Sampling Optimization for Printer Characterization by Direct Search

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***Abstract*—Printer characterization usually requires many printer inputs and corresponding color measurements of the printed outputs. In this brief, a sampling optimization for printer characterization on the basis of direct search is proposed to maintain high color accuracy with a reduction in the number of characterization samples required. The proposed method is able to match a given level of color accuracy requiring, on average, a characterization set cardinality which is almost one-fourth of that required by the uniform sampling, while the best method in the state of the art needs almost one-third. The number of characterization samples required can be further reduced if the proposed algorithm is coupled with a sequential optimization method that refines the sample values in the device-independent color space. The proposed sampling optimization method is extended to deal with multiple substrates simultaneously, giving statistically better colorimetric accuracy (at the $\alpha = 0.05$ significance level) than sampling optimization techniques in the state of the art optimized for each individual substrate, thus allowing use of a single set of characterization samples for multiple substrates.**

***Index Terms*—Color characterization, optimization, printing, sampling.**

I. Introduction

Differently from electronic displays, digital cameras and scanners, the relationship between digital inputs and the resulting color outputs printed on a substrate is highly nonlinear, and no general purpose models exist that would allow for the efficient characterization of a printing system based upon a few measured parameters [1]. A common solution adopted for printer characterization is to generate a large sampling of the printer color input space, printing this sampling and measuring the printed colors by using a colorimeter or a spectrophotometer. The input digital counts (i.e. the colors in the device-dependent space) and the corresponding measured colorimetric values (i.e. their device-independent representation) are then tessellated in one of the two color spaces so that a prediction can be made in the other by interpolation.

Large sample sizes are an issue both in terms of usability and user experience [2]. As a consequence there have been studies in the literature with the aim of reducing the number of printed and measured samples needed for successful printer characterization.

Chang et al. [3] proposed a method for approximating multidimensional nonlinear function using a partially separable grid structure allowing the allocation of more grid points to the regions where the function to be approximated is more nonlinear. Mahy [4] proposed a sample reduction approach based on the idea that a sample could be discarded if it is sufficiently well predicted using its neighbors. Monga and Bala [5] proposed a sample growing approach in which they started from as few samples as possible and added new samples where they resulted in greatest improvement. The work of Tastl et al. [6] is based on the idea of starting with as few sample as possible again and to iteratively add to them the sample that most increases the volumes of tetrahedra in the tessellation of the previous iteration. Recently Morovic et al. [2] proposed a sampling optimization based on greedy search: they started from the vertices of the input space vertices and added new samples where they made the highest prediction error. Monga et al. [7] proposed a further optimization of the node output values after a state of the art technique has initialized the node locations. Their method forms a simplex topology from the set of node location, and the node output values are then uniquely optimized by solving a standard least squares problem. In the same work they propose an iterative algorithm which involves repeated solving of the node location and node values problems in an alternating manner.

Inspired from [2], in this brief we propose a new sampling optimization method based on direct search. In section II we revise the sampling optimization proposed in [2]. In section III we discuss the proposed solution. In sections IV and V the experimental setup and experimental results are respectively reported. Finally, in section VI the conclusions are drawn.

II. Maximum Error Minimization Revised

In [2] Morovic et al. proposed a sampling optimization for printer characterization based on greedy search, which they called Maximum Error Minimization (MEM). They defined and used three datasets: a superset S which was used to select the samples to be included in the characterization set R, $R \subseteq S$ which was used for the printer characterization, and a separate test set T, $T \cap S = \emptyset$ that was used to test the quality of the characterization derived from R [2]. Their proposed approach works as follows: *"(…) start with the* 2^k *vertices of the k-dimensional hypercube as the initial characterization set R and repeat the following until the desired number of colors has been selected:*

1) *characterize the system using the current set R and use it to predict the colors of the test set T (...);*
2) *find the member of S, not included in R, that is closest to the member of T for which the prediction error is highest and add it to R (...)." [2]*

We observe that instead of keeping the test set completely separated, the authors used it in the training phase making it become a sort of validation set. In order to give an idea about the expected error of the characterized system on unseen examples, we need a further set containing examples not used in training or validation [8].

The MEM approach is valid but since we do not have a further set, we have to modify the MEM approach to use the available datasets more efficiently. We have thus decided to revise the MEM approach as follows:

1) initialize the initial characterization set R with the 2^k vertices of the color input space (i.e. RGB or CMYK);
2) characterize the system using the current set R and use the generated profile to predict the colors of the whole superset S;
3) find the member of S, not included in R, for which the prediction error is highest and add it to R;
4) repeat the last two steps until R reaches the chosen cardinality.

Only now it is possible to use the generated profile to test the performance on the test set T, since the sampling method has never seen it.

