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Qualitative Case Study Methodology: Automatic Design and Correction of Ceramic Colors

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***Abstract*—This paper is focused on two major problems within the ceramics industry. The reproduction of a desired color from pigments (which is time-intensive), and the correction of colors on the production line (which is costly) are processes which still rely heavily on numerous experiments carried out by human operators. This study presents the key aspects of these two processes and suggests some mathematical and computer sciences tools, aimed at automatizing the current procedures. Data was provided by an industrial partner, where the proposed models and solutions will be tested and validated.**

2010 *Mathematics Subject Classification:* Primary $05A16$, Secondary $05A15, 05A18, 11B75$.

Keywords and phrases: Color prediction; Case study; Automation; Simulation; Ceramic color; Ceramic pigment.

I. Introduction

The design and correction of standardized colors for ceramics is still largely based on highly skilled human operators. As such, "Although much is now known about the materials and their structures, there are so many variables and the structures so complex, that the empirical approach still largely dominates pot making" [Bre12]. An automatic decision on the pigments (and concentrations) involved would represent a significant advancement for the ceramics industry. This can be made using a variety of techniques including multi-dimensional interpolation, statistical analysis and machine learning.

This study aims to automatize the reproduction of a desired color from pigments (which is time-intensive), and the correction of colors on the production line (which is costly). We use a case study from industrial partner which is an important industrial player in the ceramics industry in Romania. The company has more than 50 preparation mills, two powder atomizers, 20 isostatic presses, 10 ceramic ovens, 30 glazing machines and more than 150 intelligent robots. At present, the company does not have an automated system that could help in the design and correction of ceramic colors. The desired colors are obtained through successive try-and-error experiments.

A. Industrial process

The industrial process for ceramics consists of the following steps: first, the porcelain clay mixture (kaolin, feldspar and quartz) are mixed together, then atomized as a fine powder; then, powder is pressed into a mold and fired at 900 degrees Celsius, producing the "biscuit"; this is dipped into a glaze (matte or glossy, containing various concentrations of pigments) and is finally fired in the oven for six hours at 1200 degrees Celsius.

This case study focuses on glaze recipes which can produce ceramics matching a desired color, and also on the correction steps involved in fine tuning the ceramic color recipes used on the production line.

B. Reproduction of a desired ceramic color from a given list of pigments

The process can often be extremely laborious and especially time-intensive. The preparation time for each laboratory sample is one hour, while the oven time is six hours at 1200C. The precise recipe for one of the Beige colors combines the following pigments: Yellow (Pr- Praseodium) , Blue (Vn - Vanadium) , Coral (Fe-Ferrum) . The development of this color took more than 300 experiments spanning over six months. Colors generally require a mix of 2-5 pigments, with concentrations between 0.01-10%. In certain cases, laborants have to test empirically concentrations with a resolution of 0.005%. Currently, six new colors are being developed (three from Pantone codes, three from shards).

To develop a color reproduction model one would first have to consider basic elements of color theory (Pantone catalogues, color spaces, colormeter), the huge size of the pigment/concentration space, as well as the variability of pigment properties (dL, dA, dB).

C. Color correction procedure on the production line

When the standard recipe for producing a desired color is known, various corrections on the production line are still often necessary, due to a wide range of factors.

For example, in a ceramics company with 30 mills installed, production data provided showed that only 5 out of 42 mill runs did not require corrections over the period 1.04-2.04.2016, with 16 mills being used. OVer a longer period, corrections were applied to 527 out of 728 mill runs (81%).

This procedure, based on intuitive approaches is widespread in many companies. As is extremely well pointed out in [CFM10] this procedure "is based on intuitive approaches involving the knowledge about the behaviour of pigments in glazes available in the company. Pigments and the type of glaze (opaque or transparent glazes) are chosen to match the required colour (called the standard colour) according to the experience of the technician."

II. Methodology

We here present some key methods and processes.

A. Color space

The CIE (Commission Internationle de l'Eclairage) Lab colour space characterises a human perceivable colour by

- Lightness (L)
- Green-Red (a)
- Blue-Yellow measure (b)

The use of parameters a and b are based on Hering's opponent process theory. Compared to the trichromatic theory, the Lab system is able to factor in the physiology of human visual perception. The CIE-Lab space can be converted to other colour spaces such as the CIE-XYZ space (Figure 1). A key feature of the CIE-Lab space is perceptual uniformity.

