Reducing the Number of Measuring Points of the LED-Based Colorimetric Probe

Milos Arbanas

University of Novi Sad Faculty of Technical Sciences

Branislav Batinic

University of Novi Sad Faculty of Technical Sciences

Jovan Bajic

University of Novi Sad Faculty of Technical Sciences

Marko Vasiljevic-Toskic

University of Novi Sad Faculty of Technical Sciences

Miodrag Brkic (✉ brkic.miodrag@uns.ac.rs)

University of Novi Sad Faculty of Technical Sciences <https://orcid.org/0000-0003-2740-450X>

Vladimir Rajs

University of Novi Sad Faculty of Technical Sciences

Research Article

Keywords: Artificial neural network (ANN), color sensing, spectrum estimation, dataset creation

Posted Date: November 30th, 2021

DOI: <https://doi.org/10.21203/rs.3.rs-1083191/v1>

License: © ⓘ This work is licensed under a Creative Commons Attribution 4.0 International License.

[Read Full License](#)

Reducing the number of measuring points of the LED-based colorimetric probe

Milos Arbanas¹, Branislav Batinic¹, Jovan Bajic¹, Marko Vasiljevic-Toskic¹, Miodrag Brkic^{1*} and Vladimir Rajs¹

^{1*}Department of Power, Electronics and Telecommunication Engineering, Faculty of Technical Sciences, Trg Dositeja Obradovica 6, Novi Sad, 21000, Serbia, Serbia.

*Corresponding author(s). E-mail(s): brkic.miodrag@uns.ac.rs;
Contributing authors: milos.arbanas@uns.ac.rs;
banebb@uns.ac.rs; bajic@uns.ac.rs; markovt@uns.ac.rs;
vladimir@uns.ac.rs;

Abstract

In this paper, reducing the number of necessary measuring points for estimating a reflected electromagnetic spectrum of a printed color patch is presented. In our previous work, a machine learning-based method was proven to be superior to Cubic Hermite interpolation in estimating spectrum based on six measured values. Now, the new hypothesis is that the number of measuring points could be decreased without the significant loss of the spectrum estimation. The ECI2002 test chart was used to create the dataset, which was further divided into training and test subset. For all the colors on the test chart, the measurements were performed on printed patches with the device proposed in our previous work, as well as with the commercial spectrophotometer X-Rite i1 Publish Pro2, which were then used as the ground truth, or reference values. The Artificial Neural Networks were trained to estimate spectrums based on measurements acquired with our device. The results proved satisfactory even when the number of measuring points is reduced from six to three.

Keywords: Artificial neural network (ANN), color sensing, spectrum estimation, dataset creation

1 Introduction

As the world of IoT, and sensor-data gathering is becoming more widespread, reducing the cost of each sensor system is becoming an important factor. In our previous work ([Batinic et al, 2021](#)) the novel way of estimating the reflected spectrum of a printed sample was presented. The good quality of the estimated reflected spectrum was achieved. One of the drawbacks of the device presented in the previous paper is that, while several of the light-emitting diodes (LEDs) are widely available (red, green, and blue), other are not that easy to acquire, like the one with a dominant wavelength at 572 nm. In this paper, we are focusing on reducing the number of needed diodes to only red, green, and blue LEDs, while still maintaining good results.

The paper by ([O'Farrell et al, 2006](#)) describes the practical usage of the expensive Ocean Optics S2000 spectrometer. In the large-scale industry of food production, the reflected spectrums of the food could be monitored online, and cooking could be fine-tuned. It is one example of a demand for such a device that could be easily produced and at a low cost, while still providing good quality estimations of the color spectrum.

The ([Yang et al, 2007](#)) proposes the method of using the RGB diodes and then multipoint calibration. Using the professional spectrophotometer PR650 by Photo Research Inc, the estimations were improved significantly after calibration. The method by [Saracoglu and Altural \(2010\)](#) is similar but uses the ANN instead of multipoint calibration. However, both of the solutions do not measure spectrums, but rather CIE XYZ tristimulus values. Our solution estimates the whole visible spectrum for the printed color patches.

