R_{\lambda,i,max}, \quad (3.4)$$

where i are the so-called Neugebauer primaries (NPs): the substrate with no ink, fulltone single ink, and ink overlap combinations (with full coverage), summing up to a total of 2^n NPs, n being the total ink number. For a three colorant example (CMY), the NPs are white (substrate), cyan, magenta, yellow, blue, red, green and three-color black. $R_{\lambda,i,max}$ are the spectral reflectance values of each NP, and a_i is the corresponding fractional ink area coverage, meaning the printed coverage of multiple ink combinations. As in the case of Murray-Davies, the Neugebauer equations do not directly account for dot gain.

3.4.2.1 Demichel's equations

The fractional ink area coverages a_i for each of the NPs can be calculated with a probabilistic model introduced by Demichel (1924). This model assumes ink dots are placed independently onto the substrate, like in FM independent halftoning. For the case of three NPs, cyan, magenta and yellow, the probabilistic area coverages are:

$$\begin{aligned}
 a_w &= (1 - c_{eff}) \cdot (1 - m_{eff}) \cdot (1 - y_{eff}) \\
 a_c &= c_{eff} \cdot (1 - m_{eff}) \cdot (1 - y_{eff}) \\
 a_m &= (1 - c_{eff}) \cdot m_{eff} \cdot (1 - y_{eff}) \\
 a_y &= (1 - c_{eff}) \cdot (1 - m_{eff}) \cdot y_{eff} \\
 a_r &= (1 - c_{eff}) \cdot m_{eff} \cdot y_{eff} \\
 a_g &= c_{eff} \cdot (1 - m_{eff}) \cdot y_{eff} \\
 a_b &= c_{eff} \cdot m_{eff} \cdot (1 - y_{eff}) \\
 a_k &= c_{eff} \cdot m_{eff} \cdot y_{eff},
 \end{aligned} \tag{3.5}$$

where c_{eff} , m_{eff} and y_{eff} are the effective coverages of cyan, magenta and yellow, respectively, a_w is the fractional coverage of the (white) substrate, a_c , a_m and a_y are the fractional coverages of, respectively, cyan, magenta and yellow, and the rest are the overlapping fractional coverage combinations, i.e. a_r the magenta + yellow, a_g the cyan + yellow, a_b the cyan + magenta, and a_k the cyan + magenta + yellow.

3.4.3 Yule-Nielsen model

Yule's and Nielsen's research about light scattering in a substrate published in Yule and Nielsen (1951) showed that the relationship between predicted and measured reflectance could be approximated with an exponent value. They approximated the reflectance of a monochrome halftone by:

$$R_\lambda = \left[a_i R_{\lambda,i}^{\frac{1}{n}} + (1 - a_i) R_{\lambda,s}^{\frac{1}{n}} \right]^n \tag{3.6}$$

In the equation, the fractional ink coverage a_i refers to physical area coverage, which includes physical dot gain. The n parameter, commonly referred to as the n -factor or n -value, accounts for light scattering and

light penetration in the substrate. For $n = 1$, Yule-Nielsen is reduced to Murray-Davies, while $n = 2$ accounts for complete scattering.

3.4.4 Yule-Nielsen modified Neugebauer model

The natural extension of the Yule-Nielsen model is its combination with the Neugebauer equation (Equation 3.4) in order to approximate the reflectance of overlapping inks. This model, proposed by Yule and Colt (1951), is known as the Yule-Nielsen modified Neugebauer model – YNMN, and is defined by:

$$R_\lambda = \left(\sum_i a_i R_{\lambda,i,max}^{\frac{1}{n}} \right)^n \quad (3.7)$$

where a_i are the fractional coverages of the aforementioned NPs. The model in the spectral reflectance space was investigated by Viggiano (1985).

3.4.5 Cellular Yule-Nielsen modified Neugebauer model

The cellular Yule-Nielsen modified Neugebauer model (cYNMN), introduced in Heuberger et al. (1992), is an extension of the YNMN model for improved precision (Hébert and Hersch, 2015) in which, in addition to the reflectance of no ink and full coverage ink combinations, additional reflectance values serve as input to the formula (Heuberger et al., 1992, Rolleston and Balasubramanian, 1993). The spectral values of the upper and lower node limits of each primary substitute the values at 0% and 100% coverages in the non-cellular YNMN model.

The algorithm performs a normalization of the effective coverage areas on each cell. New, normalized effective coverage a'_{eff} values are found

for each ink, where a_u and a_l are the nominal coverages of the ink's upper and lower nodes, respectively:

$$a'_{eff} = \frac{a_{eff} - a_l}{a_u - a_l} \quad (3.8)$$

Next, the algorithm continues as for the non-cellular model (Equation 3.7) calculating the fractional coverages of each of the primaries with Demichel's equations, using the normalized fractional coverage values.

3.4.6 Comparison of halftone reproduction models

Figure 3.11 shows the measured spectrum of a 3-ink combination composed out of 50% cyan, 20% magenta and 90% yellow coverage. In addition to the measured spectral reflectance, the figure also shows the predicted reflectance spectra according to the three presented halftone reproduction models that account for multi-ink combinations: Neugebauer, YNMN and cYNMN. The Neugebauer model does not consider dot gain, making it the most imprecise one of the three, as seen in the figure. Contrarily, both the YNMN and the cYNMN models account for dot gain, thus achieving a closer prediction of the printed result.

The prediction of the models is based on a different number of printed samples (training samples). For the instance of a 3-ink combination, the Neugebauer and YNMN models base their prediction on the measured NPs, i.e. $2^3 = 8$ samples. The cYNMN model, in this example, is calculated based on coverage values at 5 different nodes at 0%, 25%, 50%, 75% and 100% coverage, making the sample number $5^3 = 125$. In addition, the YNMN and the cYNMN both incorporate the n -value, which in this example is calculated based on 10% coverage steps of each ink, i.e. 30 samples. The total number of training samples is thus the following: 8 in the Neugebauer, 38 in the cYNMN and 155 in the cYNMN model. The complexity and the number of training samples increases in instances

Figure 3.11: Measured and predicted spectral reflectance.

with higher number of ink combinations. The accuracy of the reflectance prediction is thus a compromise between a larger or lower number of training samples.

3.5 Summary

Applying a halftoning algorithm to an image prior to printing is a pre-requisite in print reproduction systems. This chapter aimed to provide an overview of some of the halftoning algorithms, emphasizing those used in the research explained in Chapters 4 – 7. This chapter also described the physical and optical phenomena occurring between light, paper and ink, which make the halftone elements appear larger once printed. These phenomena are to be taken into consideration in order to predict the print output, which can be done by incorporating one of the

halftone reproduction models explained in this chapter.

The preprocessing steps prior to printing - halftoning algorithms, dot gain compensation and halftone reproduction models - described in this chapter, are applied in the research work presented in Chapters 4 – 7. The implementation of the prediction models, predicting the spectral reflectance or colorimetric values of an ink combination, is a single output calculation. It is the color separation model, calculating the input ink coverages needed to achieve specific target values, that is of most interest in a print reproduction workflow. The implementation of the color separation model is not a one-to-one mapping operation and thus it is necessary to consider additional factors. This is addressed in Chapters 6 and 7.

Chapter 4

Halftone quality evaluation

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4.1 Introduction

Numerous parameters influence the print result, such as the type of printing technology, paper grade, halftoning algorithm and print resolution (Hauck, 2015). To qualitatively analyze the print result, it is of importance to understand the concepts behind print quality and quality evaluation in order to choose the appropriate assessment strategies. This chapter provides an overview of print quality, centering on the evaluation methods that are employed in the later chapters.

4.2 Print quality evaluation

The general definition of quality, according to Crosby (1982), is the conformance to requirements, an interpretation which is extended to the definitions of print quality found in literature. For instance, the International Organization for Standardization in the ISO 12647 (2004) standard defines print quality in terms of quality parameters and tolerances, while Southworth and Southworth (1989) relate print quality to the absence of defects.

Print quality is evaluated using different assessment strategies that can be divided into subjective and objective methods. Subjective quality assessment involves human observers, asked for instance to grade prints according to specified criteria. Objective quality assessment is performed using measuring instruments or algorithms, the latter quantified with image quality metrics. Contrary to subjective visual assessment, image quality metrics do not fully correlate with the perception of overall print quality (Pedersen et al., 2011). Instead, these metrics assess different quality aspects – e.g. sharpness, contrast, color, mottle – called image quality attributes.

The ISO 13660 (2001) standard defines objective image quality metrics to quantify fourteen basic image quality attributes for monochromatic prints. Briggs et al. (1999) and Dhopade (2009) apply those attributes and assess their applicability. A review of a larger number of quality metrics is presented in Pedersen and Hardeberg (2012), together with a suggested disambiguation to mathematically based ones, low-level, high-level and other metrics. Mathematically based metrics evaluate the difference between the original and print with, for instance, color difference formulae (Section 2.2.2.3). Since these metrics operate by performing a comparison, both a reference and a reproduction result are needed. Low-level metrics aim to simulate the low-pass filtering characteristic of the human visual system (HVS) before applying a mathematically based evaluation. An example of such metric, S-CIELAB, is discussed in Section 4.4. High-level metrics apply a high-pass filter in order to simulate the extraction of image structures of the HVS, such as the structural similarity index metric presented in Wang et al. (2004). Other approaches include combinations of the above or other strategies.

4.3 Quality attributes for halftone evaluation

The research presented in Chapters 5 – 7 refers to strategies that perform a color separation with a specific halftoning algorithm, aiming to enhance the quality of the halftone reproduction. The quality attributes that could be significant in order to evaluate these strategies thus relate to the variables employed in this research, namely color separation strategies. The color separation affects the reproduction result, since target colors can often be reproduced using a number of different ink combinations (Section 2.3.3). Figure 4.1 shows a target color reproduced with two different sets of ink combinations, halftoned with the same halftoning algorithm, yet yielding distinct print quality results.

Figure 4.1: A target color reproduced with different ink combinations.

4.3.1 Fourier transform

The binarization in the implementation of a halftoning algorithm comprehends quantization noise (Broja and Bryngdahl, 1993, Lin, 1993, Gooran, 2001). Consequently, the frequency noise spectrum can be quantified with a discrete Fourier transform, where lower quantization noise levels denote a higher level of similarity between the original and the halftoned image. In addition, due to the low-pass filtering characteristic of the HVS, it is desirable that most of the quantization noise is located in higher frequencies. This metric has thus been utilized to evaluate the quality of halftoning algorithms (Broja and Bryngdahl, 1993, Lin, 1993, Gooran, 2001).

4.3.2 Perceived image sharpness

Another attribute related to halftone quality is the perceived image sharpness, which evaluates the halftoning algorithms' edge and detail perseverance. The structural similarity index metric – SSIM – presented in

Wang et al. (2004) is an instance of a metric that measures the structural similarity over a neighborhood, developed in order to mimic the extraction of the structure information characteristic of the HVS. In Lee et al. (2007), SSIM was extended to a color image similarity measure (CISM), also with the goal of assessing the perseverance of the image's structural pattern after applying the halftoning algorithm.

4.3.3 Color difference

A quality attribute that is commonly used in color separation is the color difference metric that assesses the colorimetric resemblance of the reproduced sample to the target color. Examples are found in papers dealing with color separation, e.g. in Taplin and Berns (2001), Chen et al. (2004), Jang et al. (2006b), Urban and Berns (2011) and Deshpande et al. (2014b).

4.3.4 Halftone visibility

Halftone visibility, also referred to as dot visibility, is a quality attribute that assesses the visibility of the halftone dots in uniform patches. It is an attribute dealt with when evaluating the visibility of halftones generated by different halftoning algorithms. Examples are found in Wang and Parker (2001), Baqai et al. (2005) and Huang et al. (2009).

In Zhang et al. (1997), the authors assess halftone visibility of black-white halftone patterns with the S-CIELAB metric and compare it with subjective evaluation, calculating a correlation factor of $R^2 = 0.89$. The spatial extension of the CIELAB color space, called Spatial-CIELAB or S-CIELAB, was initially proposed in Zhang and Wandell (1997). The filtering is designed to imitate the HVS by applying low-pass filters to an image prior to color difference calculations, thus improving the represen-

tativeness of the results of the statistical analysis. The S-CIELAB filtering is further explained in Section 4.4.

Dot visibility has been quantified with the bitmap's standard deviation in Son et al. (2011). By utilizing bitmaps to assess the attribute, printing and scanning becomes redundant, consequently reducing the number of measurement samples. However, this approach lacks the influence that the ink/paper contrast and the paper/ink/light interactions have on printed patches. The authors propose a quantitative dot visibility model based on the standard deviation of S-CIEL*, verifying it with subjective evaluation, calculating a correlation factor between the two of $R^2 > 0.9$.

Halftone visibility has been utilized in the research by Babaei and Hersch (2016a) applying the same metric, thus assigning a visibility score to halftones and incorporating it in the color separation process. The authors state that their predicted visibility score of a given color separation halftone is a rough estimation of its halftone visibility.