The colour difference in the CIE-Lab space can be calculated by various standards, (e.g., CIE 1976 - Euclidean distance) [LCR01]. It is a useful way to quantify the perceptual disparity between reproduced colour and its corresponding reference colour. The process of correcting of this disparity is known as colour calibration, which is ubiquitous in digital colour reproduction devices such as printers and monitors. In this project we will first approximate the gamut of colours produced in the lab by reconstructing the colour space from existing experiment logs. The gamut of reproduced colours will be mapped onto a CIE space.

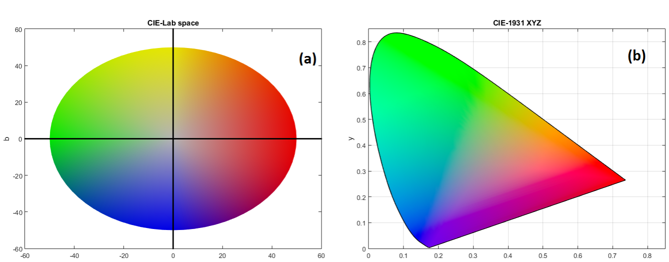

Fig. 1. Color spaces: (a) Lab color space; (b) CIE-1931 XYZ.

B. Theoretical models for mixed pigment glazes

To the best of our knowledge there are two theoretical methods in the literature dealing with the physics and chemistry involved in producing ceramics with glazes which match a given color, obtained by mixing one or more pigments.

First one, Kubelka-Munk method is used to predict the colour of a glaze containing more than one pigment. The Kubelka-Munk equation gives the light absorption

$$\frac{K}{S} = \frac{(1-R)^2}{2R} = f(R) \tag{1}$$

as a function of R (fractional reflectance) and K (absorption coefficient), where S is the scattering coefficient at each wavelength of light in the visible region.

In a mixture M, the additivity of the individual contributions of absorption and is given by the formula

$$f(R) = \left(\frac{K}{S}\right)_M = \frac{c_1K_1 + c_2K_2 + \cdots + c_nK_n}{c_1S_1 + c_2S_2 + \cdots + c_nK_n}, \tag{2}$$

caused by a mixture of n pigments; c_i are the concentrations of the pigments added to the formulation; K_i and S_i are, respectively, the absorption and scattering coefficients and R is the reflectance measured by a spectrophotometer. The values of K_i and S_i can be determined by experiments, hence the absorption coefficient K can be found as a function of the pigment volume concentration.

While very attractive for the purpose of our model, this method (also used in textile and paint industries) requires a spectrophotometer, not normally available in companies. For more detailed information on this method we can refer to [ADA08], [BMR06], [MRCB15], [SBF$^+$09], [SBF11]

The second approach is Taguchi$'$s method, which uses statistical concepts as ANOVA tests. This method is a robust engineering and has found applications in many areas. Also, an advantage of this method is the fact that this method only needs colorimeter, as opposed to a spectrophotometer in the previous case. For a detailed discussion of this topic we refer the reader to [CFM10] and the references therein.

C. Pigments and experiments

The pigments in use at the industrial partner are Yellow 001, Turquoise 002, Turquoise 003, Cobalt 004, Coral 005, Coral 006, Black 007, Pink 008, Blue 009, Black 010, Coral 011. Ceramic colors require a mix of 2-5 pigments, with concentrations between 0.01-10% and are assessed by three parameters (L, a, b), measured with a colormeter. Reproducing a color may take months, and as of June 2016 six new colors were being developed at the company.

Preliminary analysis suggests that L decreases by adding pigments (glaze darkens), while the dependence of L, a, b on pigment concentrations is nonlinear. The model will have to consider various paramaters such as different types of glaze (matte, glossy), and variable pigment properties.

III. Numerical experiments and results

A. Color reproduction

The following steps are currently used in reproducing a desired color:

1) Samples received from clients (color given by Pantone Code or measured by L, a, b values)
2) The pigments expected to produce the color are selected (from a list of 11 pigments)
3) Pigments' L, a, b values measured; Pigments mixed in varying proportions in laboratory;
4) Resulting colors are checked by measuring DL, Da, Db against the received sample
5) Various pigment proportions are checked until the tolerance prescribed by client is achieved
6) Color samples are sent to the client for approval
7) Once the color is approved, industrial tests commence

After the project implementation, the pigments and their concentration (steps 2 and 5) will be suggested automatically by the computer, significantly reducing the time required for developing new color recipes.

