CMYK-CIELAB Color Space Transformation Using Machine Learning Techniques

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Abstract

In this work four different machine learning approaches have been implemented to perform the color space transformation between CMYK and CIELAB color spaces. We have explored the performance of Support-Vector Regression (SVR), Artificial Neural Networks (ANN), Deep Neural Networks (DNN), and Radial Basis Function (RBF) models to achieve this color space transformation, both AToB and BToA direction. The data set used for this work was FOGRA53 which is composed of 1617 color samples represented both in CMYK and CIELAB color space values. The accuracy of the transformation models was measured in terms of ΔE^* color difference. Moreover, the proposed models were compared, in practical terms, with the performance of the standard ICC profile for this color space transformation. The results showed that, for the forward transformation (CMYK to CIELAB), the highest accuracy was obtained using RBF. While, for the backward transformation (CIELAB to CMYK), the highest accuracy was obtained with DNN.

Introduction

Color management is an essential task in several fields of research and industry, such as graphic design, photography, printing, and image processing, among others [13]. In general terms, color management is the process of controlling how colors are represented across different devices, such as digital cameras, projectors, printers, monitors, etc [6]. The main goal of color management is to make sure that colors will look equal (or at least as similar as possible) on different devices [9].

CMYK and CIELAB are two color spaces that are widely used today in different applications [10]. CMYK is a device-dependent color space used in the printing industry due to its subtractive nature. It represents each color using four components: cyan, magenta, yellow, and black [14]. CIELAB is a device-independent color space derived from the previous CIE 1931 XYZ color space with the aim of creating a more uniform color space. It represents each color using three values, L* for lightness, a* for the green-red component, and b* for the blue-yellow component. Like CIEXYZ, CIELAB is important in color management because it works as a profile connection space [11].

Color space transformation, also known as color space conversion, is a fundamental part of color management. Its objective is to transform the representation of a given color from one color space to a different one [2]. This is an essential issue because different devices use different color spaces depending on the specific application [16]. There are different methods to perform color space transformation. The first developed methods included polynomial regression and Look-Up Tables (LUT) [3]. A color LUT is a matrix of color information that is searched to properly convert colors from a source to a destination, where the source/destination could be either a file or a physical device.

There are recent research works where different machine learning methods have been implemented to perform and optimize color space transformations. Some of them are Artificial Neural Networks (ANN) [4], Support-Vector Regression (SVR) [7], Deep Neural Networks (DNN) [8], Radial Basis Function Network (RBF) [1], among others. However, as far as we know, there are no research works about comparing the performance of color space transformation with those machine learning techniques. Furthermore, most of the research works about this area focus on relatively simple transformations, such as RGB to XYZ, or RGB to CIELAB, which can be easily solved by simpler methods, such as polynomial regression or Tone Reproduction Curve (TRC) matrix [15][12]. There are few research papers that explore the implementation of machine learning methods to perform more complex color space transformations, such as between the CMYK and CIELAB.

In this work, four different machine learning approaches will be implemented to perform the color space transformation between CMYK and CIELAB color spaces. We explore the performance of SVR, ANN, DNN, and RBF models to perform this color space transformation, both AToB and BToA directions. The accuracy of the transformation models will be measured in terms of ΔE^* color difference. In addition, the proposed models will be compared, in practical terms, with the performance of the standard ICC profile for this color space transformation.

The structure of this work is as follows. In the next section, we will explain the most relevant related works which will serve as a starting point for the work. Then, we will explain the methodology followed to obtain our experimental results including the data set, the specifications of each model, and the accuracy measurement establishment to analyze and compare the models. After this, we will show the results from each model, and we will analyze and compare them in terms of color difference. Finally, we will present our conclusions and ideas for future works to expand the practical applications of this research.