III. Proposed Solution: the Direct Search Approach

The proposed approach is based on an extension of a Direct Search algorithm (DS) to deal with discrete spaces. DS is a derivative-free method for solving optimization problems [9]. DS is based on a sequential examination of trial solutions involving comparison of each trial solution with the "best" obtained up to that time together

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with a strategy for determining what the next trial solution will be [10]. Given an initial guess, the DS algorithm computes a sequence of points that approaches an optimal solution. At each step, the algorithm selects and compares a set of points (the *mesh*) around the current best point. The mesh is computed as a scalar multiple of a set of vectors (the *pattern*) centered at the current best point. If a point in the mesh that improves the objective function at the current best point is found, the new point becomes the current best point at the next step of the algorithm.

Formally, suppose that we want to solve an optimization problem of the form "minimize $f(x)$ subject to $x \in \Omega$", where Ω is the set of all possible solutions to our problem. At each iteration k of the implemented DS algorithm, we have the current iterate $\mathbf{x}_k$, a set D_k of n vectors which identify the search directions (i.e. the pattern), and a step-length parameter Δ_k. Usually the pattern D_k is the same for all iterations. For each direction $\mathbf{d}_{k,i} \in D_k$, $i = 1, \ldots, n$ we set $\mathbf{x}_i^+ = \mathbf{x}_k + \Delta_k \mathbf{d}_{k,i}$ and we examine $f(\mathbf{x}_i^+)$. If $\exists \mathbf{d}_{k,i} \in D_k : f(\mathbf{x}_i^+) < f(\mathbf{x}_k)$, we set $\mathbf{x}_{k+1} = \mathbf{x}_i^+$ and $\Delta_{k+1} = \alpha_k \Delta_k$; otherwise, we set $\mathbf{x}_{k+1} = \mathbf{x}_k$ and $\Delta_{k+1} = \beta_k \Delta_k$.

The main difference of our implementation with the standard implementation of a DS algorithm is the use of the weights α_k and β_k. Usually the functions to be minimized take values in continuous spaces, and thus the weights are chosen as follows: $\alpha_k > 1$ and $0 < \beta_k < 1$. This means that the mesh expands when fitter solutions are found and contracts when they are not. Since the function we are considering takes value on an discrete domain, we have decided to choose the weights as follows: $\alpha_k = \alpha = 1$ and $\beta_k = \beta_{k-1} + 1$ with $\beta_0 = 1$. This means that when fitter solution are found, the mesh reduces to the pattern and when they are not the mesh expands. Thus, the neighborhood of the current solution is first explored and if no fitter solutions are found, the search area expands.

Given the cardinality $c = |R|$ of the characterization set we want to find, we have to optimally find $c - 2^k$ samples. This is because the first 2^k samples are fixed and are located at the vertices of the color input space. In the following we will concentrate on RGB controlled printers, but the extension to CMYK controlled printers is straightforward. For 8-bit RGB controlled printers, the first $2^3 = 8$ samples are located at the vertices of the RGB color space (i.e. [0 0 0], [0 0 255], [0 255 0], [0 255 255], [255 0 0], [255 0 255], [255 255 0] and [255 255 255]). This means that we have to deal with a $(c - 8)$-dimensional fitness function where each possible solution has the form $[s_1, \ldots, s_{c-8}]$, where each entry s_j is a color sample identified by its RGB coordinates, i.e. $s_j = [R_j, G_j, B_j]$. In order to keep the number of evaluations of f low for each iteration of the DS algorithm, a possible pattern to use could be a 3-dimensional one, applied to each entry s_j. Possible choices could be the 3-dimensional 26-connected or 6-connected neighborhood. These would result in a maximum total number of $26(c - 8)m$ and $6(c - 8)m$ function evaluations respectively, where m is the maximum number of allowed iterations. A further reduction of the maximum total number of function evaluations could be achieved if all the possible samples in the superset S are enumerated. Now each possible solution has the form $[s_1, \ldots, s_{c-8}]$, where each entry s_j is an integer number (i.e. an index). This allows to use a 1-dimensional 2-connected pattern giving a maximum total number of $2(c - 8)m$ function evaluations.

We decided to use the simplest pattern considered (i.e. the 1-dimensional 2-connected pattern) extending it to speed up the convergence. The pattern adopted is $D_k = D \in [-5, 5]$, $D \in \mathbb{Z}$. The weights are chosen as described above ($\alpha_k = \alpha = 1$ and $\beta_k = \beta_{k-1} + 1$ with $\beta_0 = 1$), and the maximum number of iterations $m = 100$. The RGB triplets are indexed from black to white in the same order they would appear if they were considered as 3-digit numbers in base 256.