Mathematically, this can be seen as an inverse problem. Let $n \geq 1$ be the number of pigments available and the function $f : \mathbb{R}_+^n \to \mathbb{R}^3$, which for the given pigment concentrations $c = (c_1, \ldots, c_n)$ returns the corresponding L, a, b values, i.e.,

$$f(c) = (f_1(c), f_2(c), f_3(c)) = (L, a, b).$$

For given L^0, a^0, b^0, one has to identify pigment concentrations $c^0 = (c_1^0, \ldots, c_n^0)$ such that $f(c^0) = (L^0, a^0, b^0)$.

In practice, this is not feasible, as the problem has many variable parameters such as the L, a, b values of each pigment batch, oven and environmental temperatures, or non-homogeneity of the other ceramic ingredients.

Coming sufficiently close to the L^0, a^0, b^0 is often enough. A mixture $c^* = (c_1^*, \ldots, c_n^*)$ of pigments is accepted if the signed errors between $f(c^*) = (L^*, a^*, b^*)$ and the target color $f(c^0) = (L^0, a^0, b^0)$ defined as

$$DL = L^* - L^0, \quad Da = a^* - a^0, \quad Db = b^* - b^0,$$

fall withing certain values, specific for every desired color. An extra requirement is for the colors to be close in the Euclidean tri-dimensional space, hence the function

$$\Delta E = \sqrt{(DL)^2 + (Da)^2 + (Db)^2}$$

to be bounded by a prescribed value.

For example, when producing the Pantone Grey (Vardagen) color defined by $L = 31.3$, $a = 0.95$ and $b = 0.60$, a mix of pigments is accepted if the differences satisfy

$$-1.2 \leq DL \leq 1.2, -0.5 \leq Da \leq 0.5, -0.5 \leq Da \leq 0.5.$$

Also, as an industry standard, one requires $\Delta E \leq 1.5$.

Below we present some numerical and experimental data for the color development tests performed in the effort to obtain a gray color. First a scatter plot of the L, a, b values is shown in Figure 2, which illustrates the drastic changes produces by small variations in the pigment concentration.

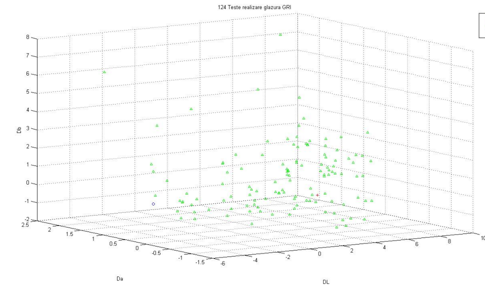

Fig. 2. Experimental data: Tests for gray glaze (L, a, b values for 124 tests).

The results for DL are shown in Figure 3. Few values fall between the maximum and minimum accepted values hence DL can be difficult to control. Interestingly, most of the values of Da displayed in Figure 4 fall in the right region.

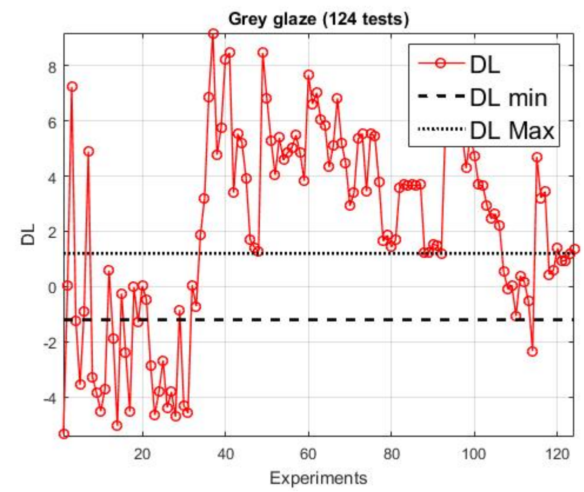

Fig. 3. Experimental data: Tests for gray glaze (DL).

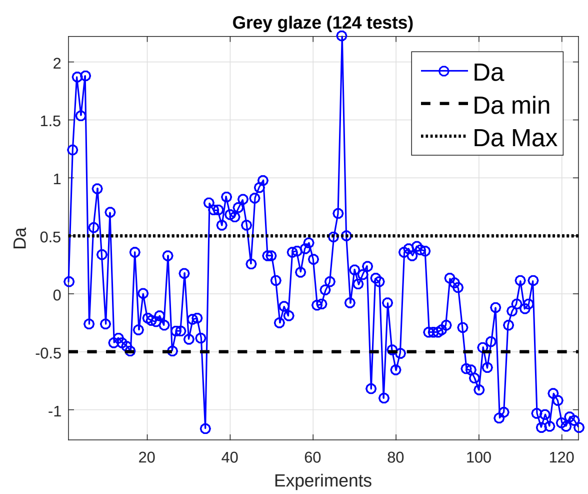

Fig. 4. Experimental data: Tests for gray glaze (Da).