Related Works

Li and Zhang [7] established a model that converts from RGB to CIELAB using SVR. For the experiment, the authors selected the ANSI/ISOIT8.7/2 as the target with D50 as the illuminant. To generate the training and test data set, they obtained the CIELAB and RGB target values with an X-Rite Eye-One spectrophotometer and Microtek ScanMaker 3750i respectively. In the results, based on the CIEDE2000 color difference formula, the model reached maximum and minimum color differences equal to 4.142 and 0.423, respectively. The average color difference obtained was 1.932.

Fdhal et al. [4] developed an ANN-based color space transformation from RGB to CIELAB and compared it, in terms of accuracy, with the corresponding LUT ICC Profile. The proposed model consisted of a three-layer ANN trained with the back-propagation Levenberg-Marquardt algorithm. This architecture is composed of an input layer with three neurons, a hidden layer with 360 neurons, and a final output layer with three neurons.

The test accuracy was analyzed in terms of E^*_{ab}. The ANN-based method obtained an average $E^*_{ab} = 0.28$, while the ICC Profile obtained an average $E^*_{ab} = 0.46$. In this way, the authors demonstrated that the proposed ANN-based method exceeded the accuracy obtained with the corresponding ICC profile. They explained that this accuracy difference is produced because LUT ICC profiles can suffer interpolation errors, while ANN-based transformation models can achieve a more continuous mapping.

MacDonald and Mayer [8] developed a variation of the previous ANN architecture to perform the transformation from RGB to XYZ. They implemented a DNN, after an optimization process they used a five-layer DNN composed of one input and one output layer of three neurons each, and three fully connected hidden layers of 21, 77, and 21 neurons. To train the model, a data set of 100,000 samples were used. The results showed that 85% of the test values were below the ΔE^*_{2000} visibility threshold, assuming a just noticeable difference of 1.

Congjun and Qiangjun [1] proposed a different machine learning approach to perform color space transformation between the CMYK and CIELAB color spaces. They implemented a RBF Network to complete this transformation in both directions (AToB and BToA). To train the model, the authors used the ECI2002 standard color target for offset printing. This data set contains 1268 CMYK color patches with their corresponding CIELAB measurements. In the results, during the forward transformation color (CMYK to CIELAB), the proposed method obtained an average $E^*_{ab} = 0.4$, and the percentage of test patches with $E^*_{ab} < 6$ reached 100%. While in the backward color transformation (CIELAB to CMYK), the proposed method obtained an average $E^*_{ab} = 4.34$, and the percentage of test patches with $E^*_{ab} < 6$ reached 80%.

Methodology

Data Set

We will use the FOGRA53 characterization data set. This data set is composed of 1617 color samples with each sample represented both in CMYK and CIELAB color space values. The measurement conditions of this data set include D50 illuminant and 2-degree observer. Unlike other characterization data sets, such as FOGRA52 or FOGRA51, the substrate in this data set is defined as "universal" which results in general printing conditions and a large gamut color exchange space.The data set will be divided into two parts. The first part contains 85% of the samples, and it will be used as the training data set for the transformation models, while the second part contains the remaining 15% which will be reserved for testing purposes.

Models

The first model that we will implement is the Support-Vector Regression (SVR) which is a special type of Support-Vector Machine (SVM) oriented to solve regression problems. The SVR architecture has some parameters such as kernel scale, epsilon, and box constraint. These parameters were assigned the same as those of the previous work of Li and Zhang [7].

The second model that we will implement is an Artificial Neural Network (ANN) with a shallow architecture.The ANN architecture that we have chosen for our specific color transformation model between CMYK and CIELAB spaces is composed of 180 RELU neurons trained with the Backpropagation Levenberg-Marquardt algorithm. The chosen architecture will be the same for both the AToB and the BToA models. The only difference between them is the input and output network size. In the AToB transformation, the input and output size will be 4 and 3 respectively, while in the BToA case the input and output size will be 3 and 4. The maximum number of epochs was set to 1000, and the learning rate was set to 0.01. The optimization method used was Adam. We have chosen this specific configuration, based on the previous work by Fdhal et al. [4] who used this to perform the transformation from RGB to CIELAB color space.