Concerning the complexity of the DS algorithm, given a h-connected neighborhood, the DS algorithm makes a maximum number of $h(c-8)m$ function evaluations; it is therefore linear in the number c of samples of the characterization set. Defining $s = |S|$, the revised MEM approach requires $\sum_{i=0}^{c-9} s - 8 - i = (c-8)(s-8-(c-9)/2)$ function evaluations, and is therefore sublinear in the number c of samples of the characterization set. The number of function evaluations required by the DS is lower than those required by the MEM if

$$h(c-8)m < (c-8)\left(s - 8 - \frac{1}{2}(c-9)\right) \quad (1)$$

which can be simplified into

$$m < \frac{\left(s - 8 - \frac{1}{2}(c-9)\right)}{h}. \quad (2)$$

The term on the right side of eq. 2 assumes its minimum value when $c = s$; it is thus sufficient that $m < (s - 7)/2h$ to be sure that the number of function evaluations required by the DS will be lower than that required by the MEM. Given the pattern adopted in our implementation of the DS (i.e. $D_k = D \in [-5, 5]$, $D \in \mathbb{Z}$) and the maximum number of iterations allowed (i.e. $m = 100$), when $s = |S| > 2207$ the number of function evaluations of the DS is lower than that required by the MEM for every choice of the characterization set cardinality $c = |R|$.

IV. Experimental Setup

The experimental results are reported on the same data used in [2]. They are composed of two separate datasets: a superset S with cardinality $|S| = 3375$, which is used to select the samples to be included in the characterization set R, $R \subseteq S$ which is be used for the printer characterization, and a separate test set T, $T \cap S = \emptyset$ with cardinality $|T| = 1161$ that is be used to test the quality of the characterization derived from R. The datasets were generated using an RGB controlled HP Designjet Z3100 printer and two different substrates: HP Heavy Weight Coated and HP Instant Dry Photo Glossy papers. As color measurement device the Z3100's embedded spectrophotometer was used. The cardinality of S assures that the number of function evaluations required by the DS will be lower than that required by the MEM (see Sec. III).

To have an idea of the size of the solution space Ω, let us suppose that we want to obtain a characterization set R with cardinality $|R| = 24$. Once the first eight samples are fixed as the vertices of the RGB cube, we have to select the remaining $24 - 8 = 16$ samples. In the superset S there are thus $3375 - 8 = 3367$ eligible samples. The number of possible 16-tuples is given by $C(n, k) = C(3367, 16) \approx 1.26 \cdot 10^{43}$, which represents the cardinality of the solution space. Given the binomial relationship between the cardinality $|R|$ of the characterization set and the cardinality $|\Omega|$ of the solution space, $|\Omega|$ further increases as $|R|$ tends to 1683.

In the experiments reported in the next section the printer is characterized using both built-in Matlab functions and an open source ICC profiler. The Matlab functions permit to interpolate scattered data by first computing the Delaunay triangulation; among the possible interpolation methods, the linear one has been chosen. When using the ICC profile created with the open source ICC profiler, the colorimetric rendering intent has been chosen. Since Morovic et al. [2] used a proprietary ICC profiler, even if the same data are used here, it is impossible to directly compare the obtained results with theirs, but we can still have a relative comparison.

TABLE I
STATISTICS OF THE TEST SET PREDICTION ERROR, FOR SIX DIFFERENT CHARACTERIZATION SET CARDINALITIES $|R| = 8, 27, 64, 216, 512, 2197$, FOR THE SAMPLING METHODS CONSIDERED

Sample size	method	ΔE_{2000} stats min	avg	50%	95%	max
8	UNIF	**0.0399**	8.0463	7.6716	15.2336	**21.2094**
	SLI*	**0.0399**	**7.2557**	**6.5647**	**14.5162**	21.8330
	MEM	**0.0399**	8.0463	7.6716	15.2336	**21.2094**
	DS	**0.0399**	8.0463	7.6716	15.2336	**21.2094**
27	UNIF	**0.0399**	4.7179	3.8401	11.1251	23.2038
	SLI*	**0.0399**	3.1911	**2.7103**	7.2345	12.2640
	MEM	**0.0399**	3.4915	3.2720	6.9217	12.2074
	DS	**0.0399**	**2.9365**	2.7272	**5.6790**	**9.8100**
64	UNIF	**0.0399**	2.8787	2.4308	6.4606	18.4575
	SLI*	**0.0399**	2.0899	1.8066	4.5363	9.8403
	MEM	**0.0399**	2.2313	2.0748	4.2124	6.1191
	DS	**0.0399**	**1.8290**	**1.6844**	**3.5464**	**5.4600**
216	UNIF	**0.0399**	1.9438	1.4860	5.3977	15.1819
	SLI*	**0.0399**	1.4204	1.2330	3.0941	5.7184
	MEM	**0.0399**	1.3455	1.2465	2.6921	**5.1737**
	DS	**0.0399**	**1.2162**	**1.1071**	**2.4317**	**5.1737**
512	UNIF	0.0399	1.3556	1.0994	3.4087	7.2379
	SLI*	0.0399	1.1292	0.9935	2.4252	**5.6021**
	MEM	0.0399	1.0214	0.9342	2.1065	6.0611
	DS	**0.0249**	**0.9651**	**0.8703**	**2.0928**	6.0611
2197	UNIF	0.0255	1.0103	0.8430	2.4355	6.6986
	SLI*	0.0302	0.9078	0.7842	**1.9330**	**5.2171**
	MEM	0.0289	0.8959	0.7307	2.2052	6.6986
	DS	**0.0227**	**0.8902**	**0.7129**	2.1310	6.6986

*SLI uses three different LUTs (one for each channel of the CIELab color space), each with the same cardinality reported. The total number of samples that have to be printed could be therefore threefold the cardinality reported.