The results for Db are plotted in Figure 5, and suggest that around 50% of experiments fall in the acceptable. However, when the three individual errors are matched to the ΔE values displayed in Figure 6, it turns out that only 10 out of the 124 performed experiments (or about 8%) were successful. Practically, this has significant impact as each individual experiment requires about 6 hours only in the oven, beyond planning and preparing the materials.

Each such experiment produces in fact a new recipe, valid under the given conditions (often unique) of the experiment.

Our aim is to collect experimental data more effectively and use some of the available models to more accurately predict the pigment combination giving a certain L, a, b value. We predict that computer science tools such as machine learning could be useful in predicting color recipes using historical data.

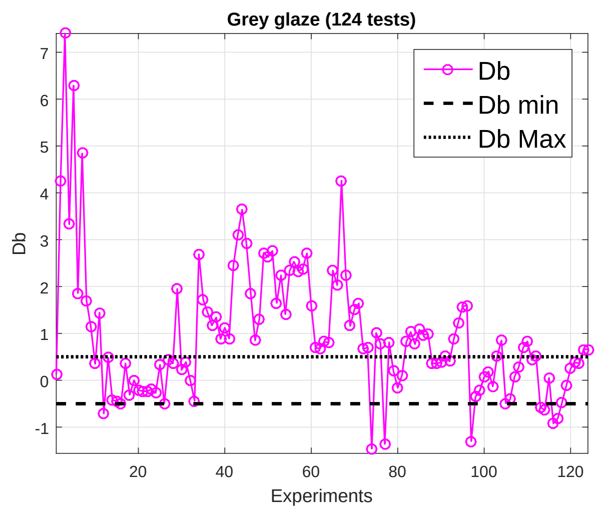

Fig. 5. Experimental data: Tests for gray glaze (Db).

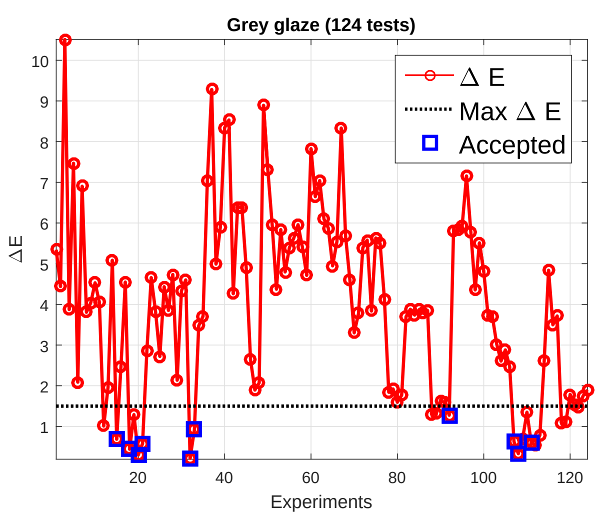

Fig. 6. Experimental data: Tests for gray glaze (Δ E).

B. Color correction

The basic principles of color correction are very similar to the color reproduction process. The main difference is that this process has a much higher frequency, hence it has a much higher economic impact.

The mill corrections showed in Figure 7 illustrate the steps undertaken to produce the Gray color by using the two pigments. While the recipe was available, the process spanned over two days, in which time the production line had to wait.

Date	DL	Da	Db	Corrections
26,04,16	2.05	-0.89	0.04	4 kg negru 10, 2 Kg coral 005
27,04,16	0.34	-0.52	0.16	2 kg coral 005
26,04,16	10.63	-2.64	-2.05	3 kg negru 10, 2 kg coral 005
27,04,16	0.31	-0.54	-0.01	2 kg coral 005
28,04,16	1.09	-0.49	0.06	2 kg coral 005
28,04,16	0.22	-0.43	0.14	ok

Fig. 7. Mill corrections L, a, b deviations.

This correction process can be easily adapted for use with other color recipes.

IV. Future work

Numerical evidence suggests a number of future paths to be explored.