The third model that we will implement is a Deep Neural Network (DNN). The configuration and functioning of this model is very similar to the previous one. However, instead of concentrating all neurons in just one single layer, this model uses multiple hidden layers to distribute the neurons and process the information sequentially layer by layer. The specific DNN architecture we will use is based on the research by MacDonald and Mayer [8] who used three fully connected hidden layers of 21, 77, and 21 neurons, respectively. Thus, we will adapt the architecture proposed by them (which was originally implemented for the transformation from RGB to XYZ) to create our transformation model between the CMYK and CIELAB color spaces.

The last model to be implemented is the Radial Basis Function Network (RBF). This is a special three-layer network that is very efficient in solving regression problems and approximation of functions. Because the neurons of this model use non-linear RBF activation functions, the training does not require a back-propagation process, which leads to a very fast training stage. The only parameter we have to adjust is the spread Value. Following the process described by Congjun and Qiangjun [1] to obtain this parameter, the spread Value for our specific color space transformation was set to 70.

Theoretical Accuracy Measurement

To compare the precision of the color transformation methods, we will use two versions of the ΔE^* formula, these are CIE1976 and CIEDE2000. The CIE1976 version, denoted as ΔE^*_{ab}, is a standard color difference formula that appeared together with the creation of the CIELAB color space. The CIEDE2000 version, denoted as ΔE^*_{2000}, is an improvement of the first formula that takes into account some non-uniformities of CIELAB space to calculate the color difference in a more accurate way. Although in the results we will calculate the color differences using both versions, during the analysis and comparison of the methods, we will focus on using the ΔE^*_{ab} version.

Forward Transformation Accuracy

In the transformation from CMYK to CIELAB color space, the accuracy will be calculated directly by applying the ΔE^* color difference formula, both CIE1976 and CIEDE2000 versions, using the actual and estimated CIELAB color values. This process is shown in Figure 1.

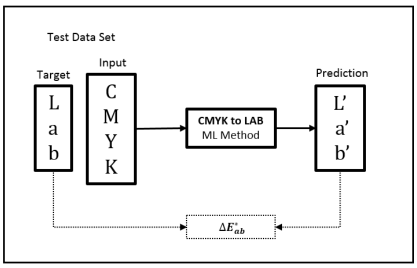

Figure 1. Forward transformation accuracy measurement.

Backward Transformation Accuracy

In the transformation from CIELAB to CMYK color space, we cannot apply the ΔE^* color difference formula directly with the estimated and actual CMYK color values. Instead, we first have to transform those values back to CIELAB space, and once there, use the color difference formula to calculate the color difference. There are different ways to do this, in our case we will use the round-trip color transformation. This means that, after performing the backward color space transformation (CIELAB to CMYK), we will use the previously implemented forward transformation (CMYK to CIELAB) to go back and obtain the CIELAB color values. This will cause the calculated color difference to be much larger than in the forward case due to the implicit error added by the second transformation. Despite that, it will serve as a good reference to compare the implemented color transformation models. This process is shown in Figure 2.

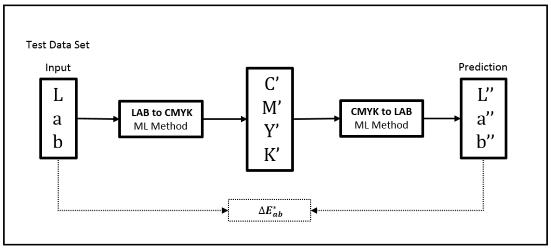

Figure 2. *Backward transformation accuracy measurement.*

Practical Accuracy Measurement

After training and testing the proposed models using the color samples of the FOGRA53 data set. It is necessary to test our models in practical terms, that is, through printing and measuring the CMYK values obtained with each model. To print the CMYK values, we use an OCE COLORWAVE 600 Poster Printer, and to measure the corresponding CIELAB values we will use a GretagMacbeth Spectro Scan. This will give us the practical accuracy of our four machine learning transformation methods.