V. EXPERIMENTAL RESULTS

A. Single Substrate Optimization

The first experiment is performed using the uniform sampling (UNIF), the Sequential Linear Interpolation (SLI) [3], the revised MEM sampling optimization and the proposed DS sampling optimization on the data printed on the HP Heavy Weight Coated paper.

The fitness function selected for the DS is inspired from [11] and [12]; it is defined as the linear combination of the median, the 95th-percentile, and maximum ΔE_{2000} colorimetric error [16] between predicted and measured CIELab values of the test set, i.e.:

$$f = \begin{bmatrix} w_1 & w_2 & w_3 \end{bmatrix} \cdot \begin{bmatrix} \text{median}(\Delta E_{2000}) \\ \text{95th-percentile}(\Delta E_{2000}) \\ \max(\Delta E_{2000}) \end{bmatrix} \quad (3)$$

In this work we have chosen $(w_1, w_2, w_3) = (1, 1, 1)$ but a different choice could be made [13], as well as a different fitness function could be used. In Table I we report the minimum, the mean, the median, the 95% percentile and the maximum of the ΔE_{2000} colorimetric error on the test set T for six different characterization set cardinalities $|R| = 8, 27, 64, 216, 512, 2197$.

To understand if the differences among the sampling optimization techniques considered are statistically significant, and what is their ranking we have used the Wilcoxon Signed-Rank Test [14]. This statistical test permits to compare the whole error distributions without limiting to punctual statistics. Furthermore, it is well suited because it does not make any assumptions about the underlying error distributions, and it is easy to find, using for example the Lilliefors Test [15], that the assumption about the normality of the error distributions does not always hold. Let X and Y be random variables representing the ΔE_{2000} prediction errors coming from the printer characterization with the characterization sets R_X and R_Y; let μ_X and μ_Y be the median values of such random variables. The Wilcoxon signed-rank test can be used to test the null hypothesis $H_0 : \mu_X = \mu_Y$ against the alternative hypothesis $H_1 : \mu_X \neq \mu_Y$. We can test H_0 against H_1 at a given significance level α. We reject H_0 and accept H_1 if the probability of observing the error differences we obtained is less than or equal to α. In this work, we have used the alternative hypothesis $H_1 : \mu_X < \mu_Y$ as implemented in the Matlab statistical package, with a significance level $\alpha = 0.05$. The count of the number of times that a sampling strategy has been considered statistically better than the others gives us a score which is reported in Table II.

TABLE II
WILCOXON SIGNED-RANK TEST SCORES FOR THE DIFFERENT SAMPLING METHODS CONSIDERED

Method	Sample Size 8	27	64	216	512	2197
UNIF	0	0	0	0	0	0
SLI	**3**	2	2	1	1	1
MEM	0	1	1	2	2	2
DS	0	**3**	**3**	**3**	**3**	**3**

TABLE III
CARDINALITIES REQUIRED BY THE SAMPLING METHODS CONSIDERED TO ACHIEVE A GIVEN LEVEL OF PERFORMANCE

		ΔE_{2000} 95th-percentile < 5	< 4	< 3	< 2	< 1
Coated superset	UNIF	216	343	1000	2197	2744
	SLI	56	85	188	530	1740
	MEM	47	67	106	273	867
	DS	**32**	**50**	**67**	**190**	**740**
Coated test set	UNIF	343	343	729	n.a.	n.a.
	SLI	56	88	212	n.a.	n.a.
	MEM	43	68	161	n.a.	n.a.
	DS	**36**	**52**	**95**	**530**	n.a.

(a)

		ΔE_{2000} 50th-percentile < 5	< 4	< 3	< 2	< 1
Coated superset	UNIF	27	27	64	125	343
	SLI	**10**	15	25	52	229
	MEM	**10**	15	29	51	212
	DS	**10**	**12**	**15**	**40**	**150**
Coated test set	UNIF	27	27	64	125	729
	SLI	**10**	**11**	24	52	570
	MEM	**10**	**11**	29	62	410
	DS	**10**	**11**	**14**	**49**	**320**

(b)

From the scores reported in Table II it is possible to notice that for all the cardinalities $|R| > 8$ reported, the proposed method was able to give the statistically best results. The errors reported for in Table I $|R| = 8$ are equal for three of the methods considered (UNIF, MEM and DS) as the selected samples are fixed and represent the eight vertices of the RGB cube, and they use the same tetrahedral interpolation scheme. The SLI method obtains better results since it uses a different interpolation scheme (sequential linear interpolation).