4.3.5 Graininess

In color reproduction, graininess is the quality attribute that expresses the amount of "grain". As halftone visibility, graininess can also be used to describe the result of local density variations of an overall uniform area (Babaei and Hersch, 2016a). Graininess not only depends on halftone visibility, but also on the color separation method, and hence on the number and type of inks present in the print. In a continuous color ramp, at a certain point there will be a switch between one set of inks and a second set of inks. Such a switch could induce graininess. If such a switch is frequent, the graininess might increase.

Sakatani et al. (1996) and Huang and Nystrom (2001) utilize the standard deviation of CIEL* to evaluate graininess, since that dimension is the one found most significant in determining graininess. However, per-

forming a pixel-by-pixel calculation is not the optimal solution for halftones. Being spatially altered samples, the results might yield largely unrepresentative.

Statistical analysis that includes a representation of the filtering of the HVS is common when assessing graininess. The standard deviation of the color fluctuations of halftones, passed through S-CIELAB filtering, has been used as a graininess metric (Son et al., 2003, 2006, Ortiz Segovia et al., 2012).

In Chen et al. (2008), the mean color difference is utilized to assess graininess. This is performed by comparing the mean CIELAB value of a printed halftone and the S-CIELAB representation of the halftone at each pixel. The authors refer to the metric as graininess index.

It is important to note that, in all these cases, the graininess is optimized for a metric that is based on calculations of certain CIELAB values. As such, those are dependent on a single type of illuminant. The transition between two sets of ink could be made invisible, but only under that illuminant. Under another illuminant, this transition could be visible.

4.3.6 Selected quality attributes

The aforementioned quality attributes evaluate different aspects of the halftoning algorithm or of the color separation. In the research presented in Chapters 5 – 7, the halftoning algorithm is not a variable. Instead, the varying factor is the choice of ink combination, both by multilevel halftoning algorithm (Section 3.2.3) and by performing a color separation. The color difference and graininess quality attributes have therefore been the ones utilized in the research presented in the following chapters. The metrics that assess color differences are more straightforward, and comprehend color difference formulae (Section 2.2.2.3). Meanwhile, available graininess metrics have been evaluated in Section 4.5. These

refer to statistical analysis of images/patches passed through S-CIELAB filtering.

4.4 Processing tools – S-CIELAB filtering

In the S-CIELAB transformation, low-pass filters are applied that mimic the HVS. This filtering is therefore used in order to obtain representative data of the perceived impression of a print. To apply S-CIELAB, an input image firstly needs to be represented in the CIEXYZ color space. A linear transformation is then performed from CIEXYZ to an opponent color space that estimates human color perception, according to Equation 4.1 (Zhang and Wandell, 1997). The opponent color space is represented with three matrices, representing an achromatic channel O_1 and two chromatic channels, O_2 (red-green) and O_3 (blue-yellow).

$$\begin{aligned} O_1 &= 0.279X + 0.72Y - 0.107Z \\ O_2 &= -0.449X + 0.29Y + 0.77Z \\ O_3 &= 0.086X - 0.59Y + 0.501Z \end{aligned} \quad (4.1)$$

These matrices are filtered by two-dimensional spatial kernels that are the Gaussian approximations of the contrast sensitivity functions of the HVS:

$$f = K \sum_i w_i E_i \quad (4.2)$$

where

$$E_i = k_i e^{-(x^2+y^2)/\sigma_i^2} \quad (4.3)$$

In Equations 4.2 and 4.3, f is the kernel filter (specific for each opponent channel), K and k_i are normalizing factors so that f and E_i sum to one, preserving the mean color value for uniform areas. The parameters w_i , the weighting factor, and σ_i , the spreading factor, defined in Johnson and Fairchild (2003), are shown in Table 4.1. The integers x and y are variables in the spatial domain.

Table 4.1: Weight and spread factors of the Gaussian filter kernel

Filter	Weight (w_i)	Spread (σ_i)
Achromatic (i=1)	1.00327	0.0500
Achromatic (i=2)	0.11442	0.2250
Achromatic (i=3)	-0.11769	7.0000
Red-green (i=1)	0.61673	0.0685
Red-green (i=2)	0.38328	0.8260
Blue-yellow (i=1)	0.56789	0.0920
Blue-yellow (i=2)	0.43212	0.6451

The contrast sensitivity functions of the human visual system are dependent on the samples-per-degree of visual angle, which simulates the sensitivity of the HVS in relation to viewing distance d , in inches, and resolution, in pixels-per-inch (ppi), according to the following equation (Johnson and Fairchild, 2003):

$$Sam/deg = \frac{resolution(ppi)}{\frac{180}{\pi} \cdot \arctan\left(\frac{1}{d}\right)} \quad (4.4)$$

The spreading factor σ_i , defined in degrees of visual angle, is consequently converted to pixels by multiplying it with the number of samples-per-degree. The filtered opponent color space matrices are converted to CIEXYZ with inverse matrix operations and then to CIELAB, resulting in matrices S-CIEL*, S-CIEa*, and S-CIEb*.

4.4.1 S-CIELAB applied to patches

Figure 4.2 shows an example of a 10% black patch at 600 dpi, where A is the bitmap, B is the printed (and scanned) patch, and C and D are the RGB representations of the S-CIELAB filtering of the image B at viewing distances of 10 cm and 40 cm, respectively, at 1200 ppi scanning resolution, calculating approximately 84 and 330 sam/deg, respectively.

Figure 4.2: 10% coverage black patch: A. Bitmap, B. Scanned print, C. S-CIELAB (10 cm distance), D. S-CIELAB (40 cm distance).

Once the S-CIELAB filtering is performed, different metrics can be ap-

plied in order to represent graininess of a patch with a single number. These are discussed in continuation.

4.5 Graininess evaluation metrics

Several metrics that evaluate graininess are found in literature. These are contemplated in order to assess their applicability to the research described in the following chapters.

4.5.1 Standard deviation of digital halftones

When a halftoning algorithm is applied to a patch of a specific tone value, the calculated mean of the 0 and 1 pixel values would correspond to that tone value. The deviation from the mean would correspond to pixel oscillations. If those oscillations were sufficient to be detected by a human observer, they would cause graininess. The larger the standard deviation, the more grainy they would appear. Therefore, the standard deviation of a halftoned patch, before print, could serve as a metric to quantify this quality attribute. An example of the relationship between the input nominal coverages and the standard deviation is shown in Figure 4.3, for the case of bilevel and multilevel halftoned patches ranging from 0% to 100% coverage. The multilevel patches were halftoned using 5 different levels (0%, 25%, 50%, 75% and 100%), forming fulltone coverage at each of them. In the digital patches with no ink and fulltone ink coverage no pixel oscillations occur, making the standard deviation equal to 0. Between 0% and fulltone coverage the standard deviation is higher, peaking at 50% of its value.

Calculations performed directly on digital halftones lack the distortion that could occur during scanning of a print. However, such calculation does not offer information about the perceived graininess once ink is de-

Figure 4.3: Standard deviation of digital halftones in increasing tone values.

posited onto the paper. The curves in Figure 4.3 calculate the same values regardless of the ink applied. Naturally, the graininess differs not only according to the ink coverage and number of levels, but also in relation to the contrast of the ink to the paper – for instance, the graininess of 50% yellow ink coverage will be different than that of 50% black ink coverage.

4.5.2 S-CIELAB standard deviation

Son et al. (2003, 2006) and Ortiz Segovia et al. (2012) calculate graininess by summing the standard deviation of all the S-CIELAB filtered channels, according to the following equations:

$$s_k = \sqrt{\frac{\sum_i \sum_j (V_k(i, j) - \overline{V_k})^2}{n}}, k = 1, 2, 3 \quad (4.5)$$

$$GS = \sum_k s_k$$

where k is the index referring to the S-CIEL*, S-CIEa*, and S-CIEb* channels, $V_k(i, j)$ are the filtered channel's pixel values and $\overline{V_k}$ is the mean of the pixel values of each filtered channel, n is the number of pixels and s_k is the standard deviation of these filtered channels. GS is the sum of the standard deviations of the three S-CIELAB channels. Lower standard deviation indicates that the perceived variation is smaller, consequently meaning lower graininess.

4.5.3 S-CIEL* standard deviation

Even though the standard deviation of S-CIEL* is used as a metric for halftone visibility in Son et al. (2011) and Babaei and Hersch (2016a), it is interesting to see its tendencies over color printed and scanned patches. This metric has therefore been included in the evaluation.

4.5.4 S-CIELAB mean – graininess index

The mean color difference, addressed as the graininess index (GI) in Chen et al. (2008), compares the mean CIELAB value of a printed halftone and the S-CIELAB values at each pixel, thus accounting for visible fluctuations. GI values (Equation 4.6) therefore represent graininess, with lower values corresponding to less perceived graininess:

$$GI = \frac{\sum_{pixel=1}^n \Delta E_{00} (SLAB_{pixel}, \overline{LAB})}{n} \quad (4.6)$$

where $\overline{LAB}$ stands for the mean CIELAB value of the scanned printed patch, $SLAB_{pixel}$ is the S-CIELAB representation of the image of the same halftoned patch, and n is the total number of pixels. The mean difference is calculated with the color difference CIE 2000 formula. The lower the GI, the lower the graininess is.

4.6 Experimental setup

The metrics discussed in Section 4.5 are implemented below. In order to apply the metrics, the employed print setup is presented, together with the workflow conducted in order to scan the printed patches. The results are also given.

4.6.1 Print setup

The printer used was a multi-channel Canon imagePROGRAF iPF6450 inkjet with 12 inks: the primary color inks – cyan (C), magenta (M), yellow (Y) and two black inks (K_1 and K_2), the light inks – light cyan (c), light magenta (m), photo gray (pgy) and gray (gy), and secondary color inks – red (R), green (G) and blue (B). The printer permits the use of only one black ink at a time, therefore making the maximum number of simultaneously employed inks 11.

The internal printer software that handles the color conversion and halftoning algorithm was overwritten with the Voxvil print engine software, therefore enabling control over the print output. The bilevel halftoning algorithm used was Iterative Method Controlling the Dot Placement (IMCDP), an iterative FM halftoning algorithm developed within our research group, explained in Section 3.2.2.1. The print resolution was 600 dpi. The paper employed (unless otherwise stated) was 170 g/m² matte coated.

The spectrophotometer used was Barbieri Spectro LFP RT. Samples were measured under D50 illumination and 2° standard observer. The spectrophotometric output were CIEXYZ values and/or spectral data, the latter consisting out of 41 reflectance values at wavelengths ranging from 380 nm to 780 nm in 10 nm steps.

4.6.2 Scanning workflow

In order to perform S-CIELAB filtering, printed patches are scanned. The scanning resolution was determined following the Nyquist sampling theorem, which dictates a scan resolution of (at least) double the print resolution. Since print resolution was 600 dpi, black patches from no tone to fulltone coverage (in 1% steps) were scanned at 1200 ppi and 2400 ppi. The GI (Equation 4.6) of those patches was calculated with a chosen viewing distance of 25 cm. The GI results, shown in Figure 4.4, indicate that the 2400 ppi scanning resolution did not improve the precision of the results. The scanning resolution of 1200 ppi was thus selected.

The scanner Epson Perfection V500 Photo was used to scan the printed patches. An ICC scanner profile was created to reduce the color errors, using the iPro1 and i1Profiler software with the X-Rite ColorChecker 24. The conversion from scanner RGB to CIEXYZ was carried out using polynomial regression techniques for device characterization, expressing X, Y and Z as polynomial functions of R, G and B (Nyström, 2007).

By using a 3rd order polynomial function, optimized for the given ink and substrate combination, the mean and maximum color difference between the estimated CIEXYZ values and the corresponding measurements by a spectrophotometer were 1.21 and 5.52 ΔE_{94} , respectively, for 1024 printed and scanned color patches in different coverages. As discussed in Section 2.2.2.3, these results prove satisfactory for our scanning setup.

Figure 4.4: GI dependent on scanning resolution.

4.6.3 Metrics

The metrics that calculate the graininess of color prints found in literature are the graininess index (Equation 4.6) and standard deviation of the S-CIELAB channels (Equation 4.5). The standard deviation of the S-CIEL* channel has also been included in the analysis. The exact values of these three metrics are not to be compared to each other, since each performs different statistical calculations. However, it does make sense to compare their tendencies over linearly increasing coverage values. Since the S-CIELAB standard deviation was the only one of these metrics that performed a sum of the standard deviation of the three channels, the values in this metric were divided by three.

Figure 4.5 shows printed and scanned 10%, 30%, 60% and 100% coverage patches of the black, blue and yellow inks. Note that the blue ink is in reference to the denomination attributed by the manufacturer, rather

than a credit to its hue.

Figure 4.5: Black, blue and yellow ink at (left to right) 10%, 30%, 60% and 100% coverage.

The three metrics were applied to patches of black (Figure 4.6), blue (Figure 4.7), and yellow (Figure 4.8) inks in increasing 0% to 100% coverages in 1% steps.