We will use the eciCMYK profile, which is the commercial profile for the CIELAB to CMYK transformation generated using FOGRA53. This ICC profile is available on the web page of the European Color Initiative (ECI). This profile will serve us to perform two fundamental steps. On the one hand, it will help us to generate a new CIELAB test data set with 225 samples (different from those present in FOGRA53), ensuring that all those samples are inside the gamut of the transformation. On the other hand, eciCMYK will serve as a reference point to calculate the color differences obtained with the four proposed methods. This practical comparison process is explained in Figure 3.

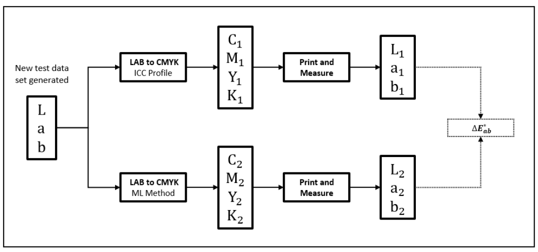

Figure 3. *Practical accuracy measurement with respect to the ICC Profile.*

Experimental Results

Forward Transformation Accuracy

In Table 1 we can see the accuracy obtained with the four models for the transformation from CMYK to CIELAB color space. This table shows the accuracy in terms of minimum, maximum, and average ΔE^*. Furthermore, this table includes an interpretation of ΔE^*_{ab} in terms of perceptibility and acceptability. Based on the work of Hardeberg [5], for industrial applications, the color differences can be classified into three groups. A ΔE^*_{ab} color difference less than 3 is defined as “Hardly perceptible”, a ΔE^*_{ab} between 3 and 6 is defined as “Perceptual, but acceptable”, and a ΔE^*_{ab} greater than 6 is defined as “Not acceptable”.

Table 1. Forward transformation accuracy

	ΔE^*_{2000} Mean	ΔE^*_{ab} Min	ΔE^*_{ab} Max	ΔE^*_{ab} Mean	$\Delta E^*_{ab} <$ 3.0	$3.0 \leq \Delta E^*_{ab} <$ 6.0	$\Delta E^*_{ab} \geq$ 6.0
SVR	0.194	0.027	3.674	0.299	99,59%	0,41%	0,00%
ANN	0.225	0.022	3.870	0.318	99,59%	0,41%	0,00%
DNN	0.201	0.009	10.693	0.284	99,59%	0,00%	0,41%
RBF	0.135	0.012	2.973	0.195	100,00%	0,00%	0,00%

We can notice that, in the forward transformation, the performance of all models is very high. In the four models almost 100% of color differences were defined as “hardly perceptible” because they were less than 3. The RBF model had the lowest average $\Delta E^*_{ab} = 0.1947$. The transformation from CMYK to LAB is relatively easy, and therefore the four proposed models complete this color transformation with high precision.

Backward Transformation Accuracy

In Table 2 we can see the accuracy of the backward transformation, where the DNN model obtained the lowest average with a $\Delta E^*_{ab} = 3.236$, and only 11% of its color differences were defined as “not acceptable” because they were greater than 6.

Table 2. Backward transformation accuracy

	ΔE^*_{2000} Mean	ΔE^*_{ab} Min	ΔE^*_{ab} Max	ΔE^*_{ab} Mean	$\Delta E^*_{ab} <$ 3.0	$3.0 \leq \Delta E^*_{ab} <$ 6.0	$\Delta E^*_{ab} \geq$ 6.0
SVR	2.457	0.262	25.262	3.988	44.44%	38.68%	16.87%
ANN	2.573	0.268	25.105	4.098	49.38%	32.51%	18.11%
DNN	2.109	0.127	31.3202	3.236	62.55%	26.34%	11.11%
RBF	2.198	0.492	37.592	3.590	62.96%	21.40%	15.64%

If we consider just the “hardly perceptible” color difference percentage, the performance of the RBF and DNN transformation methods might seem equal because both methods reached almost the same percentage in that category. However, if we also consider the “not acceptable” category, the DNN method performs better than the other three methods since it has the lowest percentage of error in that category, which is equal to 11% of the total test samples. This can also be seen in Figure 4.