A similar problem of reducing the number of measuring points, while maintaining good results, is presented in a paper by ([Ciosek et al, 2004](#)). The sensor array was used to classify the brands of water and juice. The initial network used a 17-sensor array, and the authors tried to reduce the number of sensors. In the end, they concluded that it was possible to get satisfactory results with only 9 sensors. In the ([Winqvist et al, 1993](#)), the authors tried to reduce the number of sensors of an electronic nose. The results were partially good, the prediction of a type of meat stayed on the same level, but the estimation of storage time significantly worsened. It was apparent that some sensors are more important than others in case of estimation of storage time. Some important ones for that functionality were removed. The sensors that are removed should be carefully picked because not all of the sensors carry the same amount of information.

The Artificial Neural Networks (ANNs) are great approximators of non-linear functions, and there is a possibility that some of the measured values are less important, so the ANN would be able to estimate spectrum without them. The goal is to try to make a device that will be able to estimate the whole spectrum in the visible range using the fewest measuring points.

The CIEDE2000 metric is going to be used to measure the quality of the estimated spectrums, as it has a strong agreement with human perception of the colors ([Ortiz Jaramillo et al, 2016](#)).

2 Methodology

The measurements of the color patches are acquired by driving one LED of a certain frequency for a short amount of time and measuring the reflected amount of the light using a broadband detector. There are a total of six measuring points, using LEDs of different wavelengths, as shown in Fig. 1. The diodes are at 400 nm, 457 nm, 517 nm, 572 nm, 632 nm, and 700 nm.

The reference values for training and testing are provided by spectrum measures provided by commercial spectrophotometer X-Rite i1 Publish Pro2, which gives the resulted spectrum in equidistant 36 points. The idea is to use a subset of measured values and train an Artificial neural network (ANN) to estimate a spectrum based on our measurements, the goal is to determine how much the reduction of the number of input values affects the estimated spectrum.

Fig. 1 Spectral distributions of the LEDs used for measurement [Batinic et al \(2020\)](#)

Proposed combinations, besides using all of the measuring points: **1.** Five measuring points, without the diode on 400 nm **2.** Four measuring points, without the diodes on 400 and 700 nm **3.** Three measuring points acquired by using RGB diodes. For each combination, the ANN would be trained to estimate spectrum using specific measured values for inputs and ground truth from a commercial spectrophotometer as output. The quality of the neural network output spectrum would be estimated using ΔE_{00} (CIE2000) metric.

2.1 Creating the dataset

2.1.1 Analysis of the dataset values

To show the complexity of the problem, and the challenge of approximating the function for spectrum estimation based on measured points, a few representative examples from the dataset will be analyzed. In Fig. 2, the input values (measurement points) are presented with dots, while the reference spectrum is presented with dashed lines.

From Fig. 2 it can be observed that, for saturated colors, measured values follow the spectrum closely. For the dark colors, on the other hand, there are some discrepancies. The main reason for that is that the intensity of reflected light for dark colors is low, so the measurement errors are more pronounced. The most notable difference is with the first measurement point (400 nm) when the colors are darker, the first diode does not carry almost any information.

For each of the printed color patches, the measurement is done manually with both EyeOne Pro and our device. Each measurement is susceptible to the imperfect placing of instruments or similar human error, finite sensitivity of sensing element, and errors due to quantization. Also, for the colors close to white, there are some small discrepancies that could lower the approximation quality. However, if the discrepancy is consistent, the Artificial neural network should be able to compensate for it.

Fig. 2 Examples of dataset samples. Dots represent six input measurement points, while dashed lines represent referent spectrum. Color patches and rows and columns on the ECI2002 chart are included for each color.

The importance of the each measuring points is also taken into consideration. Some of the diodes carry more information than others. From the graphs in Fig. 2 it is quite obvious that the last measurement point (700 nm) could be less important than the fourth (572 nm) measuring point.