It can be seen in Figures 4.6 and 4.7 that the curves of the metrics exhibit similar behavior for the black and the blue inks. The plotted graphs in these figures peak at approximately 15% – 20% nominal ink coverage and gradually decrease, ultimately maintaining the same values from approximately 80% coverage, which approximately corresponds to effective fulltone coverage.

The three curves for the yellow ink, shown in Figure 4.8, do not display

Figure 4.6: Graininess calculation metrics applied to black patches.

Figure 4.7: Graininess calculation metrics applied to blue patches.

Figure 4.8: Graininess calculation metrics applied to yellow patches.

the same tendencies. The standard deviation of the summed S-CIELAB values displays a consistent rising tendency, which is not in line with the GI and standard deviation of S-CIEL*. These two display a more uniform behavior, although while the first one shows a peak at around 5% – 10% nominal ink coverage, the latter one maintains an approximately constant value.

The S-CIELAB standard deviation is therefore not consistent with the graininess behavior expected in uniformly increasing coverages. The detected increase in graininess was found to originate from the increase in the standard deviation of the S-CIEb* channel, due to the large difference between the S-CIEb* values of the yellow ink and the paper. Consequently, this metric was not employed in the research presented in the later chapters.

GI and the standard deviation of S-CIEL*, displayed different behaviors

in the uniformly increasing yellow coverage patches (Figure 4.8). A potential issue with S-CIEL* could be its disregard for color. Since the perceived noise can also originate from the chromatic channels (Johnson and Fairchild, 2005), instances could occur in which the graininess would derive from the hue. In these instances, the calculated graininess would incorrectly be low. In order to verify this, subjective evaluation should be carried out. This remains part of future work. The metric GI, already utilized in published work (Chen et al., 2008), has thus been the one chosen to evaluate graininess.

4.6.4 Viewing distance

The dependance of the viewing distance on the graininess, expressed with the GI metric, is shown in Figure 4.9 for patches of increasing black ink coverage.

Figure 4.9: GI of black patches in relation to viewing distance.

The figure shows that, the shorter the viewing distance is, the larger is the perceived graininess. Moreover, the difference between the GI at viewing distances of 10 cm and 25 cm is much larger than the GI at viewing distances of 50 cm and 75 cm. The distance of 25 cm was selected as the viewing distance in the further studies.

4.7 Conclusions

Different strategies can be employed in order to evaluate print reproduction. Graininess and color difference were the attributes in focus to perform a quantitative evaluation of the color separation and halftoning strategies employed in Chapters 5 – 7. Therefore, several metrics assessing these quality attributes presented in literature were implemented to printed patches. The implementation workflow was discussed, together with the results of the evaluation. The graininess index (GI) was selected as the most suitable metric to evaluate the research presented in the later chapters.

Chapter 5

Multilevel halftoning – implementation and analysis

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5.1 Introduction

In traditional CMYK printing, images are separated into 4 channels, each intended for its respective primary ink. Multi-channel printing includes a higher number of colorants, for instance the light versions of (some of) the primary inks. Potential issues when employing additional inks are an increase of both the amount of possible ink overlap and the print characterization complexity.

A possible solution to these issues is employing the multilevel halftoning algorithm (Section 3.2.3) proposed in Gooran (2006). This algorithm separates a channel into different regions as part of the halftoning process. Thus, instead of performing a color separation to each of the available inks, multilevel halftoning allows a color separation to ink subsets that vary in lightness. In the print setup utilized in this research, the three ink subsets are: 1) light cyan and cyan, 2) light magenta and magenta, and 3) the two grays and black (Figure 5.1).

Figure 5.1: Bilevel halftoned channels intended for single inks (left) and multilevel halftoned channels intended for ink subsets (right).

This chapter deals with the implementation of multilevel halftoning, with the aim of generating an implementation workflow. Two challenges are

identified and addressed. Firstly, employing several inks in one channel means that appropriate ink limits (thresholds) should be found. Secondly, in order to control the print output, it is necessary to account for the dot gain (Section 3.3) of the multiple inks in a channel. In addition, the performance of the multilevel halftoning is analyzed and discussed.

The implementation is performed for the sets of inks that vary in lightness in the present print setup, i.e. for light cyan (c) and cyan (C), for light magenta (m) and magenta (M), and for photo gray (pgy), gray (gy) and black (K). Each ink subset is employed for its respective subset channel, C_S , M_S and K_S .

The research explained in this chapter has been published in Žitinski Elías et al. (2014), Žitinski Elías (2014), Gooran and Žitinski Elías (2015) and Žitinski Elías et al. (2015).

5.2 The multilevel halftoning algorithm

The multilevel halftoning operates in three steps, pre-processing, bilevel halftoning and post-processing. Figure 5.2 shows the effects of these steps on a continuous-tone image (ramp), displayed in low resolution for better illustration purposes. For this example, the following specifications are defined. First, the original ramp (shown as A in the figure) is a grayscale image, corresponding to the achromatic channel K_S . Secondly, the channel is halftoned for three achromatic inks – light gray, gray and black. Lastly, the thresholds (limits between inks) are at 33% and 66% nominal K_S coverage. The threshold calculation will be explained in Section 5.3.2.

Figure 5.2: Workflow of the multilevel algorithm.

5.2.1 Workflow of the multilevel halftoning algorithm

In the first step of multilevel halftoning, pre-processing, the image is divided into regions (B in Figure 5.2). Since the channel in this example is halftoned for three inks, the channel is divided into three regions, separated with two region limits (thresholds). In order to determine which part of the ramp belongs to which region, each pixel is compared to the thresholds. For instance, if a pixel value is lighter than the first threshold it belongs to region 1, if it is darker than the first threshold, but lighter than the second threshold, it belongs to region 2, and if it is darker than the second threshold, it belongs to region 3. The values of each region are normalized (linearly scaled) to values between 0 and 1, in a way that a gradual transition between regions is always achieved. For instance, region 1 is normalized to $[0, 1]$, region 2 to $[1, 0]$ (inverted order), and region 3 to $[0, 1]$. The inverted order in every other region helps to ensure a smooth transition between inks by avoiding sudden "jumps" between values around thresholds.

The next step of the multilevel halftoning algorithm is the halftoning itself. Since each region has been scaled to values between $[0, 1]$, any bilevel halftoning algorithm could be applied to such a pre-processed image. The result is a bitmap, i.e. an image consisting of only zeros and ones, shown as C in Figure 5.2.

In the final step, post-processing, the algorithm translates the binary zeros and ones to multilevel values. The binary zeros of the first region are mapped to 0 and the binary ones to 0.33 (the value of the first threshold). The binary ones of region 2 are mapped to 0.33 (the first threshold) and the binary zeros to 0.66 (the second threshold). Similarly, the binary zeros of region 3 are mapped to 0.66 and the binary ones to 1. The result is a multilevel halftoned image (shown as D in Figure 5.2), in which each pixel contains the values 0, 0.33, 0.66 or 1. The value 0 means no ink

is printed at that pixel location, 0.33 means the lightest ink is used (light gray), 0.66 means the next darker ink (gray), and 1 means the darkest ink (black). Therefore, region 1 is printed using only one ink – light gray, region 2 is printed with light gray and gray, and region 3 with gray and black.

5.2.2 Benefits and considerations of the algorithm

The multilevel halftoning algorithm represents a straightforward workflow in which any bilevel halftoning algorithm can be incorporated without adaptations.

The algorithm halftones an image so that the first region is the only one containing the value 0 (paper). Therefore, it is the only region not completely covered by an ink layer, as any nominal coverage value above the first threshold results in fulltone coverage.

The full ink coverage that starts at the first threshold is achieved by printing one or two inks. When two inks are involved, they are printed dot-off-dot, i.e. with no overlap between them. This is due to the result of the post-processing, which maps each of the channel's pixel values to either an individual ink or paper. Avoiding ink overlap within a channel represents a benefit of multilevel halftoning, since one multilevel channel results in a maximum of 100% ink coverage. In other words, light inks can be added to a print setup without an increase of the ink layer.

Another aspect is the characterization complexity, usually increased when adding inks in multi-channel printing. However, employing multilevel halftoning means that there is only one channel for the inks of varying lightness. Therefore, it is the multilevel algorithm itself that handles the classification of the inks within the channel, thus maintaining the print characterization complexity. This represents a benefit of the method, and, given a correct implementation, a possible incorporation of the al-

gorithm in a color separation workflow, addressed in Chapter 6.

5.3 Methodology

This section deals with the implementation of multilevel halftoning as part of a setup for multi-channel inkjet printing. The steps of the implementation are shown in Figure 5.3 and discussed in the following subsections.

Figure 5.3: Flowchart of the creation of a multilevel halftoned channel.

5.3.1 Print setup

The devices and setup employed were described in Section 4.6.1. A 90 g/m² uncoated office paper and 170 g/m² matte coated paper were used.

5.3.2 Locating thresholds between inks

The multilevel halftoning algorithm separates a channel into regions. When locating the thresholds between the primary inks and their light versions, initially, CIEY values were used (correlating with lightness) to determine the thresholds to separate a channel into different regions (Žitinski Elías et al., 2014). However, further research showed that the light inks exhibited a hue difference from the primary inks. This will be further explained in Section 5.5.4. The conclusion was made that metrics that account for both lightness and hue should instead be used to calculate the thresholds (Žitinski Elías et al., 2015), such as color difference formulae. This approach could also be discussed, since there is not an exact colorimetric match between the primary and the light inks. Again, this will further be analyzed in Section 5.5.4. For now, both workflows to find the thresholds are presented.

The CIEY values were used in order to locate the threshold for the achromatic channel K_S . CIEY of fulltone coverage of the lighter inks, photo gray and gray, were obtained. A coverage of the darkest ink, black, needs to be located at which its CIEY value matches the fulltone CIEY value of the photo gray. This coverage corresponds to the first threshold. Similarly, the CIEY value of fulltone coverage of gray is measured. The coverage at which the darkest ink, black, matches that CIEY value is the second threshold.

Instead of matching the CIEY values, the lowest ΔE_{94} color difference and the lowest spectral root mean square difference, ΔRMS , as defined in Equation 5.1, could also be calculated to locate the thresholds. This was performed for the chromatic channels, C_S and M_S . The nominal area coverage at which the darkest ink (cyan/magenta) has the smallest $\Delta E_{94} / \Delta RMS$ difference to the 100% coverage of the lightest ink (light cyan/light magenta) determines the threshold. The results are presented

in Section 5.4.1.

$$\Delta RMS = \sqrt{\frac{1}{n} \sum_{\lambda=l}^u (R_1(\lambda) - R_2(\lambda))^2}, \quad (5.1)$$

In Equation 5.1 λ is the wavelength, l and u are the lower and upper limits of the wavelength (380 and 780 nm), n is the number of wavelength samples used, i.e. 41, and R_1 and R_2 are the spectral reflectances of the two compared spectra.

In order to find the thresholds, patches from 1% to 100% nominal ink coverages, in steps of 1%, were printed for the darker inks – cyan, magenta and black. In addition, patches of 100% coverage of the lighter inks – light cyan, light magenta, photo gray and gray – were printed. For the achromatic inks, the CIE XYZ values were measured. For the chromatic inks, CIELAB and spectral data were obtained.

5.3.3 Workflow for dot gain compensation

Paper/ink/light interactions cause dot gain, resulting in ink areas appearing larger once printed (Section 3.3). Dot gain is a consequence of multiple factors, one of them being the ink used. In order to compensate for dot gain so that the final result has the intended tone value, the nominal ink coverage of each channel has to be adjusted prior to halftoning and printing. Nevertheless, in multilevel halftoning, each channel is printed using multiple inks, each with different dot gain curves. Consequently, dot gain compensation for all the inks should be expressed in terms of nominal tone coverage of a channel's coverage. The following methodology was performed.

Multilevel halftone patches from 1% to 100% ink coverages, in steps of 1%, of the C_S , M_S and K_S channels were printed. The Murray-Davies

formula was used in order to compensate for the channel's dot gain response. The formula, as stated in Section 3.4.1, specifies the relationship between the predicted reflectance of the halftone (R), the fractional ink area coverage (a_i), the reflectance of the full coverage ink (R_i) and the substrate's reflectance (R_s).

$$R = a_i R_i + (1 - a_i) R_s \quad (5.2)$$

The reflectance values were replaced by the CIEXYZ values of patches of each multilevel channel. Specifically, the CIEX values for the C_S channel, and the CIEY values for the M_S and K_S channels were used. As explained in Gooran et al. (2009), since cyan is most absorbent in the longer wavelength interval, using the CIEX values is the most suitable choice for the cyan ink, and, correspondingly, CIEY is for magenta.

The effective coverage values of each channel were linearly interpolated. Afterwards the input reference coverages of the darkest ink (C/M/K) were matched to the effective coverages of the corresponding multilevel halftoned print, enabling control over its dot gain response.