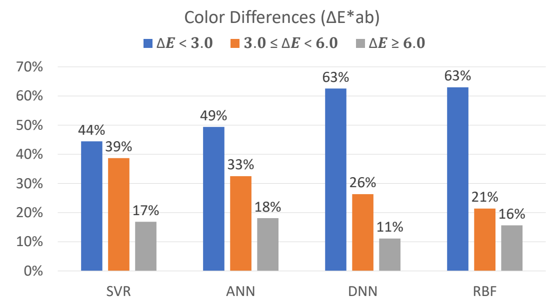

Figure 4. ΔE^*_{ab} *histogram analysis for the backward transformation*

It is important to note that the accuracy obtained in the backward transformation is lower than in the forward transformation. This is because of two important reasons. The first reason is that the transformation from CIELAB to CMYK is more complex than in the opposite direction because of the existence of non-unique solutions. The second reason is due to the round trip that was made to return to CIELAB space and calculate the ΔE^* color difference, as we already saw in Figure 2. This causes the forward transform error to be implicitly included in the precision calculation of the backward model.

Practical Accuracy

After printing and measuring the CMYK values obtained with the four models, they were compared with the CMYK values (also printed and measured) obtained with the ICC profile. In Table 3 the method that showed the best performance was the DNN-based transformation method. We can notice that this method obtained the lowest average $\Delta E^*_{ab} = 4.649$, and 20% of its color differences were defined as "not acceptable" because they were greater than 6.

Table 3. Practical accuracy measurement

	ΔE^*_{2000} Mean	ΔE^*_{ab} Min	ΔE^*_{ab} Max	ΔE^*_{ab} Mean	$\Delta E^*_{ab} <$ 3.0	$3.0 \leq \Delta E^*_{ab} <$ 6.0	$\Delta E^*_{ab} \geq$ 6.0
SVR	3.687	0.143	35.838	5.370	36.89%	34.22%	28.89%
ANN	3.796	0.154	41.588	5.568	33.78%	34.67%	31.56%
DNN	3.115	0.437	22.190	4.649	44.00%	35.78%	20.22%
RBF	3.556	0.333	40.477	5.367	38.78%	33.78%	627.44%

In Figure 5 we can notice that the DNN-based transformation method reached the highest percentage of color differences categorized as "hardly perceptible". Additionally, it reached the lowest percentage of color differences categorized as "not acceptable" compared with the other three methods.

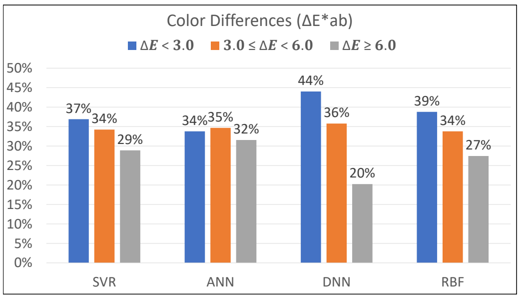

Figure 5. *ΔE^*_{ab} histogram analysis for the practical accuracy measurement*

To be able to analyze the color differences in more detail, the individual ΔE^*_{ab} of each of the 225 test color samples is represented in Figure 6. We can notice how the graph of the color differences produced by the DNN method concentrates on a lower average ΔE^*_{ab} compared to the other three methods. In addition, we can notice that the methods SVM, ANN, and RBF have maximum color differences up to 40, while the maximum color difference of the DNN method is lower.