2.1.2 Dividing the dataset

The ECI2002 chart, provided in Fig. 3 is divided into several groups. For example, the first group, which covers rows 1-27 and columns 1-27, contains only combinations of CMY colors, without any black. Then there are groups that add a certain amount of black and make patches in that group darker. The group that covers rows 1-8 and columns 38-45 is printed with 80% black and different CMY combinations, while the group rows 9-28, columns 42-45 show different saturation of pure CMYK colors.

Fig. 3 Test chart ECI2002 with marked color patches. The patches that are marked with dotted frames are the test samples. Ones that are marked with red X are considered measurement errors. The rest of the samples are used for training of the ANN.

In order to test the trained network properly, the test patches should cover all of the distinct groups equally. On the other hand, there should be enough data for the ANN to learn properly. Therefore, the process of test sample selection was carefully conducted with the intention of having around 20% of the samples for the testing purposes and the 80% to be used in the training process.

Some of the values (marked with red X in Fig. 3) are considered to be measurement errors. Upon finishing the training for the first time, with the whole dataset, some samples had extremely high ΔE_{00} values. When comparing measured points and the spectrum of each of these samples it was evident that some of the measured values are significantly different than the measured values for similar colors/spectrums. Most probable, the probe was not placed ideally and that introduced the random error. The ANN can not compensate for those errors, and they introduce significant problems for the training of the network. Around 1.5% of the colors are removed completely. After removing measurement error samples, there is a total number of 1463 samples left in the dataset. The number of test samples is 277 or around 19%, while the rest (1186) is used for training purposes.

2.2 Choosing model and training of the Artificial Neural Network

The essence of this paper is to approximate the 4 functions using machine-learning techniques. The input of those functions is a combination of the amount of reflected light measurements on certain wavelengths (6, 5, 4, or 3 measurement points), and the output is the spectrum estimation in 36 equidistant wavelengths in the visible spectrum range. The simple Multilayer

Perceptron (MLP) (Haykin, 1999) is used to approximate the needed functions. The MLP was trained on the training data, and the quality of estimated spectrums was calculated using ΔE_{00} metrics on the test data, which is not used during training.

The size of the MLP greatly influences the quality of the estimated spectrums, but also the time that is needed to train such a network. The larger the network, the faster MLP converges, but there is a possibility that the network would overfit (Haugen and Kvaal, 1998). If the network is smaller, it learns at a slower pace, needs more time to converge, but the overfitting of the network is less likely to happen.

The training of the MLPs of the different sizes provided insight into the optimal number of layers and their sizes. The model of the Fully Connected Neural Network that has an input layer of 3-6 input floating-point values, a hidden layer of 72 neurons, and an output layer of 36 floating-point numbers, turned out to be the optimal configuration. If the additional layer is added, the loss function would drop significantly and rapidly during the training, but the estimated spectrums on the test data would, after initial improvement, begin to significantly worsen, and the best results are not as good as with the smaller network, as the neural network with more neurons overfits. The network with one hidden layer of 72 neurons converges to good results, but at a slower pace than the larger network, and oscillates upon further training around it, showing no signs of overfitting. The MLP smaller than 72 neurons in one hidden layer could not provide satisfactory results. The activation function that provided the best result is the Sigmoidal activation function. All of the input and output values are in the range 0-1, so the sigmoidal nonlinear characteristics provide a good foundation for the approximation of needed nonlinear functions. The framework used for all of the training and testing was Tensorflow. The training of the neural network was handled by using the Nadam optimizer where the learning rate was gradually lowered after a certain number of training epochs. The larger learning rate at the start provides faster convergence times, and the lowering of the learning rate, while the function approaches minima, ensures better results. After a series of experiments the learning rates that were used are as follows: the initial learning rate is set to 0.03, after some time the learning rate is set to 0.01 (the default value of learning rate in Tensorflow/Keras), and lastly, the learning rate is set to 0.005, at which point, after a small amount of time, the results are slowly oscillating around results provided in this paper, there are no significant improvements, even though the loss function is getting smaller. The further tries to reduce the learning rate did not provide any significant improvement in the results.

All of the training configurations were trained several times, in order to avoid getting stuck in local minima, and the results were mostly similar, with minor differences in results. For each configuration, the best results were presented in this paper.