One important direction to investigate is the use of data mining and machine learning techniques to solve the problem of automatic design and correction of ceramic colors. In particular, we plan to further investigate deep learning techniques.

Deep learning [Hin06], [LY15] is a composite model of neural networks which has been shown recently to be very successful in classifying images, audio, and speech data. Deep learning is rapidly advancing many areas of science and technology with multiple success stories in image, text, voice and video recognition, robotics, and autonomous driving.

A convolutional neural network (CNN) is capable of composing features of increasing complexity in each of its successive layers. The deep neural network is formed by an input layer which communicates with one or more hidden layers, which in turn are connected to the output layer. These multiple layers allow CNN to represent non-linear functions. In this way, CNN are much more efficient than shallow networks on more complex problems.

For images, nearby pixels are more correlated than distant pixels, and this property is being exploited by extracting local features which depend on small sub-regions of the image. Furthermore, these local features are being used to detect higher-order features ending with features for the whole image. It is also probable that a local feature which is useful in one region of the image is also useful in other regions. An illustration of the deep learning framework used is shown in Figure 8.

V. Acknowledgments

The statistical analysis of data and the numerical simulations utilised specialist mathematical software including Matlab/R,

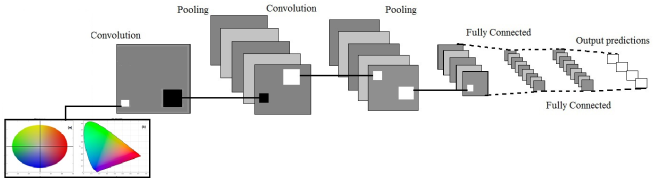

Fig. 8. Convolutional and a subsampling layer in a CNN.

as well as computer hardware. This was available through the Simulation and Control Lab of the Research Center for Electronic Systems and Intelligent Control, supported by the ERRIS platform https://erris.gov.ro/RC-for-ESIC. We would like to thank the anonymous referees for their helpful comments which improved the quality of the paper. This work was supported by a grant of the Romanian National Authority for Scientific Research and Innovation, CNCS/CCCDI UEFISCDI, project number PN-III-P2-2.1-BG-2016-0333, within PNCDI III.

REFERENCES

[ADA08] I.S. Ahmed, H.A. Dessouki, and A.A. Ali, *Synthesis and characterization of new nano-particles as blue ceramic pigment*, Spectrochimica Acta Part A: Molecular and Biomolecular Spectroscopy **71** (2008), no. 2, 616–620.

[BMR06] Federica Bondioli, Tiziano Manfredini, and Marcello Romagnoli, *Color matching algorithms in ceramic tile production*, Journal of the European Ceramic Society **26** (2006), no. 3, 311–316.

[Bre12] Stephen Breuer, *The chemistry of pottery*, EiC (2012), no. 7, 17–20.

[CFM10] A.O. Castela, A.T. Fonseca, and P.Q. Mantas, *Development of coloured glazes for tile applications using taguchi's method*, Journal of the European Ceramic Society **30** (2010), no. 12, 2451–2455.

[Hin06] Osindero S. Teh Y.W. Hinton, G.E., *A fast learning algorithm for deep belief nets*, Neural computation **18** (2006), no. 7.

[LCR01] M. R. Luo, G. Cui, and B. Rigg, *The development of the CIE 2000 colour-difference formula: CIEDE2000*, Color Research & Application **26** (2001), no. 5, 340–350.

[LY15] Hinton GE LeCun Y, Bengio Y, *Deep learning*, Nature **521** (2015), 436–444.

[MRCB15] Edgar Andrs Chavarriaga Miranda, Nelson Alonso Correa Rojas, Juan Fernando Montoya Carvajal, and Oscar Jaime Restrepo Baena, *Color prediction in ceramic enamels using the kubelka-munk model*, TECCIENCIA **7** (2015), no. 19, 1–5.

[SBF+09] L.M. Schabbach, F. Bondioli, A.M. Ferrari, C.O. Petter, and M.C. Fredel, *Colour in ceramic glazes: Efficiency of the kubelka-munk model in glazes with a black pigment and opacifier*, Journal of the European Ceramic Society **29** (2009), no. 13, 2685–2690.

[SBF11] L.M. Schabbach, F. Bondioli, and M.C. Fredel, *Colouring of opaque ceramic glaze with zircon pigments: Formulation with simplified kubelka-munk model*, Journal of the European Ceramic Society **31** (2011), no. 5, 659–664.