5.4 Implementation results and discussion

Implementation of the multilevel halftoning algorithm comprehends locating thresholds between inks and dot gain compensation. The results are categorized and presented in this section.

5.4.1 Calculated thresholds between inks

Figures 5.4 and 5.5 show the CIEY values of the three inks - pgy, gy and K, plotted against their nominal ink coverages, for the uncoated 90 g/m²

paper and 170 g/m² matte coated paper. The thresholds between the regions (marked with T_1 and T_2) are also shown.

For the uncoated paper in Figure 5.4, the CIEY value of fulltone gy matches the CIEY value of 38% K, while the CIEY value of fulltone pgg corresponds to the CIEY value of 28% K. Thus, for this setup, the limits between the regions are at 28% and 38% channel coverage. At each of these intervals ([0, 0.28], [0.28, 0.38], [0.38, 1]) the inks used span from 0% to 100% coverage. The thresholds for the coated paper were at 42.5% and 62.5% channel coverage (Figure 5.5).

Note that the only difference between the print setups in Figures 5.4 and 5.5 is in the paper grade; all of the other aspects are unaltered – ink type and quantity, halftoning algorithm, print resolution, etc. Therefore, the thresholds between the inks are highly dependent on the paper grade. This can be explained with the dot gain effect. The uncoated paper has a higher ink absorption, higher ink spreading and light diffusion. Therefore, the inks placed on it exhibit more dot gain than when placed on the coated paper. In the latter case, the inks can reproduce darker tones, which is noticeable when comparing the CIEY values of fulltone inks.

The thresholds between the chromatic channels were calculated for the coated paper. The threshold between cyan and light cyan was found with the CIELAB values at 38% cyan coverage with $\Delta E_{94} = 2.04$, and with the spectral values the threshold was at 37% coverage with $\Delta RMS = 0.02$. The threshold between magenta and light magenta was at 36% according to the CIELAB values, with $\Delta E_{94} = 1.67$, and at 34% according to spectral values, with $\Delta RMS = 0.02$.

The results indicate a slight discrepancy between the thresholds calculated with the CIELAB and spectral values, with a variation of 1% – 2% coverage between them. Figure 5.6 shows the calculated ΔE_{94} and ΔRMS differences between the fulltone light magenta and the nominal

Figure 5.4: Finding thresholds for the uncoated 90 g/m² paper.

Figure 5.5: Finding thresholds for the coated 170 g/m² paper.

coverages of magenta. The lowest point of each curve is where the difference between the two inks is minimal, making that coverage value optimal as threshold. The thresholds are marked as T_1 according to the spectral values and T_2 according to CIELAB values.

Figure 5.6: ΔE_{94} and ΔRMS differences between 100% m and M at each nominal area coverage.

It was resolved to use the ΔE_{94} to determine the thresholds, since this metric is the one designed to correlate to the perceived color difference. This makes the threshold for the C_S channel at 38% channel coverage and for the M_S channel at 36% channel coverage.

5.4.2 Dot gain compensation results

The dot gain curves of each ink and multilevel channel were calculated and plotted in Figures 5.7, 5.8, and 5.9. Each curve is in reference to the nominal area coverage of its channel.

Figure 5.7: Dot gain curves of the c, C and C_S channels.

Figure 5.8: Dot gain curves of the m, M and M_S channels.

Figure 5.9: Dot gain curves of the pgy, gy, K and K_S channels.

It can be seen that the dot gain curves vary from ink to ink. Moreover, the multilevel channels C_S , M_S and K_S exhibit larger dot gain earlier in the nominal area coverages. This is due to the fact that the multilevel halftoning, compared to bilevel halftoning, uses larger amounts of ink to reproduce the same nominal area coverage. In other words, the C_S , M_S and K_S channels employ the lightest ink from zero to fulltone coverage in roughly the first 40% of nominal coverage. Meanwhile, the effective area coverages of the bilevel halftoned channels are much lower in that region.

It is also visible that the dot gain curves of the multilevel channels and the darkest ink roughly coincide from approximately the first threshold onwards. This fact can be explained by the large dot gain that the darkest inks exhibit. For instance, black ink around 40% nominal coverage has a dot gain of approximately 0.5, making the effective coverage around 90%. As such, this almost completely covered surface coverage re-

sults in little difference between the dot gain curves of the multi-channel halftones and the darkest ink.

Figure 5.10 shows the effective vs the nominal coverage of the K_S channel on coated paper after dot gain compensation. As can be seen, the plot constitutes a straight line, proving a successful dot gain compensation. It can also be seen that there are no unordinary fluctuations around the thresholds (around 42.5% and 62.5% nominal coverage), which indicates smoothness around the limits between inks. The results of the compensated C_S and M_S channels displayed the same tendencies.

Figure 5.10: Effective vs nominal coverage of the K_S multilevel channel.

5.5 Analysis of multilevel halftoned prints

The implemented multilevel halftoning algorithm was assessed in terms of two parameters. Firstly, smoothness was verified around ink transi-

tions, as it is important that the halftoning algorithm does not demonstrate artifacts around the thresholds. Secondly, since using different inks should improve the results in terms of visual pleasantness, graininess was calculated and compared for different patches, using graininess index (GI) as a metric (Section 4.5.4).

5.5.1 Smoothness across ink transitions

The smoothness across ink transitions has already been verified, as shown in Figure 5.10. In addition, Figure 5.11 shows a ramp from 1% to 100% coverage. The ramp was compensated for dot gain, multilevel halftoned, printed on the coated paper, and scanned at 1200 ppi. Parts of the ramp (around the thresholds) were enlarged, showing smoothness around the ink transitions. Note that, in order for the ramp to appear smooth in the printed dissertation, dot gain compensation must be performed for that specific ink and paper. Since that information is unavailable, the ramp may not appear smooth on the printed manuscript.

Figure 5.11: Multilevel halftoned ramp with enlarged areas around ink transitions.

5.5.2 Graininess

The goal of employing light inks is achieving a less grainy result and, therefore, a visually more pleasant image. In order to illustrate this, a 20% nominal coverage patch was created and halftoned in two different ways - once using only one, black, ink and bilevel halftoning it with IMCDP (Section 3.2.2.1) and the second time with the three achromatic inks and multilevel halftoning the patch using IMCDP as the bilevel halftoning method. These patches were printed and scanned at 1200 ppi, and shown in Figure 5.12.

Figure 5.12: 20% nominal coverage patch printed using (left) bilevel and (right) multilevel halftoning.

Although both halftoned images have the same mean value of 20% black ink nominal coverage, it can easily be seen that the multilevel halftoned patch (right) shows a less grainy result. This is because the bilevel halftone algorithm employs a single colorant (in this case K), while the multilevel algorithm halftones under the assumption of multiple colorants. For this example, and keeping in mind that the first threshold of the K_S channel is at 42.5% coverage, the 20% nominal ink coverage corresponds to $20\% \cdot 1/42.5\% \approx 47\%$ pgy ink coverage. The multilevel halftoning algorithm makes use of the lighter ink pgy, printed in a denser configuration, resulting in a less grainy result. The GI of the bilevel halftoned patch is 1.28, while the GI of the multilevel halftoned patch is 0.53.

Figure 5.13 shows the calculated GI for printed patches with nominal coverages ranging from 0% to 100%, in 1% step, bilevel and multilevel halftoned, for the channels C, M, K, C_S , M_S and K_S . The minor oscillations seen in all the plots are a consequence of unavoidable patch and/or scanner glass impurities.

Figure 5.13: Graininess index of the printed patches.

The figure shows that the channels that use primary and light inks display different GI tendencies than the ones using only primary inks. C_S , M_S and K_S almost consistently show low GI throughout their nominal coverages, while the C, M and K channels show higher GI values. These higher GI values are mostly located through the channels' lower nominal coverages, up to approximately 40% – 60%, depending on the ink. This range (from 0% to approximately 40% – 60%) is equivalent to the effective coverages at which there is a higher amount of paper visible, resulting in graininess due to its higher contrast against the ink. This is specially prominent for the K channel, a fact explained by the high contrast of this ink against the paper, which makes its halftone dots more

prominent than those of the rest of the inks.

Out of the three channels that use light inks, K_S is the one that displays most fluctuation, due to the higher contrast against the paper compared to the other inks. Moreover, the K_S is the only channel with a GI increase (occurring from approximately 60% nominal coverage), explained by the presence of the black ink in this area of the multilevel channel, since the second threshold was around 60%.

The GI behavior shown in Figure 5.13 correlates with the perception of graininess, where the bilevel printed patches display higher graininess than the multilevel ones, especially at lower coverage values.

5.5.2.1 Multilevel halftoning applied to images

A grayscale image was halftoned using the bilevel and the multilevel algorithm. The images were compensated for dot gain, printed on the matte coated paper at 600 dpi and scanned at 1200 ppi. The results are shown in Figure 5.14 with enlarged areas.

A color image was also halftoned using the bilevel and the multilevel algorithm. The input was given in the RGB color space. The conversion from RGB to CMYK was performed using the conversion shown below.

$$\begin{aligned} \begin{bmatrix} C_1 \\ M_1 \\ Y_1 \end{bmatrix} &= \begin{bmatrix} 1 - R \\ 1 - G \\ 1 - B \end{bmatrix} \\ \begin{bmatrix} K \\ C \\ M \\ Y \end{bmatrix} &= \begin{bmatrix} \min(C_1, M_1, Y_1) \\ \frac{C_1 - K}{1 - K} \\ \frac{M_1 - K}{1 - K} \\ \frac{Y_1 - K}{1 - K} \end{bmatrix} \end{aligned} \quad (5.3)$$

Figure 5.14: Grayscale image: (top) bilevel halftoned, (bottom) multilevel halftoned.

After the conversion, the color image thus consisted of four channels, CMYK. As for the grayscale image, the aim is also to print this image by employing only the primary inks and both the primary and light inks. Each channel was thus compensated for dot gain, halftoned with the bilevel or multilevel algorithm, printed at 600 dpi on the matte coated paper and scanned at 1200 ppi. The results are shown in Figures 5.15 and 5.16 for the bilevel and multilevel halftoned result, respectively.

Figures 5.14, 5.15 and 5.16 show that the bilevel halftoned images display more graininess than the multilevel halftoned ones. This can be explained by the inks employed in the multilevel algorithm. While the bilevel algorithm only employs one ink to reproduce all the nominal coverages, the multilevel algorithm employs multiple inks, each ranging from 0% to 100% ink coverage.

5.5.3 Gamut comparison

Multilevel halftoning employs a primary and its light inks in a way that no overlap between them occurs. Meanwhile, it has been shown that dot-off-dot reproduction gives a different impression than an impression with random ink overlap (Gooran et al., 2009).

Therefore, a comparison was made between the colors that can be reproduced with random ink overlap and the ones that can be reproduced dot-off-dot, with multilevel halftoning. The comparison was performed between patches created with random ink overlap of the cyan, light cyan, magenta and light magenta inks, and with the multilevel C_S and M_S ink combinations. Note that the goal was not to represent a color separation to C_S and M_S for a given target color. The goal was instead to use the colors inside the gamut of random overlap using C , M , c and m as the target and evaluate to what level it would be possible to reproduce them by multilevel halftoning C_S and M_S .

Figure 5.15: Bilevel halftoned color image.

Figure 5.16: Multilevel halftoned color image.

The random ink overlap patches were created by reproducing ink combinations of: C+c, C+m, C+M, M+m, c+m, and c+M. Each of these 6 ink combinations was reproduced in 0% to 100% coverages in 5% steps (21 steps), meaning $21 \cdot 21 = 441$ patches. This equals to a total of $441 \cdot 6 = 2646$ patches. Their CIELAB values served as a target. The multilevel halftoned patches were reproduced in 0% to 100% coverages in 5% steps, i.e. 441 patches. Their CIELAB values were measured and interpolated to 1% steps.

For each random ink overlap patch, the multilevel halftoned patch with the smallest ΔE_{94} was found. The calculated mean and maximum color differences were $\overline{\Delta E_{94}} = 0.69$ and $\Delta E_{94,max} = 2.40$, respectively, while the 90th percentile was $\Delta E_{94} = 1.48$. Multilevel halftoning is thus the optimal choice if color difference values up to 2.40 can be tolerated.

5.5.4 Hue inconsistencies between inks

When referring to hue differences between inks in this chapter, the reference is to the hue and/or chroma differences between the inks that should ideally not display any – light cyan and cyan, light magenta and magenta, and the grays and black. Even though the main reference is to differences in hue, it is plausible that differences in chroma also exist. In other words, the reference is to changes in CIEa* and/or CIEb* values between those inks.

Figure 5.6 shows that the lowest color difference calculated, at the threshold, is not zero. In fact, the lowest ΔE_{94} between cyan and fulltone light cyan is 2.04, and between magenta and fulltone light magenta is 1.67. This points to a chromatic difference between the fulltone light inks and the color that the darkest ink halftones can reproduce.

To further investigate this, CIELAB values of C, M, K patches served as target to the C_S , M_S and K_S patches. The data were gathered from

samples between 1% and 100% coverage in 1% steps. Figure 5.17 shows the lowest calculated ΔE_{94} at each C, M and K nominal coverage.