3 Results and discussion

In this chapter, the results of calculating ΔE_{00} of estimated spectrums for over 277 test samples will be presented in several different ways in order to show how reducing the number of measurement points affects the quality of spectrum estimations. From Table 1 it is evident that the greatest change is with the maximal value of ΔE_{00} , while the mean, median and minimal values are not affected significantly.

Table 1 ΔE_{00} for different number of measurement points (whole test set)

ΔE_{00}	Mean	Median	Maximum	Minimum
6 diodes	1.15	0.96	3.11	0.08
5 diodes	1.13	0.99	3.44	0.15
4 diodes	1.21	1.03	3.62	0.07
3 diodes	1.23	1.01	4.25	0.1

Fig. 4 Histograms of ΔE_{00} for the whole test set (277 values) and different number of measurement points

The nature of the change is most apparent in histograms that are presented in Fig. 4. and the ΔE_{00} maps for 3 and 6 diodes in Fig. 5. The number of samples with $\Delta E_{00} > 3$ rises as the number of measuring points is reduced. If observed closely, in Fig. 5, it is evident that the majority of the colors that have $\Delta E_{00} > 3$ are dark colors. It can be seen that for the median and mean values, the number of measurement points is not of great importance. Therefore, for most test samples in the test set, the reduction of the number of measuring points is not detrimental. Some of the test samples are actually better with fewer measurement points.

Finally, a few examples of the estimated spectrums are going to be analyzed in more detail. In Fig. 6 the measurement points are presented with small triangles. Each of the combinations of diodes is distinguished by color. For

Fig. 5 Comparing the map of ΔE_{00} for 6 and 3 diodes. This graph corresponds to the test samples from Fig. 3. The gray squares are the training samples from the dataset, and are not being used for testing purpose. The color of the other squares corresponds to ΔE_{00} value for each sample. Gradient from 0 ΔE_{00} (green) to 5 ΔE_{00} (red)

example, the Red triangles represent measurements for the 3 diodes, and the Red dashed line presents the estimated spectrum. The gray line is a referent spectrum. The most common is that the value of ΔE_{00} stays around 1. In Fig. 6 graph 1, that particular case is shown.

Fig. 6 Comparing resulting spectrum estimations for different number of diodes

In Fig. 6 graph 2, the drastic worsening of the estimated spectrum is apparent when the number of measurement points is lowered from 6 to 3. The most interesting and unexpected case is shown in Fig. 6 graph 3. For the particular blue color, the estimation is better with fewer measurement points. The explanation for this could be that the measurements with the diode on 400 nm are not that reliable, so it introduces non-systematic error. The last graph in Fig. 6 shows estimated spectra of all of the combinations. The color is black, so

the measuring errors are becoming more important, which needs to be taken into consideration. The quality of all of the spectrums is comparable, and the number of measurement points does not influence the ΔE_{00} significantly.

4 Conclusion

In electrophotography and ink-jet printing, the reproduction accuracy is considered satisfactory if the color difference of 5 ΔE_{00} is not exceeded (IDE-Alliance, 2017 [Online]). In graphic industry and offset-printing, tolerances for satisfactory color reproduction are 3.5 ΔE_{00} for Cyan, Magenta, Yellow, and 5 ΔE_{00} for black (ISO 12647-2: 2013). With that in mind, this paper confirms that even with only 3 measuring points, the results are satisfactory. The main advantage over other colorimeters that use RGB diodes is that our device can estimate the whole visible spectrum, while similar devices can estimate only XYZ tristimulus values.

The greatest challenge proved to be the estimation of the spectrum of the darker colors. The measurement errors are also more prominent for smaller reflection values. As the number of measurement points decreases, it is harder to compensate for those errors, and we get significantly worse ΔE_{00} for dark colors. For the light and saturated CMYK colors, there is almost no difference if the spectrum is estimated using 3 measurement points or all 6. All of the spectrums are around 1 ΔE_{00} . There is always the possibility that the more balanced dataset would improve the results of the dark color estimations. Another technique that could be utilized is Principal component analysis (Jolliffe and Cadima, 2016) on the input values of the dataset. A more analytic approach could provide a better understanding of what measuring points to remove, and possibly provide even better results.

