

# APPLICATION OF JENCOLOR MULTISPECTRAL SENSORS IN DERMATOLOGY

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**Abstract** – The fields of dermatological research, development and applications are seeing an increasing demand for colorimetric skin analysis. The results from these measurements can be used both for assessing skin diseases as well as evaluating the success of treatments. If nothing else, the method can be exploited for numerous cosmetic applications which require  $\Delta E$  (CIE1976) accuracies better than 0.5.

The current theoretical limit achievable using analytical technique is determined using spectroscopic methods which evaluate in small increments (e.g. 1 nm, 5 nm, ...) the total passively scattered spectral distribution from the target being scanned by the measuring device. Using mathematical algorithms, the spectral distribution values are then converted to color values or other results such as the concentration of material parts, the presence of elements, etc. Spectral solutions based on these methods are highly complex systems and are used only with high-end instruments in special stand-alone laboratory solutions due to the attendant high costs.

The multiple color sensor offers a cost-effective approach. The sensor is built using semiconductor sensor technologies with 7 integrated interference filters ranging from 380 to 780 nm. In the case of this sensor, a color is rated on the radiometric level with the help of spectral approximation.

The absolute accuracy of this spectral estimate is highly dependent on the calibration method used. This publication demonstrates a simple optimization method that significantly improves the accuracy that can be achieved for particular applications. Thus, the multiple color sensor makes it possible to realize levels of color accuracy which were only possible with expensive laboratory solutions until now.

**Keywords** (not more than three): spectral approximation, color measurement, analysis of skin

## 1. BASIC INFORMATION

This publication examines multiple color sensors with seven levels of spectral sensitivity (Fig. 1) on a systems theory level. The aim is to find a method that optimizes the system response with respect to the calibration method for a given application. In the final step, the simulation is verified with real measurements.

Based on the numerous combination possibilities for the calibration, a system identification in

conjunction with mathematical optimization methods generates the best possible approximation of the sensor system.

The other parameters are:

- Target (spectra being measured)
- Standard illuminant
- spectral sensor sensitivities
- Illumination of the sensor
- Calibration method

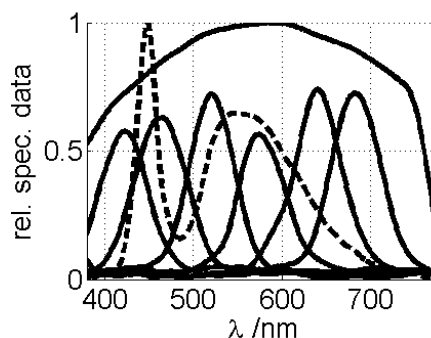


Fig. 1. Sensor sensitivity of the multiple color sensor (line) and emission spectrum of a white-light LED (dotted line).

The latest technological developments do not offer any method able to determine the best possible calibration on the basis of a given application. A system theory-based model offers the benefits of time and cost savings, reduced risk and shorter feasibility studies. In addition, existing products with multiple color sensors can be optimized with respect to accuracy and with comparatively little effort.

## 2. MATHEMATICAL MODEL

The mathematical model consists of input parameters. The targets  $T_n(\lambda)$  are always present, where  $n$  represents the number of targets. With the help of spectrometers, each  $n$  target is measured in the desired frequency band. Using a multiple color sensor, it is necessary to determine  $T_n(\lambda)$  as closely as possible for later use.  $T_n(\lambda)$  consists of linearly dependent and/or independent functions.

Standard illuminant  $N(\lambda)$  is required for measuring remitting surfaces in the visible range. The remitted spectrum is derived from (1). [1]

$$\theta_n = T_n(\lambda) \cdot N(\lambda) \quad (1)$$

Similar to  $T_n(\lambda) \cdot N(\lambda)$ , an additional illumination  $B(\lambda)$  is needed when measuring remitting surfaces with the multiple color sensor  $S_m(\lambda)$ , where  $m$  represents the number of channels. White-light LEDs are normally used for illumination. The resulting sensor response is (2). [2]

$$\sigma_n = S_m(\lambda) \cdot T_n(\lambda) \cdot B(\lambda) \quad (2)$$

### 2.1. Calibration Method

The application-specific calibration method involves calculating a matrix  $K$ , which “teaches” the response of the sensor system to the target. For the polynomial regression of the first degree, for example, matrix  $K$  is determined by (3), whereby calibration targets  $T_h(\lambda)$  are used instead of the targets  $T_n(\lambda)$ . [3]

$$K = (\theta_h(\lambda) \cdot \sigma_h(\lambda)^T) \cdot (\sigma_h(\lambda) \cdot \sigma_h(\lambda)^T)^{-1} \quad (3)$$

### 2.2 Optimizing the Calibration Method

This chapter examines a method for optimizing the calibration method. To perform an optimization in a color space, the standard observer  $O(\lambda)$   $2^\circ$  or  $10^\circ$  must also be selected.