It should be noted however that the SLI uses three different look-up-tables (LUTs), one for each color channel of the CIELab color space, each with the cardinality reported. Thus the number of color samples that actually have to be printed can potentially be threefold the cardinality reported (in case of no common samples among the three LUTs).

TABLE IV

CARDINALITIES REQUIRED BY THE SAMPLING METHODS CONSIDERED COUPLED WITH SOLVE TO ACHIEVE A GIVEN LEVEL OF PERFORMANCE

		ΔE_{2000} 95th-percentile				
		< 5	< 4	< 3	< 2	< 1
Coated superset	UNIF+SOLVE	125	216	343	1331	2744
	SLI+SOLVE	24	45	89	270	1012
	MEM+SOLVE	24	47	74	177	642
	DS+SOLVE	**23**	**34**	**54**	**150**	**540**
Coated test set	UNIF+SOLVE	125	343	729	n.a.	n.a.
	SLI+SOLVE	34	53	112	726	n.a.
	MEM+SOLVE	37	55	96	617	n.a.
	DS+SOLVE	**26**	**50**	**78**	**450**	n.a.

(a)

		ΔE_{2000} 50th-percentile				
		< 5	< 4	< 3	< 2	< 1
Coated superset	UNIF+SOLVE	**8**	27	27	64	343
	SLI+SOLVE	**8**	**9**	13	28	160
	MEM+SOLVE	**8**	**9**	14	29	138
	DS+SOLVE	**8**	**9**	**12**	**23**	**91**
Coated test set	UNIF+SOLVE	**8**	27	64	125	729
	SLI+SOLVE	**8**	**10**	**13**	39	403
	MEM+SOLVE	**8**	**10**	14	49	297
	DS+SOLVE	**8**	**10**	**13**	**36**	**200**

(b)

TABLE V

STATISTICS OF THE ΔE_{2000} PREDICTION ERROR ON THE SUPERSET S SELECTING THE 64 SAMPLES OF THE CHARACTERIZATION SET R USING THE SAMPLING APPROACHES CONSIDERED COUPLED WITH THE ICC PROFILER

	ΔE_{2000} stats						
Method	min	5%	avg	50%	95%	max	std
UNIF	**0.0256**	**0.5027**	2.1719	1.8265	5.0245	15.4287	1.5658
SLI	0.0576	0.5755	2.3355	2.0544	5.0969	12.0642	1.4489
MEM	0.0982	0.5967	1.9392	1.7801	3.7709	5.8358	0.9792
DS	0.0366	0.5459	**1.7350**	**1.6225**	**3.2110**	**4.6639**	**0.8386**
UNIF+SOLVE	0.1377	0.6824	2.3666	2.0470	5.0093	10.8403	1.4808
SLI+SOLVE	0.1434	0.7595	2.3779	2.1238	4.9209	9.8066	1.3146
MEM+SOLVE	0.0843	0.8399	2.4622	2.3029	4.5759	8.6768	1.1737
DS+SOLVE	0.1759	0.8438	2.4979	2.3855	4.5155	8.6214	1.1448

TABLE VI

STATISTICS OF THE ΔE_{2000} PREDICTION ERROR ON THE TEST SET T SELECTING THE 64 SAMPLES OF THE CHARACTERIZATION SET R USING THE SAMPLING APPROACHES CONSIDERED COUPLED WITH THE ICC PROFILER

	ΔE_{2000} stats						
Method	min	5%	avg	50%	95%	max	std
UNIF	**0.0399**	**0.6163**	2.2557	**1.9814**	4.6675	15.2431	1.4616
SLI	0.0274	0.7625	2.6566	2.3830	5.8539	13.1542	1.6467
MEM	0.0634	0.7882	2.2475	2.0866	4.1586	7.2932	1.0508
DS	0.0651	0.6973	**2.0605**	1.9823	**3.7186**	**6.5669**	**0.9406**
UNIF+SOLVE	0.1964	0.8432	2.7275	2.3913	6.0132	11.5232	1.6714
SLI+SOLVE	0.2952	0.8594	2.7448	2.4000	5.9470	10.9288	1.6119
MEM+SOLVE	0.0721	0.9360	2.6612	2.4515	5.0172	9.9856	1.3071
DS+SOLVE	0.1657	0.9791	2.7905	2.6687	5.1382	9.8035	1.2791

TABLE VII

WILCOXON SIGNED-RANK TEST SCORES FOR THE DIFFERENT SAMPLING METHODS CONSIDERED COUPLED WITH THE ICC PROFILER

	Data Set	
Method	Coated superset	Coated test set
UNIF	5	5
SLI	3	1
MEM	6	5
DS	**7**	**7**
UNIF+SOLVE	3	1
SLI+SOLVE	2	1
MEM+SOLVE	0	1
DS+SOLVE	0	0