Acknowledgement

This research was financially supported by the Ministry of Education, Science and Technological Development of the Republic of Serbia (Grant No. 451039/202114/200156)

References

- Batinic B, Bajic J, Dedijer S, et al (2020) Colorimetric fiber-optic sensor based on reflectance spectrum estimation for determining color of printed samples. *Optical and Quantum Electronics* 52. <https://doi.org/10.1007/s11082-020-02458-7>
- Batinic BD, Arbanas MS, Bajic JS, et al (2021) Using machine learning for improvement of reflected spectrum estimations of colorimetric probe. *IEEE Transactions on Instrumentation and Measurement* 70:1–7. <https://doi.org/10.1109/TIM.2020.3011763>

- Ciosek P, Brzzka Z, Wrblewski W (2004) Classification of beverages using a reduced sensor array. *Sensors and Actuators B: Chemical* 103(1):76–83. <https://doi.org/https://doi.org/10.1016/j.snb.2004.04.038>, URL <https://www.sciencedirect.com/science/article/pii/S0925400504002151>, the 17th European Conference on Solid-State Transducers, University of Minho, Guimares, Portugal, September 21–24, 2003
- Haugen JE, Kvaal K (1998) Electronic nose and artificial neural network. *Meat Science* 49:S273–S286. [https://doi.org/https://doi.org/10.1016/S0309-1740\(98\)90054-7](https://doi.org/https://doi.org/10.1016/S0309-1740(98)90054-7), URL <https://www.sciencedirect.com/science/article/pii/S0309174098900547>, meat Consumption and Culture 44th International Congress of Meat Science and Technology
- Haykin SS (1999) *Neural networks : a comprehensive foundation*. In: *Neural networks : a comprehensive foundation*. Upper Saddle River: Prentice Hall
- IDEAlliance (2017 [Online]) Digital Press Certification Program Version 2.3.6. URL <http://connect.idealliance.org/HigherLogic/System/DownloadDocumentFile.ashx?DocumentFileKey=ef430ae7-2fcc-cd3a-2ff3-eab28265eaal>
- Jolliffe I, Cadima J (2016) Principal component analysis: A review and recent developments. *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences* 374:20150,202. <https://doi.org/10.1098/rsta.2015.0202>
- O’Farrell M, Lewis E, Flanagan C, et al (2006) Design of a system that uses optical-fiber sensors and neural networks to control a large-scale industrial oven by monitoring the food quality online. *Sensors Journal, IEEE* 5:1407 – 1420. <https://doi.org/10.1109/JSEN.2005.858963>
- Ortiz Jaramillo B, Kumcu A, Philips W (2016) Evaluating color difference measures in images. In: *Evaluating color difference measures in images*, pp 1–6, <https://doi.org/10.1109/QoMEX.2016.7498922>
- Saracoglu G, Altural H (2010) Color regeneration from reflective color sensor using an artificial intelligent technique. *Sensors* 10(9):8363–8374. <https://doi.org/10.3390/s100908363>, URL <https://www.mdpi.com/1424-8220/10/9/8363>
- Winqvist F, Hörnsten EG, Sundgren H, et al (1993) Performance of an electronic nose for quality estimation of ground meat. *Measurement Science and Technology* 4:1493–1500
- Yang PK, Chen JC, H. CY (2007) Improvement on reflective color measurement using a tri-color led by multi-point calibration. *Optics Communications* 272:320–324. <https://doi.org/10.1016/j.optcom.2006.11.051>

Statements and Declarations

Funding: This work was supported by the Ministry of Education, Science and Technological Development of the Republic of Serbia (Grant No. 451039/202114/200156); **Authorship principles:** All authors made substantial contributions to the conception or design of the work; **Data Availability:** The datasets generated during and/or analysed during the current study are available from the corresponding author on reasonable request.; **Competing Interests:** The authors have no relevant financial or non-financial interests to disclose.