Figure 5.17: Color difference between inks.

The maximum ΔE_{94} between cyan and its closest match in the C_S channel is 1.99, that between magenta and M_S is 1.29, and between black and K_S is 5.15. While the color differences are generally below 1 ΔE_{94} for magenta, they are larger for cyan (below 2 ΔE_{94}) and much larger for black. Each curve displays a peak, consistent with the coverages of the primary inks at which the multilevel channel is reproduced with the light inks. For cyan and magenta, the color difference curves peak at lower coverage values (between approximately 10% to 40% coverage of darker ink, where only lighter ink is used) and remain low ($\Delta E_{94} < 1$) between 50% and 100% coverage, where ink combinations with higher percentages of the primary inks are used. For black, it is only at low and high coverages where a close colorimetric match can be found. This result again points to a hue discrepancy between the tone values of the

primary and lighter ink halftones.

Since the halftones of the achromatic inks exhibit a hue difference between each other, metrics such as color difference formulae are more appropriate for locating ink thresholds. The thresholds were now found at 40% and 65% channel coverage for the coated paper, with ΔE_{94} differences of 3.92 and 4.14, respectively. The thresholds were also calculated using ΔRMS in order to perform a spectral comparison. The smallest ΔRMS between the spectra of 100% coverage of the lighter inks (photo gray and gray) and the darkest ink (black) was found at 39% and 59% black ink halftone coverage, respectively, for the coated paper. The ΔRMS between the coverages of these inks was 0.0217 and 0.0115, respectively. Figure 5.18 shows their spectral reflectance.

Figure 5.18: Spectral reflectance values of pgy, gy and K inks at coverage values with smallest ΔRMS between them.

Ideally, fulltone achromatic inks should not display spectral variations, and should instead reflect all the wavelengths equally. However, in case

with halftones, when the ink droplets are mixed with paper, variations across the spectrum are expected since paper wouldn't have the same hue as the inks. It is thus logical that the calculated Δ_{RMS} difference and the plotted spectral values point to hue discrepancies between full-tone inks and halftones.

A dot-off-dot halftoning approach has been proposed in Gooran and Žitinski Elías (2015) as a way of compensating for the hue differences between achromatic ink halftones. In this research, a separation approach was suggested of a target reference color, given as a K ink. The results show that the dot-off-dot halftoning approach is able to reproduce all tones of K with a maximum color difference of 1.8, without ink overlap. It was also shown that dot-off-dot halftoning results in less grainy halftones.

5.6 Conclusions

A multilevel halftoning approach introduced in (Gooran 2006) has been implemented in this chapter for a multi-channel printing setup. The implementation was performed for the primary inks and their lighter versions – light cyan and cyan, light magenta and magenta, and photo gray, gray and black. Implementation challenges included determining the threshold between the inks and compensating for a channel's dot gain.

The first benefit of employing this algorithm is that the inks are printed dot-off-dot, i.e. with no overlap between them. This means that the maximum amount of ink thickness remains unaltered when adding light inks.

The second benefit relates to the number of channels in the color separation. Normally, employing the primary and the light inks means that each

ink is represented with one channel. In the case of four primary and four light inks, each target color is thus separated into eight channels. Characterizing the print reproduction for eight channels (as opposed to four channels) means an increase of the number of training samples, computation time and complexity. However, multilevel halftoning groups the primary and light inks in single channels. Thus, the color separation is to four channels, instead of eight. From then on, it is the multilevel halftoning algorithm that performs the step that the color separation normally does, separating each channel subset into individual colorant channels. Thus, by grouping the primary and lighter inks in channels, the characterization complexity is not increased with the addition of lighter inks.

Implementation results confirm that the multilevel halftoning workflow for the printer, inks and substrates used was successfully controlled. Analysis proves smooth tonal transitions around the ink thresholds. Graininess has also been evaluated, with calculated GI values of the primary inks much higher than for the printed multilevel halftoned channels. This is particularly prominent for the case of the black ink. The decrease in graininess when employing multilevel indicates an increase in image quality.

Suppressing ink overlap between the primary and the light inks comes at a cost of a somewhat reduced color gamut. The calculated color reduction arguably does not impose a big constraint of the method.

A chromatic comparison between the primary and their light inks showed hue discrepancies between them, indicating that a color difference formula is the most suitable one in order to locate the thresholds between the inks in multilevel halftoning. However, differences of several ΔE units at the thresholds indicate that an exact match between the dark and light inks cannot be found.

Nevertheless, when performing a color separation, it can be argued that

a colorimetric match between a target color and the color of a multi-level halftoned channel is of more significance for a correct characterization. Therefore, any chromatic discrepancies of the inks within a channel could be overcome with a correct color separation. Chapter 6 addresses the color separation in a print setup in which both the primary and the light inks are employed, utilizing multilevel halftoning.

Chapter 6

Print characterization employing multilevel halftoning

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6.1 Introduction

Color reproduction models (forward models) input nominal ink coverages, predicting the printed outcome in terms of colorimetric or spectral values. Color separation (inverse) models input target colors, expressed as colorimetric or spectral values, and determine the nominal ink combination that reproduces them (Section 3.4). Print characterization refers to achieving an accurate color reproduction and color separation for a given print setup.

The additional colorants in multi-channel printing normally mean reproducing and measuring additional training samples to conduct the print characterization, as well as a rise in computational time and complexity. The research presented in this chapter deals with the characterization of a multi-channel printing system, comprehending the primary and light inks, based on colorimetric and spectral data. The characterization is achieved by employing the multilevel halftoning algorithm, which allows the use of additional (light) inks without increasing the channel number (four). The algorithm, implemented in the research presented in Chapter 5, is intended for channels reproduced with ink subsets, consisting out of primary and their light inks. The algorithm halftones a channel to multiple levels, performing then the division into colorants. It is thus the algorithm itself that performs this part of the print characterization, maintaining the characterization complexity. This chapter addresses the accuracy of the method, evaluated for both colorimetric and spectral data.

The research presented in this chapter was published in Žitinski Elías, Gooran and Nyström (2016).

6.2 Previous work

When the additional colorants in multi-channel printing are the lighter versions of the primary inks, the color separation problem has previously been tackled by introducing an in-between step, where colorants are separated into four channels first and then to multi-channel (Noyes et al., 2000, Agar, 2001, Agar et al., 2002, Son et al., 2003, Jang et al., 2006a, Son et al., 2011).

For instance, Agar (2001) and Agar et al. (2002) performed the spectral characterization to the CMYK gamut, then further dividing it to the light cyan and light magenta inks by using their colorimetric values. A similar approach was introduced by Noyes et al. (2000) by performing a separation based on colorimetric data. Their division from the CMYK to the CMYK + light ink space was performed using linearization curves. Meanwhile, Son et al. (2003, 2006) and Son et al. (2011) utilize granularity metrics in order to achieve a six-channel separation employing lighter inks. The separation was performed using colorimetric data in Son et al. (2003) and Son et al. (2006), and spectral data in Son et al. (2011).

Spectral modeling of a multi-channel printer can be performed also directly, by printing all the combinations of the NPs (Neugebauer Primaries). In those instances, the ink overlap needs to be controlled, which was performed in Hardeberg and Gerhardt (2004) by imposing an ink superposition limit in the utilized printer software.

Alternatively, an algorithm was introduced called Halftone Area Neugebauer Separation (HANS) in which the separation is performed, instead to ink channels, to possible printable patterns (Morovič et al., 2010). The benefit of this method is that it is equally applicable to duotone or multi-channel printing systems by applying a halftoning algorithm based on error diffusion (Morovič et al., 2012). The separation is based on colori-

metric data. This approach is, however, incompatible with e.g. security printing, in which a different halftoning matrix should be applied to each colorant. A PARAWACS (Parallel Random Weighted Area Coverage Selection) method, an approach in which halftone matrices are applied to each channel, was thus proposed, offering a large degree of control over the binarization pattern (Morovič et al., 2016).

As seen, the color separation techniques can be performed based on spectral data (Agar, 2001, Agar et al., 2002, Hardeberg and Gerhardt, 2004, Son et al., 2011) or using colorimetric data (Noyes et al., 2000, Son et al., 2003, Jang et al., 2006*b*, Morovič et al., 2012).

Oppositely to the aforementioned color separation approaches, the one proposed in this chapter does not represent a rise in computational complexity, nor does it require an in-between color separation step in the instances when the light inks are incorporated in the print setup. Instead, the number of channels in the color separation remains the same. In the next step of the workflow, the halftoning algorithm itself performs the binarization to the channels, creating bitmaps for each of the primary and light inks.

6.3 Methodology

A workflow is proposed in which a color separation to eight inks (CMYK + lighter inks) is computed directly, avoiding the in-between step of a four-color CMYK separation. This is achieved by bundling inks of same hues in one channel, yielding four channels with eight inks – cyan (C) and light cyan (c), magenta (M) and light magenta (m), yellow (Y), and black (K) and two grays (pgy, gy). The channel subsets are named C_S , M_S and K_S . After the halftoning, the channels yield eight bitmaps, one for each ink (Figure 6.1).

Figure 6.1: Proposed separation into eight bitmaps.

Given a target image with colorimetric or spectral data as an input, the goal is to perform a separation into four channels, hence achieving control over the output in the printing process. Once these four channels are generated, they are halftoned using the multilevel halftoning algorithm, thereafter separated into eight bitmaps for eight inks. Specifically, the cyan and magenta channels are each transformed to two bitmaps, created by the multilevel halftoning. Meanwhile, the black channel is transformed to three bitmaps represented by the black and two gray inks. The yellow channel yields a single bitmap, therefore it is directly bilevel halftoned.

6.3.1 Print characterization

The color separation is performed using the cellular Yule-Nielsen modified spectral Neugebauer (cYNSN) color model, with spectral data, and with the cellular Yule-Nielsen modified Neugebauer (cYNMN) model for colorimetric values (Section 3.4.5). To implement the models, the n -factor and the effective area coverages of a channel are calculated us-

ing an iterative loop in which the YNSN formula is applied, computing the spectral root mean square ΔRMS error between the YNSN and measured values at every iteration. For each nominal coverage, the effective coverage resulting in the smallest error is chosen. The n -factor giving the smallest error for all the effective coverages is the one selected. Such n -factor was calculated for the four channels. The mean n -factor was the one selected (Agar and Allebach, 1998).

Based on the color prediction model, a computational inverse model is generated. Two color look-up tables (CLUT) were created, one using cYNSN model (spectral data) and the other using the cYNMN model (colorimetric data). In both cases, the colorimetric/spectral values of the four channel combinations from 0% to 100% coverage were obtained in 5% steps. This result is cubically interpolated to 1% steps. Based on these tables, a calculation is performed that locates the color separation of a given input.

6.3.2 Print setup

The general print setup was described in Section 4.6.1. The thresholds between the inks in the multilevel channels were those specified in Section 5.4.1. Both colorimetric and spectral data were employed to compute two look-up tables.

Each look-up table was delimited by 0%, 25%, 50%, 75%, and 100% surface coverages. In the 4 dimensional ink coverage space, this division yields $4^4 = 256$ subcubes, with the YNMN/YNSN model applied inside. The training patches, constituting of 0%, 25%, 50%, 75%, and 100% coverage values of the four channels, yield a total of $5^4 = 625$ measurement samples. In addition, the calculation of the n -factor is required. For this purpose, the spectral values of halftoned and printed patches of the four channels (C_S , M_S , Y , K_S) from 10% to 100% in 10% steps were

measured to calculate the optimal n -factor. A totality of $625 + 4 \cdot 10 = 665$ patches were thus printed to characterize the eight ink gamut of the present device setup.

6.4 Accuracy of the print characterization

The accuracy of the print characterization was performed by comparing the predicted spectral data to the measurement of 50 randomly chosen patches. This arguably low number was selected in order to perform an initial verification. In Chapter 7 the number of test patches is increased by several orders of magnitude. Here, the root mean square difference ΔRMS between the test patches and the predicted spectral data was calculated. The ΔE_{94} color difference between measured and predicted patches was also calculated. The mean and the maximum differences were $\overline{\Delta E_{94}} = 0.98$ and $\overline{\Delta RMS} = 0.009$, and $\Delta E_{94,max} = 1.77$ and $\Delta RMS_{max} = 0.022$, respectively. Results are shown in forms of histograms in Figures 6.2 and 6.3.

The inverse color model was evaluated by measuring the spectral reflectance values of 50 samples printed with randomly chosen C_S , M_S , Y and K_S coverages as target to the color separation. Halftone patches of the obtained coverages were printed and the ΔRMS difference calculated. The ΔE_{94} was also calculated. Figures 6.4 and 6.5 show the results in form of histograms of the errors. The mean and the maximum differences were $\overline{\Delta E_{94}} = 0.94$ and $\overline{\Delta RMS} = 0.006$, and $\Delta E_{94,max} = 1.77$ and $\Delta RMS_{max} = 0.012$.