In Tables III.a and III.b the number of samples required in the characterization set R to achieve a given level of colorimetric accuracy are reported. They are relative to the uniform sampling (UNIF), the sequential linear interpolation (SLI), the revised MEM method (MEM) and the proposed method (DS). In Table III.a the goal was to achieve a 95th-percentile of the ΔE_{2000} prediction error under the thresholds of 5, 4, 3, 2, and 1 ΔE_{2000} units. In Table III.b the same thresholds are considered taking the 50th-percentile of the ΔE_{2000} prediction error (i.e. the median value) as reference statistic. When the required level of colorimetric accuracy was not achieved by the sampling method considered, a "n.a." (i.e. not achieved) is reported in the corresponding entry of the table.

From the results reported in Tables III.a and III.b it is possible to notice that the proposed DS approach needs characterization sets with a cardinality which is on average 26.32% of that required by the uniform sampling to achieve the same level of performance. Compared to the SLI and MEM approaches, the DS needs characterization sets which respectively contain on average 32.63% and 24.06% less samples.

As a further experiment, the sampling strategies considered, i.e. the uniform sampling (UNIF), the sequential linear interpolation (SLI), the revised MEM method (MEM) and the proposed method (DS), are all coupled with the sequential optimization of node values (SOLVE) [7]. In Tables IV.a and IV.b the number of samples required in the characterization set R to achieve a given level of colorimetric accuracy are reported.

From the results reported in Tables IV.a and IV.b it is possible to notice that the proposed DS approach coupled with SOLVE needs characterization sets with a cardinality which is on average 26.32% of that required by the uniform sampling coupled with SOLVE to achieve the same level of performance. Compared to the SLI and MEM approaches both coupled with SOLVE, the DS needs characterization sets which respectively contain on average 16.68% and 13.02% less samples.

It is also important to notice that all the four sampling methods considered take great benefit when coupled with the SOLVE algorithm: the number of samples required by the uniform sampling coupled with SOLVE is on average the 72.49% of that required by the uniform sampling alone; that of the SLI coupled with SOLVE is on average the 61.81% of that required by the SLI alone; that of the MEM coupled with SOLVE is on average the 68.22% of that required by the MEM alone; finally, that of the DS coupled with SOLVE is on average the 76.43% of that required by the DS alone. These results could be probably further improved using an iterative application of the proposed algorithm coupled with SOLVE, as proposed by Monga et al. [7].

We have also tested the proposed DS approach replacing the Matlab routine for the calculation of the printer profile with an open source ICC profiler. The software used is the Argyll Color Management System v1.3.2 which is released under the GPL (http://www.argyllcms.com/). The Argyll ICC profiler is used as a black box. We have decided to run the test with the ICC profiler for a characterization set cardinality $|R| = 64$. The results obtained for the UNIF, SLI, MEM and DS methods using the Argyll ICC profiler

TABLE VIII

STATISTICS OF THE ΔE_{2000} PREDICTION ERROR ON THE SUPERSET S AND TEST SET T OF THE DATA PRINTED ON THE COATED AND GLOSSY SUBSTRATE SELECTING THE 64 SAMPLES OF THE CHARACTERIZATION SET R USING THE SAMPLING APPROACHES CONSIDERED

Data set	Method	ΔE_{2000} stats 5%	avg	50%	95%
Coated superset	UNIF	0.4461	2.9981	2.3428	7.8059
	SLI-C	0.5145	2.0042	1.7335	4.4534
	SLI-G	0.6009	2.5892	2.2867	5.6654
	MEM-C	0.5135	2.0806	1.9347	4.0882
	MEM-G	0.5095	2.6164	2.3125	5.7272
	DS-C	0.3864	**1.6242**	**1.5276**	**3.1843**
	DS-G	0.4309	2.1999	1.8394	5.1801
	DS-X	**0.3768**	1.9558	1.6710	4.4002
Coated test set	UNIF	0.5181	2.8787	2.4308	6.4606
	SLI-C	0.5037	2.0899	1.8066	4.5363
	SLI-G	0.6165	2.5593	2.0915	5.8703
	MEM-C	0.7028	2.2313	2.0748	4.2124
	MEM-G	0.5208	2.5471	2.2066	5.6149
	DS-C	0.5545	**1.8290**	1.6844	**3.5464**
	DS-G	0.4680	2.1893	1.8034	5.1928
	DS-X	**0.4672**	1.9963	**1.6599**	4.4613

(a)