The objective function of the optimization (4) is a minimization of the maximum differences between  $g_j(\lambda) = \sigma_j$  and  $f_j(\lambda, \beta_h) = \theta_j$  using the Euclidean distance  $d$  in the color space  $L^*a^*b^*$  (CIE1967).  $\beta_h$  is considered as an additional weighting factor for each calibration target  $T_h(\lambda)$ . By optimizing  $\beta_h$  with the constraint (5), the aim is to minimize the objective function.

$$\begin{aligned} \min \max(d(g_j(\lambda), f_j(\lambda, \beta_h))) \\ g_j(\lambda) = T_j(\lambda) \cdot N(\lambda) \\ f_j(\lambda, \beta_h) = K(\lambda, \beta_h) \cdot S_m(\lambda) \cdot T_j(\lambda) \cdot B(\lambda) \quad (4) \\ j = 1, \dots, n \end{aligned}$$

If  $\beta = 0$ , the corresponding calibration target is not factored into the calculation of  $K$ . If  $\beta > 0$ , the calibration target is weighted in the calculation.

$$0 \leq \beta_j \leq 1, \quad j = 1, \dots, h \quad (5)$$

The quasi-Newton method is used to minimize nonlinear functions. The function is available in the MATLAB Optimization Toolbox from MathWorks. One significant criterion for the success of the optimization is the selection of the starting value for  $\beta_h$ . Because it is only possible to find one of many local minima when using numerical methods for nonlinear optimization problems, the starting value must be determined experimentally. Finding a global minimum is impossible. [4]

Particle swarm optimization PSO is used to solve the problem of the initial value. PSO was originally developed to simulate the social behavior of flocks of birds. Enhanced for today's multi-dimensional spaces and the latest technological developments, it is used to optimize continuous, non-linear functions. Similar to genetic algorithms, it is used to generate various different solutions optimizing analytically unsolvable problems. Here the position  $\beta_h$  of a particle describes a solution to the problem (4). First, a number of particles is initialized with random positions in space. In the following steps, the new position of a particle is governed by its own local minimum, the global minimum of all particles and the speed. To avoid synchronization of the particles, random numbers are also included to calculate the speed. [5] [6]

### 2.3 Results

To verify the optimization of the calibration method, the mathematical model presented here has been implemented in MATLAB. In addition, actual measurements with the X-Rite ColorChecker are performed for this simulation.

TABLE I. Input parameters for the model

Input parameter	Symbol	Selected
Target	$T_n(\lambda)$	RAL Classic <sup>1</sup> xRite ColorChecker <sup>2</sup>
Calibration target	$T_h(\lambda)$	xRite ColorChecker
Illuminant	$N(\lambda)$	D65
Standard observer	$O(\lambda)$	$10^\circ$
Sensor sensitivity	$S_m(\lambda)$	Multiple Color Sensor
Illumination	$B(\lambda)$	Luxeon Rebel cool white <sup>1</sup> Nichia NSPW500BS-E <sup>2</sup>

1: Simulation only (see Table II)

2: Simulation and Measurement (see Table III)

Table I lists the input parameters. The RAL Classic set is selected for the target,  $n = 188$ , not factoring in neon and metallic colors for colorimetric reasons. The target set for the calibration of the X-Rite ColorChecker consists of 19 independent linear targets and 5 additional gray levels ( $h = 24$ ). The SpectroDens

from Techkon was used in order to determine the spectra of the RAL Classic and X-Rite ColorChecker targets.

TABLE II. Results with Target to RAL Classic according to CIE1976

	Calibration	Max $\Delta E$	Mean $\Delta E$
Simulation	Standard	3.89	0.68
Simulation	Optimized	1.64	0.60

TABLE III. Results with Target X-Rite ColorChecker according to CIE2000

	Calibration	Max $\Delta E$	Mean $\Delta E$
Simulation	Standard	1.70	0.46
Simulation	Optimized	1.19	0.56
Measurement	Standard	2.28	0.75
Measurement	Optimized	1.52	0.72

Tables II and III show the results from the simulation and actual measurements taken with the multiple color sensor. It is apparent that the actual measurements exhibits even greater differences than the mathematical model. This is due to the following factors:

- Precise transmittance and reflectivity of the color target are unavailable since they were determined by measurement. [7]
- The spectral function of the light source cannot be accurately determined. [7]

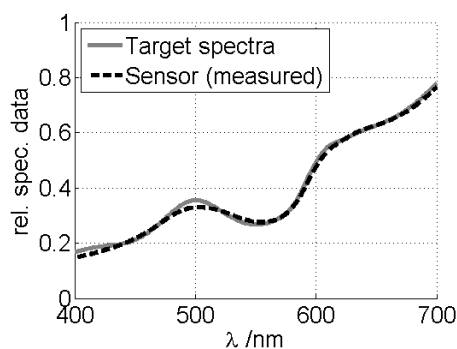


Fig. 2. Spectra of target "Light Skin"

Nevertheless, the simulation has a tendency for real measurements to verify whether a particular tolerance that is desired can be achieved. However, these tolerances constantly have to be verified with a real measurement system. Figure 2 shows the measured spectrum of the target number 2 "Light Skin" of the X-Rite ColorChecker, which corresponds to the color spectrum of a light skin. The color difference between the multiple color sensor and the SpectroDens is  $\Delta E(\text{CIE2000}) = 0.45$  and  $\Delta E(\text{CIE1976}) = 0.52$ .

### 3. CONCLUSION

The  $\Delta E$  (CIE1976) of less than 0.5 required in dermatology can be achieved using the optimization discussed here. There are currently no measurements of skin samples available. As part of a project funded by the Thüringer Aufbaubank (Thuringian Development Bank) in cooperation with the Jena University Hospital/Clinic for Skin Diseases, ART-KON-TOR Produktentwicklung GmbH and MAZeT GmbH, a measurement device is currently being developed which performs spectral scans of skin samples. By optimizing the calibration of the multiple color sensor being used, the hope is that this instrument will meet the necessary requirements. This will be confirmed by the simulation and measurement results being presented.

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