The low color differences indicate that the proposed separation was successfully characterized by using the cYNMN/cYNSN models with 5 different nodes (ink limits). The number of patches used to perform this characterization was 665. Since this is a direct characterization of an

Figure 6.2: Accuracy of the forward model, expressed with ΔE_{94} .

Figure 6.3: Accuracy of the forward model, expressed with ΔRMS .

Figure 6.4: Accuracy of the inverse model, expressed with ΔE_{94} .

Figure 6.5: Accuracy of the inverse model, expressed with ΔRMS .

eight-channel printing system resulting in low color differences, it could be argued that this number of patches to accomplish it is not excessive. Moreover, keeping in mind the low color difference, a training sample reduction could be performed by decreasing the number of nodes used in the characterization of the model.

6.5 Image as target to the color separation

An image represented in CIELAB color space was used as target to the color separation to the $C_S M_S YK_S$ gamut, employing the multilevel halftoning algorithm. The resulting channels were halftoned, printed at 600 dpi and scanned at 1200 ppi. The result is shown in Figure 6.6 with certain areas enlarged.

The difference between the image in Figure 6.6 and the one in Figures 5.15 and 5.16 is that input images in the latter case were converted to CMYK from RGB using simple color conversion equations (Equation 5.3), while Figure 6.6 was obtained by the proposed color separation model using CIELAB values that served as input to the $C_S M_S YK_S$ gamut.

The image in Figure 6.6 shows no visible graininess, with even the enlarged areas appearing smooth. The printed result shows a colorimetric difference from the one obtained in Figures 5.15 and 5.16. This is, firstly, due to the different input to both methods (RGB vs CIELAB color space). Secondly, the approach employed in order to transform the image to the CMYK color space was different (Equation 5.3 vs color separation). The color accuracy of the separation using CIELAB as input has been addressed in Section 6.4.

Figure 6.6: Image as input to the color separation incorporating multilevel halftoning.

6.6 Conclusions

A characterization of a multi-channel printing workflow was performed, from colorimetric and spectral data directly to eight colorants. This is achieved by performing the color separation to four channels, which are then separated by the multilevel halftoning algorithm to the corresponding number of primary and light inks. Consequently, the number of training samples required for multi-channel color modeling remains feasible. Moreover, the multilevel algorithm does not allow ink superposition in the same channel, thus avoiding possible over-inking. In addition, incorporating the light inks in the print setup adds to visual pleasantness of images by reducing the perceived graininess. It has been shown that the multilevel halftoning algorithm, by limiting ink superposition within a channel, reduces graininess when compared to the conventional halftoning approach using the primary inks only.

Employing the light inks in multi-channel printing clearly improves the perceived image quality in terms of graininess. However, the inks that could also be employed in multi-channel printing are the secondary color inks, e.g. red, green and blue. Incorporating those inks in the print characterization, being complementary to the primary inks, has the potential of extending the scope of reproducible colors. Their incorporation in the color separation, however, opens research questions such as print characterization complexity, color redundancy and the graininess of the secondary color inks. These issues are further explained and addressed in Chapter 7.

Chapter 7

Color separation for improved image quality

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7.1 Introduction

Chapter 6 presented the color prediction and color separation models employing the multilevel halftoning algorithm. The benefits of the approach, utilizing the light versions of the primary inks, are reducing graininess while maintaining the print characterization complexity of a four-channel print setup.

To fully exploit the benefits of multi-channel printing, the secondary color inks should also be incorporated in the print setup. However, when more than three inks are used, color separation models constitute a one-to-many mapping problem, in which several ink combinations yield same/similar colorimetric values. This is particularly prominent in multi-channel printing.

In the research presented in this chapter, a multi-channel print characterization approach is proposed in form of a color separation in which both the light inks and the secondary color inks (red, green, blue) are included, meaning printing with 11 inks. Four main challenges are identified and addressed: 1) employing 11 inks potentially increases the complexity of color characterization, 2) control over the ink overlap between 11 ink combinations needs to be achieved to avoid over-inking, 3) the secondary color inks potentially result in high graininess at low area coverages, and 4) the conversion from the 3-dimensional CIELAB color space to multi-channel ink coverages in the inverse model constitutes a one-to-many mapping problem. Several color separation approaches for multi-channel printing exist in literature (Boll, 1994, Tzeng and Berns, 2000, Chen et al., 2004, 2008, Urban and Berns, 2011, Jewell et al., 2013, Deshpande et al., 2014a, Le Moan and Urban, 2014, Babaei and Hersch, 2016a,b). The color separation presented in this chapter deals with these challenges by distincting itself from the separations methods found in literature by: 1) the separation is performed using both light inks

and secondary color inks, 2) a multilevel halftoning algorithm is incorporated (Chapter 6), creating one channel for each set of inks of similar hues without overlap between them, and 3) the graininess perception is quantified, predicted for each colorant combination, and incorporated into the separation look-up table.

In order to resolve the one-to-many mapping problem, the proposed color separation method utilizes a cost function, weighting selected factors that influence print quality, i.e. color accuracy and graininess perception, also taking into account ink consumption. The multilevel halftoning algorithm, incorporated in the separation approach, employs light inks, thus lowering graininess, without increasing the color characterization complexity or the ink overlap. In addition, graininess perception is evaluated with the graininess index GI metric (Section 4.5.4), which leads to a generalization and prediction of the graininess behavior.

The research presented in this chapter was published in Žitinski Elías, Nyström and Gooran (2016), and Nyström et al. (2017).

7.2 Print characterization of 11 inks in multi-channel printing

When secondary color inks are incorporated in a multi-channel print setup, the print characterization can be performed either directly or by dividing the gamut into subgamuts and characterizing each. An example of the first approach was performed in Slavuj et al. (2013), where spectral modeling of a CMYKRGB printer was performed by overlaying the seven-channel NP (Neugebauer primary) combinations of the YNSN model. A multilevel halftoning algorithm was applied by the print software to control the amount of ink overlap.

The 11 inks available in the print setup (Section 4.6.1) can be over-

lapped, i.e. placed on top of each other, in numerous ways in order to reproduce different target colors. However, it makes sense to restrict the number of overlapping inks. One reason is to avoid over-inking, which could cause ink bleeding. The other reason is that increasing the number of overlapping inks above four does not spectrally augment the gamut (Slavuj et al., 2014, Le Moan and Urban, 2014). Naturally, the amount of overlap needs to be further reduced in the cases where four overlapping inks exceed the maximum amount that a specific paper substrate can absorb.

7.2.1 Gamut division

Different ways of grouping overlapping inks have been found in literature. Boll (1994) suggests a method of multi-channel characterization in which the gamut is divided into subgamuts of ink quadruplets, each containing the achromatic ink (K) and three chromatic ones, adjacent on the chromaticity plot. The number of subgamuts can increase depending on whether all ink quadruplet combinations are used (Tzeng and Berns, 2000, Urban and Berns, 2011, Le Moan and Urban, 2014). However, since a high degree of overlap between such subgamuts is found (Boll, 1994, Deshpande et al., 2014a), the subgamut choice can be constrained to those adjacent on the chromaticity plot (Deshpande et al., 2014a, 2015).

The multilevel halftoning algorithm (Chapter 5) bundles the primary C, M and K inks and their light inks, forming ink subsets C_S (cyan and light cyan), M_S (magenta and light magenta) and K_S (black and two gray inks). The implementation of such algorithm comprehends expressing the coverages of the inks in a subset in terms of the channel's coverage. Each of the subsets thus represents a channel intended for multiple inks, meaning a reduction in the complexity of the characterization of 11 colorants

to a 7-channel characterization: $C_S M_S Y K_S RGB$.

In the available print setup, the gamut division yields four subgamuts consisting of channel quadruplet combinations – $C_S M_S Y K_S$ (primary ink subgamut), $M_S Y K_S R$ (red subgamut), $C_S Y K_S G$ (green subgamut) and $C_S M_S K_S B$ (blue subgamut). This is visualized in Figure 7.1, where the space between the dashed lines represents the primary ink subgamut, and the space between the solid lines the red, blue and green subgamuts. Multilevel halftoning makes it possible to include the light inks without an increase of the total ink coverage (Section 3.2.3), achieving an up to four overlapping ink combinations in each subgamut.

Figure 7.1: Division of the $C_S M_S Y K_S RGB$ gamut.

7.2.2 Print characterization – method and results

Each of the four subgamuts is characterized with the cellular Yule-Nielsen modified Neugebauer (cYNMN) model. As discussed in Section 3.4.5, the cellular model extends the base (YNMN) model by dividing each ink surface coverage into several segments (cells). Here, these were delimited by 0%, 25%, 50%, 75% and 100% surface coverages. In the 4 dimensional ink surface coverage space associated to each of the subgamuts, this division yields $4^4 = 256$ subcubes, with the YNMN model applied inside each one. Each 4-ink subgamut requires training patches, constituting of 0%, 25%, 50%, 75% and 100% coverage values of the four channels, yielding a total of $5^4 = 625$ measurement samples. In addition, cYNMN requires the calculation of the n -factor. For this purpose, the CIEXYZ values of halftoned and printed patches of the seven channels (C_S , M_S , Y , K_S , R , G , and B) from 10% to 100% in 10% steps were measured to calculate the optimal n -factor. A totality of $4 \cdot 625 + 7 \cdot 10 = 2570$ patches were thus printed to characterize the 11 ink gamut of the present print setup.

The color separation, i.e. inverse color model, was executed by computing a color look-up table (CLUT) for each of the four subgamuts. Each CLUT was computed by calculating the CIELAB of the four channel combinations in the subgamut, ranging from no tone to fulltone coverage, using the cYNMN model. The CIELAB values were transformed from the CIEXYZ color space under D50 illuminant.

The input to the color separation are CIELAB values. The color separation strategy, aiming to resolve the one-to-many mapping problem, will be presented in Section 7.5.

In order to test the forward color model of this implementation, patches were created in 10% coverage steps for each channel in the $C_S M_S K_S B$ subgamut, totaling $11^4 = 14641$ patches. This subgamut was chosen

since it incorporates all the light inks, therefore including the highest number of colorants (eight).

The CIELAB values of these 14641 patches were measured and compared to the CIELAB values of the same coverages predicted with the forward model. The mean and maximum color differences were calculated at $\overline{\Delta E_{94}} = 0.80$ and $\Delta E_{94,max} = 4.38$, respectively. The 90th error percentile was 1.82. The histogram of the color difference error is displayed in Figure 7.2.

Figure 7.2: Accuracy of the forward model for the C₅M₅K₅B subgamut.

These results are largely representative, since they were obtained based on very large number of samples varying in the whole range of coverages. They indicate sufficient color accuracy in order to create color profiles. In addition, they are in line with the mean color difference that was calculated in Section 6.4 using fewer samples.

7.3 Colorimetric redundancy

When employing more than three inks, the color separation model constitutes a one-to-many mapping problem, since several ink combinations could reproduce the same colorimetric result. Colorimetric redundancy increases with each additional ink introduced. Multilevel halftoning reduces the redundancy due to the grouping of the primary and the light inks (Section 5.5.3). Figure 7.3 shows the colorimetric redundancy of the print characterization in the $C_S M_S K_S B$ subgamut, plotted in the CIELAB color space. Each dot is colored to represent the number of different ink combinations within the subgamut, in 2% coverage steps, that can reproduce a specific CIELAB value within the just noticeable difference $\Delta E_{94} = 1$.

Figure 7.3: Colorimetric redundancy in the $C_S M_S K_S B$ subgamut.

Figure 7.3 shows that the colorimetric redundancy varies across the subgamut; lighter colors, with higher CIE-L*, have smaller colorimetric redundancy than the darker ones, with lower CIE-L*. Even when considering ink coverages in only steps of 2%, at times thousands of ink combinations reproducing certain CIELAB values exist.

Colorimetric redundancy requires a selection in the color separation, determining the optimal ink combinations, e.g. based on different quality criteria (Agar, 2001, Taplin and Berns, 2001, Chen et al., 2004, Jang et al., 2006b, Chen et al., 2008, Urban and Berns, 2011, Jewell et al., 2013, Babaei and Hersch, 2016a). The regular inverse model finds the ink combination giving the smallest colorimetric difference to the target color (Taplin and Berns, 2001, Chen et al., 2004, Jang et al., 2006b, Urban and Berns, 2011). In the separation model by Agar (2001), the preference is given to colorants with CIE-L* values closest to paper. By doing so, the contrast between ink and paper is minimized, thus prioritizing visual pleasantness. Jewell et al. (2013) base their proposed separation to 7 inks on ink saving, prioritizing ink combinations with lower summed coverages and cheaper inks. They also impose limitations on the dot size, favoring ink combinations that avoid very high ink coverages (deep shadows) or very low coverages (low highlights). Babaei and Hersch (2016a) perform the color separation based on halftone dot visibility and smoothness across subgamuts. Chen et al. (2008) perform the color separation to 6-channel printing with colorimetric similarity across different illuminants and perceptual image quality, i.e. graininess and smoothness across ink coverages. In their approach, however, graininess is not fully minimized, since light inks are not included in the characterization, nor do they perform a graininess prediction of ink combinations, instead offering a general description of the graininess impression over an area. Moreover, their method omits control over the halftoning algorithm, consequently assigning the management of over-inking to the printer soft-

ware.