Data set	Method	ΔE_{2000} stats 5%	avg	50%	95%
Glossy superset	UNIF	0.6093	4.7151	3.9232	11.3185
	SLI-C	0.8602	3.6225	3.1597	7.8245
	SLI-G	0.7413	3.4074	2.9873	7.5139
	MEM-C	0.7732	3.9694	3.4360	8.8377
	MEM-G	0.7539	3.2541	3.1031	6.3169
	DS-C	0.6592	3.6423	3.1967	8.2137
	DS-G	**0.5699**	**2.4661**	**2.2554**	**4.9443**
	DS-X	0.6192	2.6459	2.4325	5.3465
Glossy test set	UNIF	**0.5033**	4.9070	4.2963	11.0598
	SLI-C	0.6255	3.5509	3.0677	8.2253
	SLI-G	0.6323	3.4058	2.9831	7.9670
	MEM-C	0.7580	4.3941	3.8609	9.6650
	MEM-G	0.7387	3.1878	2.9548	6.2826
	DS-C	0.7255	4.3227	3.6057	10.0233
	DS-G	0.5658	**2.5957**	**2.3974**	**5.1975**
	DS-X	0.5932	2.7114	2.4524	5.6968

(b)

TABLE IX

STATISTICS OF THE ΔE_{2000} PREDICTION ERROR ON THE SUPERSET S AND TEST SET T OF THE DATA PRINTED ON THE COATED AND GLOSSY SUBSTRATE SELECTING THE 64 SAMPLES OF THE CHARACTERIZATION SET R USING THE SAMPLING APPROACHES CONSIDERED COUPLED WITH SOLVE

Data set	Method	ΔE_{2000} stats 5%	avg	50%	95%
Coated superset	UNIF+SOLVE	0.5877	2.3407	1.9623	5.4192
	SLI-C+SOLVE	0.4455	1.5710	1.3649	3.4241
	SLI-G+SOLVE	0.5133	1.8642	1.6084	4.1013
	MEM-C+SOLVE	0.4627	1.5664	1.4377	3.2098
	MEM-G+SOLVE	0.5355	1.9318	1.6688	4.2356
	DS-C+SOLVE	**0.4157**	**1.3695**	**1.2333**	**2.6832**
	DS-G+SOLVE	0.4551	1.7824	1.4683	4.1714
	DS-X+SOLVE	0.4380	1.6023	1.3637	3.6061
Coated test set	UNIF+SOLVE	0.6518	2.5929	2.2485	5.9488
	SLI-C+SOLVE	0.5601	1.8341	1.6027	3.8110
	SLI-G+SOLVE	0.6477	2.1020	1.8517	4.2041
	MEM-C+SOLVE	0.5985	1.8012	1.6510	3.5085
	MEM-G+SOLVE	0.6186	2.1303	1.9222	4.5158
	DS-C+SOLVE	0.5227	**1.6286**	**1.4662**	**3.2629**
	DS-G+SOLVE	**0.4753**	1.9312	1.6619	4.2359
	DS-X+SOLVE	0.4970	1.7857	1.5093	3.9266

(a)

Data set	Method	ΔE_{2000} stats 5%	avg	50%	95%
Glossy superset	UNIF+SOLVE	0.9019	3.6014	3.0507	8.1283
	SLI-C+SOLVE	0.7030	2.7172	2.2918	6.2898
	SLI-G+SOLVE	0.6702	2.6187	2.2408	5.8753
	MEM-C+SOLVE	0.8284	3.0585	2.6099	6.7691
	MEM-G+SOLVE	0.7858	2.5939	2.3924	5.2569
	DS-C+SOLVE	0.7813	2.8403	2.4501	6.2483
	DS-G+SOLVE	0.6411	**2.1118**	**1.8930**	**4.2651**
	DS-X+SOLVE	**0.6340**	2.2314	1.9668	4.7418
Glossy test set	UNIF+SOLVE	1.1519	4.0466	3.6167	8.2939
	SLI-C+SOLVE	0.6815	2.8650	2.3560	6.5680
	SLI-G+SOLVE	**0.6381**	2.7767	2.3684	6.3517
	MEM-C+SOLVE	0.9507	3.5231	3.0584	7.3550
	MEM-G+SOLVE	0.8313	2.7822	2.5824	5.5819
	DS-C+SOLVE	0.9447	3.4233	3.0224	7.2847
	DS-G+SOLVE	0.7637	**2.3271**	**2.0810**	**4.6023**
	DS-X+SOLVE	0.6406	2.3731	2.1123	5.0812

(b)

on both the training and test set are reported in Tables V and VI. In the same tables the results obtained coupling the sampling methods considered with the SOLVE are also reported.

From the results reported in Tables V, VI, and VII it is possible to notice that using the chosen open source ICC profiler, the DS sampling makes it possible to achieve the highest colorimetric accuracy on both the superset and the test set. Whatever is the sampling strategy considered, the chosen ICC profiler does not take advantage of the application of the SOLVE algorithm. This is probably due to the different interpolation scheme adopted in the profiler.

B. Multiple Substrate Optimization

In the experiments reported in the previous section we have shown that the proposed DS method is able to find the best samples to use to characterize a printer when a single substrate is considered. In this section we show how it is possible to generalize the method and to find a set of samples that is optimal for different substrates, thus preventing the need to use a different color chart for each substrate considered.

In order to deal with s multiple substrates, the fitness function becomes

$$f = \max_{sub=1 \ldots s} f_{sub} \tag{4}$$

where f_{sub} is the same as Eq. 3 applied to the current substrate.

The characterization set R is composed of 64 samples chosen according to eight different methods: uniformly sampled (UNIF), SLI selecting the best samples for coated data (SLI-C), SLI selecting the best samples for glossy data (SLI-G), MEM selecting the best samples for coated data (MEM-C), MEM selecting the best samples for glossy data (MEM-G), DS selecting the best samples for coated data (DS-C), DS selecting the best samples for glossy data (DS-G), and DS selecting the best samples optimized for the coated and glossy data simultaneously (DS-X).

The numerical values for the 5th-percentile, the average, the median and the 95th-percentile of the ΔE_{2000} prediction error are reported in Tables VIII.a and VIII.b for the coated and glossy substrate respectively. In Tables IX.a and IX.b the same error statistics are reported for the considered methods coupled with the sequential optimization of node values (SOLVE).

TABLE X
WILCOXON SIGNED-RANK TEST SCORES FOR THE DIFFERENT SAMPLING METHODS CONSIDERED

	Data Set			
Method	Coated superset	Coated test set	Glossy superset	Glossy test set
UNIF	0	0	0	0
SLI-C	5	4	2	3
SLI-G	0	2	4	4
MEM-C	3	2	1	1
MEM-G	0	1	5	4
DS-C	**7**	**6**	2	2
DS-G	4	4	**7**	**6**
DS-X	6	**6**	6	**6**

TABLE XI
WILCOXON SIGNED-RANK TEST SCORES FOR THE DIFFERENT SAMPLING METHODS CONSIDERED COUPLED WITH SOLVE

	Data Set			
Method	Coated superset	Coated test set	Glossy superset	Glossy test set
UNIF+SOLVE	0	0	0	0
SLI-C+SOLVE	5	4	4	4
SLI-G+SOLVE	2	2	4	4
MEM-C+SOLVE	3	3	1	1
MEM-G+SOLVE	1	1	3	3
DS-C+SOLVE	**7**	**6**	2	1
DS-G+SOLVE	3	3	**7**	**6**
DS-X+SOLVE	5	**6**	6	**6**

From the analysis of Tables VIII and IX it is possible to notice that the lowest prediction errors are achieved using the DS sampling approach optimized for the corresponding substrate. To understand if the differences among the sampling optimization techniques considered are statistically significant, and what is their ranking we have used the Wilcoxon Signed-Rank Test [14]. The count of the number of times that a sampling strategy has been considered statistically better than the others gives us a score, which is reported in Tables X and XI.

The analysis of the results on the supersets in Tables X and XI shows that on both the glossy and coated substrates, the proposed DS sampling optimization technique optimized for the corresponding substrate ranked 1st, reaching the statistically best performances. The DS sampling optimization technique extended to deal with multiple substrates simultaneously (i.e. DS-X) ranks 2nd, thus outperforming the uniform, the SLI and the MEM samplings optimized for a single substrate. On the test sets tied for 1st place are the DS sampling optimization technique optimized for the corresponding, single, substrate and DS sampling optimization technique extended to deal with multiple substrates simultaneously. The result of the Wilcoxon test showed that their performances are statistically equivalent and both statistically better than the uniform, the SLI and the MEM samplings optimized for a single substrate.

VI. CONCLUSION

In this work we presented a sampling optimization for printer characterization based on direct search. We tested it on the same experimental data used in [2]. The experimental results using a Matlab built-in characterization routine showed that the proposed method is able to match a given level of color accuracy on average requiring 26.32% of the samples required by the uniform sampling, 67.37% of those required by SLI [3] and 75.94% of those required by MEM [2]. The number of samples required to achieve a given level of color accuracy can be further reduced if the sampling methods considered are coupled with a sequential optimization of node values (SOLVE [7]). In this case, it is possible to match a given level of color accuracy on average requiring 32.26% of samples required by the uniform sampling, 83.32% of those required by SLI [3] and 86.98% of those required by MEM [2]. The experimental results using an open source ICC profiler confirm the feasibility of the proposed method, and put in evidence that whatever is the sampling algorithm adopted, the ICC profiler is unable to take advantage of the SOLVE post-processing. We extended the proposed DS sampling optimization in order to simultaneously select the best characterization samples for two different substrates (DS-X): coated and glossy. The experimental results showed that the proposed DS-X approach was able to give a statistically better colorimetric accuracy (at the $\alpha = 0.05$ significance level) than state-of-the-art algorithms optimized for each individual substrate, thus permitting to use a single set of characterization samples for multiple substrates.

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