7.3.1 Criteria of the proposed color separation

Three criteria have been chosen for the proposed color separation: color accuracy, graininess and ink consumption.

Graininess was incorporated as a criterion because the integration of the light inks in the multi-channel print setup reduces the perceived graininess (Section 5.5.2). Utilizing light inks instead primary inks in low coverage areas thus enhances the perceived image quality. However, the secondary color inks (red, green and blue) could potentially result in visible graininess, which could be remedied with utilizing light inks. Consequently, graininess was selected as a selection criterion in the proposed color separation, measured with the graininess index GI (Section 4.5.4).

Graininess reduction is usually achieved utilizing a higher coverage of lighter inks instead of low coverage of the primary or secondary inks. Therefore, graininess and ink consumption are potentially inversely proportional. An attempt to lower ink consumption, when possible, is made by including it as the third selection criterion in the proposed color separation.

The feasibility of improving graininess and reducing ink consumption was investigated for the example of reproducing three different target colors. Figures 7.4, 7.5 and 7.6 illustrate the different ink coverages that reproduce a target color within the just noticeable difference $1 \Delta E_{94}$. The figures are composed out of columns. Each column consists out of an ink/paper combination, colored accordingly, that reproduces the target color.

Figure 7.4 shows the individual ink coverages of the 20 ink combinations that reproduce the target color CIELAB = [70, 21, -30], together with the

resulting GI. The ink combinations are sorted after total ink coverage, which varies from 14% (left) to 53% (right). For this target color, the ink combination with the lowest ink consumption is the one most to the left (22% total coverage, GI = 0.84), while the one that minimizes graininess is the one most to the right (53% total coverage, GI = 0.48). Clearly, ink consumption and graininess can be contradictory criteria in a color separation.

Figure 7.4: Ink combinations reproducing the target CIELAB = [70, 21, -30], within 1 ΔE_{94} and their GI.

Since this is a relatively light target color, the colorimetric redundancy is not very large, with only 20 possible ink combinations. Still, it is obvious that the graininess is strongly dependent on the selected ink combination, with GI values ranging from 0.48 to 0.86. It is also clear that, here, the GI is reduced with higher total ink coverage, and when not using the

blue ink.

Figure 7.5 shows the GI and the individual ink coverages of the ink combinations that can reproduce the target color $\text{CIELAB} = [56, 31, -42]$. Since this is a slightly darker color, the colorimetric redundancy is increased to 137 possible ink combinations. The total ink coverage ranges from 27% to 122%, and the GI from 0.48 to 0.78. It is clear that the GI again decreases with total ink coverage and when replacing the blue ink with combinations of light cyan and light magenta. It is also noticeable that the GI drops when the total ink coverage reaches 100%, thus completely covering the paper. It is, however, worth noticing that the reduction in graininess by using lighter colorants comes with the cost of increasing the total ink consumption by 450%, compared to the most ink saving alternative.

Figure 7.5: Ink combinations reproducing the target $\text{CIELAB} = [56, 31, -42]$ within $1 \Delta E_{94}$ and their GI.

Figure 7.6 shows the individual ink coverages for ink combinations that can reproduce the darker target color CIELAB = [30, 15, -31]. The colorimetric redundancy is now large, with 8660 possible ink combinations reproducing it within $1 \Delta E_{94}$. The GI (not displayed) is all below 0.45, a consequence of the higher total ink coverage, ranging from 113% – 224%. This figure also illustrates the way in which the multilevel halftoning algorithm handles the subsets C_S and M_S . The individual ink coverages vary within each subgroup, yet the ink coverage of the channel never surpasses 100%.

Figure 7.6: Ink combinations reproducing the target CIELAB = [30, 15, -31] within $1 \Delta E_{94}$.

7.4 Constructing a GICLUT

Graininess, expressed as the GI metric, is one of the criteria in the proposed color separation. Nevertheless, incorporating graininess in the CLUT, resulting in a GICLUT, is not straightforward, and is discussed in continuation.

7.4.1 CICLUT based on a large dataset

A GI prediction was attempted for the channels with most graininess – K_S and B. At first, the prediction was based on input channel coverages in 10% steps, cubically interpolated to 1% steps. However, it was noted that the input was insufficiently accurate in the lightest areas (up to 10% coverage), in which the GI rapidly increases (solid lines in Figure 7.7). Therefore, 2% coverage steps in areas up to 10% were added as input to the GI prediction (dashed lines in Figure 7.7). As seen the figure, the prediction serves as a good indicator of the GI behavior.

Thus, to achieve an accurate graininess prediction, the GI of ink combinations were calculated in 2% steps up to 10% coverage, and in 10% steps onwards. Therefore, the created patches were 0% to 8% in 2% steps (5^4 patches), and from 10% to 100% in 10% steps (11^4 patches). This totaled $5^4 + 11^4 = 625 + 14641 = 15266$ patches. Their calculated GI was cubically interpolated to 1% steps and added to the CLUT, producing a GICLUT for the $C_S M_S K_S B$ subgamut.

7.4.2 GI for different ink combinations

Understanding the GI for different ink combinations is useful to reduce the number of input patches needed for a GI prediction and the computation cost when performing an interpolation.

Figure 7.7: Measured and predicted GI of the K_S and B channels.

Firstly, as noted in the discussion of Figure 7.6, the GI of all the possible ink combinations for that target color are below 0.45, a consequence of the higher total ink coverage. The relationship between summed (total) ink coverages and GI was thus further investigated and shown in Figure 7.8. In the figure, if multiple ink combinations with the same summed coverage exist, the one with highest GI is shown. For the case of the multilevel channels, the coverage used in the calculations was the nominal coverage of the channel; recall that the algorithm results in full coverage from the first threshold onwards. As can be seen, the GI values up to approximately 150% summed coverage are erratic, while the ones above 150% are consistently less grainy.

Secondly, GI is related to the contrast between the ink/paper combination of a specific patch (Section 5.5.2). Figure 7.9 shows the predicted GI of $C_S M_S$ ink combinations, combined with 0% blue coverage (upper left in the figure), 10% blue coverage (upper right), 20% (bottom left)

Figure 7.8: Relationship between summed ink coverages and GI.

and 40% (bottom right). As can be seen, graininess is dependent on the ink and its coverage. $C_S M_S$ combinations generally produce lower graininess, which is to be expected given their respective low individual GI. $C_S B$ and $M_S B$ ink combinations, however, result in higher graininess, particularly in low B nominal coverage areas, a consequence of the high GI the single B ink produces. In addition, $C_S B$ combinations generally result in lower graininess than $M_S B$ ink combinations, explained by the higher color difference between the inks in the latter ink combination.

The highest contrast that an ink could exhibit is when that sole ink is placed on the paper substrate. Consequently, in these instances the ink produces the highest GI values. Any inclusion of another ink, resulting in an ink combination, results in lower contrast between the two inks and paper, lowering the graininess. Indeed, as seen for instance in Figure 7.9 for the $C_S M_S$ example with 10% B coverage, the 10% B coverage, without cyan nor magenta inks, exhibits the highest GI. When adding

Figure 7.9: Graininess index of $C_S M_S$ combinations at 0%, 10%, 20% and 40% B coverage.

C_S and/or M_S inks, the contrast in the ink combination lowers, resulting in decreased GI values. Therefore, the GI of an ink combination is not higher than the GI of the ink coverage with the highest GI in the combination.

7.5 The proposed color separation

The selected factors of importance in the proposed color separation are, as discussed, the color difference, calculated based on the ΔE_{94} for-

mula, graininess, calculated using the GI prediction, and ink consumption, calculated based on the summed ink coverage. Since graininess and ink consumption could be contradictory criteria, the latter was given the least order of importance. Cost functions are therefore computed based on color accuracy $f_{\Delta E}$ and graininess f_{GI} , according to the following equations:

$$f_{\Delta E} = W_{\Delta E} \cdot \max [\Delta E_{94} (\text{LAB}_{\text{in}}, \text{LAB}_{\text{GICLUT}}) - \text{JND}, 0] \quad (7.1)$$

$$f_{GI} = W_{GI} \cdot \max (\text{GI}_{\text{GICLUT}} - \text{JNGI}, 0) \quad (7.2)$$

In Equations 7.1 and 7.2, JND and JNGI are user-defined parameters that correspond to threshold values for acceptable color difference and graininess, respectively. $W_{\Delta E}$ and W_{GI} are the weighting factors of the color difference and the GI, respectively. LAB_{in} is the target color that is the input to the color separation model, which is compared to the LAB values in the GICLUT, $\text{LAB}_{\text{GICLUT}}$. Meanwhile, $\text{GI}_{\text{GICLUT}}$ refers to the GI value of each possible ink combination.

The equations are constructed to assign a cost to the values above the JND and JNGI, thus penalizing color inaccuracy and high graininess. However, color differences and GI below JND and JNGI, respectively, are assigned no cost. The cost function f is used to locate the ink combinations for which the sum of the two weighted functions is minimal, as shown in Equation 7.3:

$$f = f_{\Delta E} + f_{GI} \quad (7.3)$$

This may result in instances in which multiple ink combinations exist that minimize f , allowing the incorporation of the ink consumption criterion

into the proposed separation by choosing the ink combination with the lowest summed coverage.

7.5.1 Values of the cost function parameters

The parameters in the proposed cost function are user-defined, and should be adjusted to meet the at times contradictory criteria of color accuracy, graininess and ink consumption. The parameters JND and JNGI are threshold values, which can be set to define the satisfactory limit at which colorimetric accuracy and graininess index will no longer contribute to the cost function. In our experiments we selected JND $JND = 1\Delta E_{94}$, which is commonly used as the just noticeable color difference. The interpretation of the absolute values of the graininess index is not as straight forward, and heavily depends on the print resolution and the selected viewing distance. Based on our initial experiments, we found that for $GI = 0.5$, there was no visible graininess, for our 600 dpi patches at the viewing distance 25 cm, and therefore decided to use $JNGI = 0.5$ in the following experiments. Moreover, as seen in Figure 5.13, the channels that incorporate the lighter inks have GI below 0.5. The choice of JNGI also supports the proposed generalization of computing GI only up to 150% total ink coverage, since higher summed ink coverages give GI below 0.5 (Figure 7.8). It should, however, be noted that the selected JNGI of 0.5 is in no way a general recommendation, instead a choice based on a specific experimental setup in which the most influential factors are the print resolution and the selected viewing distance.

The weights of the cost function were adjusted accordingly, setting the GI weight at least double the color difference weight, i.e. $W_{\Delta E} = 1$ and $W_{GI} = 2, 3$ or 4 ; the higher W_{GI} , the more importance the GI was given as opposed to color difference, representing a trade-off between

low graininess and color accuracy.

7.6 Results and discussion

Color accuracy, graininess and ink consumption of the proposed color separation based on a GICLUT are investigated. As mentioned, the focus is on the $C_S M_S K_S B$ subgamut, since it is the subgamut employing the highest number of inks and the one most prone to graininess. In addition, possible sources of discrepancies, both within a subgamut and between different subgamuts, are discussed.

7.6.1 $C_S M_S K_S B$ subgamut

The proposed color separation strategy based on the computed GICLUT was compared to the regular color separation, finding the best colorimetric match of these target colors in a CLUT. This was performed for the $C_S M_S K_S B$ subgamut, based on the measured $11^4 = 14641$ patches. Table 7.1 shows the mean, maximum and 98th percentile of GI , ΔE_{94} and summed ink consumption SIC of the the regular and the proposed color separation model using three different GI weights. The 98th percentile of the values is displayed to offer additional insight of the result. Since the number of samples is very high, the mean might not show a large difference between the methods. While displaying the maximal value might offer further comprehension of the results, it is expected that there will be certain samples whose color accuracy, GI and/or SIC cannot be lowered. Therefore, choosing to calculate the 98th percentile shows the majority of the results lay, and can be used to evaluate the effectiveness of the method.

The results in Table 7.1 show that higher W_{GI} lowers the GI at the cost of reduced color accuracy. The 98th percentile indicates that 98% of

Table 7.1: Comparison between the regular inverse model CLUT and the proposed GICLUT in terms of ΔE_{94} , GI and SIC.

	CLUT	GICLUT $W_{GI} = 2$	GICLUT $W_{GI} = 3$	GICLUT $W_{GI} = 4$
$\overline{GI}$	0.45	0.41	0.41	0.40
GI_{max}	0.89	0.85	0.85	0.78
GI 98th percentile	0.77	0.53	0.51	0.50
$\overline{\Delta E_{94}}$	0.84	0.85	0.85	0.85
$\Delta E_{94,max}$	1.00	1.44	1.78	2.23
ΔE_{94} 98th percentile	0.99	1.01	1.03	1.05
$\overline{SIC}(\%)$	96	108	108	108
SIC 98th percentile (%)	146	138	138	138

the GI and color differences in the proposed model falls below or close to our selected JNGI and JND. Meanwhile, the regular model displays the same color accuracy percentile, but with increased graininess. The mean ink consumption of the regular and proposed inverse models are 96% and 108%, respectively. The rise is a consequence of selecting ink combinations with lower graininess. However, ink consumption is very similar between the methods, since multilevel halftoning results in full ink coverage in most of a channels nominal coverage.

Figure 7.10 shows patches reproduced with the regular inverse model, finding the best colorimetric match (top row), and with the proposed GICLUT (bottom row), with $W_{GI} = 2$. The GI of the first row are (left to right) 0.83, 0.88, 0.87, 0.70 and of the bottom row 0.45, 0.53, 0.57, 0.53. Figure 7.11 displays the magnification of the same patches. The two ink combinations displayed most to the left in these figures are the two extreme cases in Figure 7.4 (lowest ink consumption with large graininess vs. largest ink consumption with lowest graininess). Similarly, the two

Figure 7.10: Patches produced with the regular inverse model (first row) and the proposed model with $W_{GI} = 2$ (bottom row).

Figure 7.11: Magnified patches, produced with the regular inverse model (first row) and the proposed model with $W_{GI} = 2$ (bottom row).

ink combinations most to the right are the two extremes in Figure 7.5.

Figure 7.12 shows a continuous-tone image (ramp), created with the regular inverse model (top ramp) and the proposed model (bottom ramp) with $W_{GI} = 2$. While the regular inverse model performed the sep-

aration to the blue ink, the proposed model, predicting its high graininess, avoided this ink in low coverage regions, and selected instead light cyan and light magenta ink combinations. The replacement resulted in a graininess decrease at a negligible cost of color difference.

Figure 7.12: Ramps: regular inverse model (top), proposed GICLUT with $W_{GI} = 2$ (bottom).

The results displayed in Table 7.1, Figures 7.10, 7.11 and 7.12 show that there exist ink combinations that closely resemble a colorimetric input, reducing graininess, most of times at slight cost of color accuracy and ink consumption. When performing a color separation, the closest colorimetric match could be highly grainy, while colorimetrically undistinguishable ink combinations could exist with no visible graininess. Thus, predicting graininess and considering it in the ink selection improves the perceived image quality.

Nevertheless, visible discrepancies may be present in some continuous-tone images, particularly when using higher GI weights. Most of these discontinuities occur due to a change of the ink in neighboring regions, resulting in visible color and graininess variation. One such example was observed when reproducing a ramp image with CIELAB inputs equivalent to B nominal coverages between 20% and 25%, where the proposed method using $W_{GI} = 3$ resulted in visible discontinuities, shown on the bottom ramp in Figure 7.13.

Figure 7.13: Discontinuities present in proposed GICLUT with $W_{GI} = 3$ (bottom) not visible in the regular inverse model (top).

In order to remedy discontinuities, the GI weight could be adjusted according to the type of image or user preference. For example, in the images with continuous-tone regions, in which graininess discrepancies diminish the perceived image quality, a lower W_{GI} will increase the impor-

tance of color accuracy, thus reproducing smoother tone variations. On the contrary, in light image regions for which low graininess is of importance, the W_{GI} could be accordingly increased. Another approach could be a post-processing step in our proposed color separation model. The post-processing would minimize the GI standard deviation of ink combinations over a subspace in the GICLUT. In the cases of high standard deviation, a re-calculation of the color separation would be performed, e.g. using smaller W_{GI} , thus penalizing the change of ink combination within the subspace. This remains part of future work.

7.6.2 Shift between subgamuts

Discrepancies could also be caused by instances in which the colorant combinations shift between subgamuts, potentially inducing further undesirable discontinuities. It could occur that subgamut transitions cause undesirable discrepancies that should be addressed. Babaei and Hersch (2016a) resolve this problem by optimizing the smoothness across subgamuts by introducing weights that give preference to the subgamuts of adjacent pixels.

Figure 7.14 shows a continuous tone ramp with varying target colors, defined in CIELAB, ranging from light red to light blue. The color separation was based on the regular (top) and proposed (bottom) color separation with $W_{GI} = 3$. The magnifications at the beginning and end of the ramps illustrate that the graininess is lowered in the ramp produced with the proposed color separation. The magnification of the center region, where the transition between the two neighboring subgamuts occurs, displays a small degree of discontinuity. The quantification of discontinuities between subgamuts and attempts for homogenous subgamut transitions are part of future work.

When it comes to controlling the ink overlap, the division of the 11-ink

Figure 7.14: Ramp transitioning from $M_S YK_S R$ to $C_S M_S K_S B$. Top: regular model, bottom: GICLUT with $W_{GI} = 3$.

gamut into 4-channel subgamuts results in a maximum of 400% ink layer to each colorimetric input. However, when reproducing regular images, the successively applied halftoning may result in image areas that exceed the 4 ink overlap, since the usual algorithm places the halftone dots of each channel independently. The areas with exceeding ink limit could be rectified by processing the channels after halftoning, locating the areas with binary 1s in more than the allowed number of channels, and successively performing a replacement using the proposed color separation model. This remains part of future work.

7.7 Conclusions

The proposed method handles the color separation of a multi-channel printer, employing the primary inks, their light inks and secondary inks. The separation incorporates a multilevel halftoning algorithm that combines the primaries and their corresponding light inks in single channels. Consequently handling 11 individual colorants as 7 unique subgroups, the complexity of the color separation is reduced.

The extensive amount of data collected for this study provides valuable insight into the relation between ink combinations, total ink coverage, and the resulting image quality in terms of graininess. To select a unique ink combination in the color separation process, colorimetric redundancy calls for additional constraints. The result will be greatly affected by the criterion used, where ink saving and low graininess generally are directly contradictory. For instance, the secondary colorants contribute to expanding the gamut of reproducible colors and to reducing ink consumption, inherently increasing graininess if used in light areas. However, when also employing light inks (naturally increasing ink consumption), the main focus is typically image quality and reduced graininess, not ink saving. Thus, when combining both lighter and complementary inks,

special attention should be given to the usage of the secondary inks.

The results show that the colorimetric redundancy is particularly extensive for dark colors. However, graininess is generally low for dark colors with high ink coverage, since the paper is then fully covered. Thus, if image quality in terms of graininess is of importance, special attention must be given the lighter colors in the color separation.

The one-to-many mapping problem when performing the color separation was resolved with a cost function, weighting selected parameters that influence image quality, i.e. colorimetric accuracy, and graininess perception. The weights in the cost function represent a trade-off between these parameters, and can be fully adjusted according to the type of image and user needs. In addition, ink saving was incorporated in the ink selection process. This approach was statistically evaluated, demonstrating improvement in the perceived image quality when compared with the regular separation approach.

Chapter 8

Conclusions and future work

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8.1 Conclusions

This dissertation addresses some of the research questions occurring in multi-channel printing, with the goal of increasing the reproduced image quality in terms of augmented color gamut and decreased graininess.

One of the addressed challenges has been to characterize a print setup in which both the primary inks CMYK and their light versions are used. The light inks are usually incorporated in order to reduce the perceived graininess of the print. Such reproduction means employing, in our case, twice as many colorants compared to traditional CMYK printing. Normally, this would introduce a number of challenges, such as an increase in the number of training patches, an increased computational complexity of the color separation and risk of over-inking. However, in the research presented, such challenges have been dealt with by employing a different methodology approach. Instead of the usual way in which each ink is treated separately in the color separation, the presented approach groups the primary inks and their lighter versions in ink subsets, i.e. the cyan, magenta and black subset. Each subgroup is a channel that is reproduced with multiple inks, and therefore the color separation is performed to ink subsets, instead as to single colorants. Consequently, the print characterization complexity remains unaltered when employing the light inks.

In the next step of any print characterization, the channels are halftoned. Here, a specific multilevel halftoning algorithm has been employed that halftones each channel to multiple levels. Each level represents the location of a primary ink, a light ink, or no ink (paper). It is therefore this halftoning algorithm that performs the binarization from the ink subsets to each separate colorant. In addition, the inks within one channel do not overlap, thus reducing the risk of over-inking.

This methodology is applicable when the added colorants in multi-channel printing are the light versions of the primary inks. The benefits of the presented method are that the print characterization complexity remains unaltered, since it is the multilevel halftoning algorithm that deals with the binarization to each separate colorant. In addition, introducing the light inks does not increase the risk of over-inking, when compared to traditional CMYK printing. Moreover, the added light inks would normally induce a colorimetric redundancy in the color separation. However, grouping the added inks together with the primary ones in one channel solves such colorimetric redundancy.

The light versions of the primary inks are employed in order to decrease the perceived graininess of the reproduction. In order to verify this benefit in our proposed color separation approach that employs the multilevel halftoning algorithm, a research investigation was opened into metrics that quantify graininess. The need to address this research question was amplified since the goal was to employ also the secondary color inks in a color separation, which potentially increases the perceived graininess. In order to quantify graininess of any ink combination, a large dataset was constructed, in which graininess was quantified for each ink combination. Interpolation was performed to finer steps, resulting in a graininess look-up table.

The main purpose of incorporating the secondary color inks is to take advantage of the benefits of multi-channel printing by increasing the reproducible color gamut. Utilizing them, however, opens research questions such as the aforementioned graininess characterization and a method for print characterization. Specifically, the color separation is not straightforward: employing the primary, secondary and light inks means a color separation from a three-channel CIELAB space into a multi-channel colorant space. This means that multiple ink combinations can reproduce the same target color. A proposed cost function, incorporated in the

color separation approach, weighs factors that influence the reproduced image quality, namely graininess and color accuracy, in order to select the optimal ink combination.

Consequently, the presented research deals with exploiting some of the improved image quality factors that are possible when employing additional inks in multi-channel printing. The results indicate an accurate print reproduction utilizing both the secondary and the light inks, in which the perceived graininess is decreased.

8.2 Future work

Several research questions, identified through the course of this investigation, are left to be answered, and belong to future investigation efforts.

One of the research directions is the continuation of the proposed color separation approach in order to further improve certain quality aspects. Specifically, the increased number of colorants in multi-channel printing allows the possibility of spectral reproduction. Although spectral reproduction has been tackled as part of the work, it has not been implemented when utilizing secondary inks; since the graininess quantification metrics perform the calculations in the CIELAB color space, only colorimetric separation was carried out. However, spectral reproduction could still be attempted, at an increased computation cost, possibly utilizing separate look-up tables for spectral color separation and graininess reduction.

To fully finalize any color separation approach, images should also pass through the separation and be printed. Three challenges remain in order to achieve full control over the color separation for images – the accuracy of the print characterization, smoothness across subgamuts and control over the halftone dot placement.

The first challenge is identified when observing results of the eleven ink print characterization, in which some of the ink combinations suffer from an increased color difference from the target, compared to the mean color differences. This could be problematic when attempting to reproduce images with continuously increasing tones and/or large areas with slight colorimetric variance. Indeed, the implemented color separation is based on a look-up table, created from CIELAB values of channels reproduced in 5% coverage steps and cubically interpolated to 1% steps. Due to the effect of dot gain, such look-up table makes the CIELAB values in areas with low coverage scarcer than the CIELAB values in areas with high coverage. Chen et al. (2008) resolved this problem by building their look-up table using a two-dimensional quad-tree decomposition, achieving sufficient samples across the entire color space. Utilizing such strategy could result in an increased colorimetric accuracy.

The second challenge is related to possible discrepancies in instances in which the colorant combinations shift between subgamuts, potentially inducing undesirable discontinuities. Babaei and Hersch (2016a) resolve this problem by optimizing the smoothness across subgamuts by introducing weights that give preference to the subgamuts of adjacent pixels.

The third challenge when reproducing images is the risk of over-inking. When reproducing patches with the proposed approach, the color separation limits the number of overlapping colorants. However, in images, the successively applied halftoning may result in image areas that exceed the assigned ink overlap restriction, since the used algorithm places the halftone dots of each channel independently. The areas with exceeding ink limit could be rectified by processing the channels after halftoning, locating the areas with binary 1s in more than the allowed number of channels, and successively performing a replacement using the proposed color separation model.

Another possible research direction is improvement of the graininess

characterization. In the proposed approach, graininess has been calculated by reproducing a large dataset upon which a graininess look-up table was constructed. Optimally, graininess should be characterized with a greatly reduced number of training patches than this dataset. Investigation into the plausibility of such generalization is a research question that could be addressed by generating additional datasets of ink combinations and measuring their graininess, with the goal of forming conclusions about the graininess behavior of ink combinations.

Lastly, both the color separation and the graininess characterization has been performed based on CIELAB values, which are dependent on the type of illuminant. Consequently, these have been optimized for ink combinations under only one illuminant. A method for a multi-illuminant color separation and graininess reduction also remains part of future work.

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