In Figure 7 we can see the measured color difference between the printed color test chart produced using the ICC and DNN-based method. We can see that the results obtained with both methods are visually very similar, except for a few color patches that have a very noticeable color difference. Those color patches have been represented with yellowish color in Figure 7.

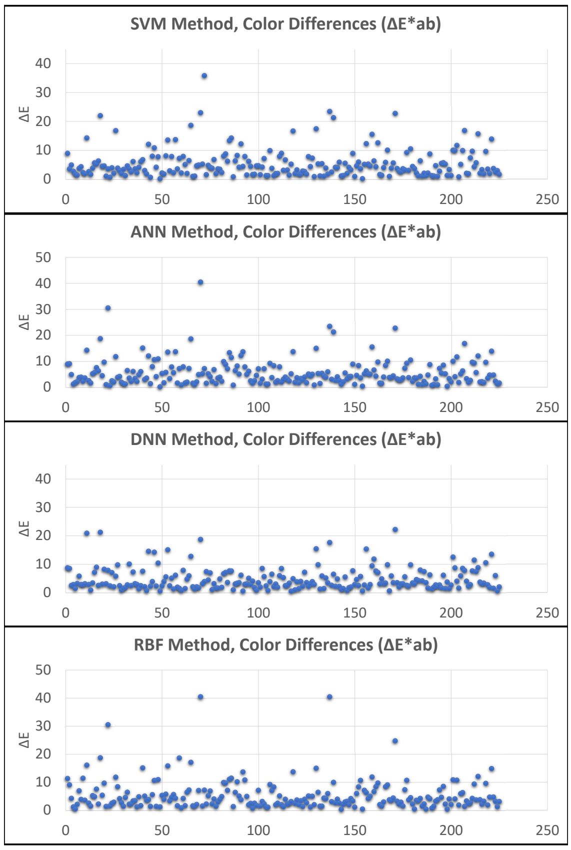

Figure 6. *Color difference distribution for the practical accuracy measurement. The x-axis is the sample index, and the y-axis is the ΔE^*_{ab} value.*

Conclusions

In this work, four different machine learning approaches have been implemented to perform the color space transformation between CMYK and CIELAB color spaces. We have explored the performance of SVR, ANN, DNN, and RBF models to perform this color space transformation both AToB and BToA directions. The accuracy of the transformation models was measured in terms of ΔE^* color difference.

The results showed that, for the forward transformation (CMYK to CIELAB), all four methods obtained a very high transformation accuracy. In particular, the RBF method obtained the lowest average ΔE^*_{ab} color difference equal to 0.1947. Moreover, all color difference values obtained with this transformation method were less than 3. In the backward transformation (CIELAB to CMYK), the transformation accuracy obtained with all methods is lower compared to the forward transformation. We showed that the DNN model obtained the lowest average $\Delta E^*_{ab} = 3.236$, and only 11% of its color differences were greater than 6.

We proceeded to make a practical comparison of our methods with respect to the original ICC profile. The method that obtained the least color difference with respect to the ICC profile was the DNN-based transformation method. This method obtained the lowest average $\Delta E^*_{ab} = 4.649$, and 20% of its color differences were larger than 6.

Finally, for future works, it would be recommended to perform these approaches with more color space transformations. In particular, it would be interesting to implement these transformation methods with the CcMmYK model which is a six-color model very used in the industry and professional printing.

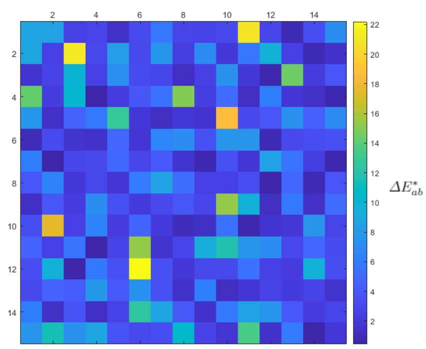

Figure 7. *Representation of the ΔE^*_{ab} between the ICC and the DNN-based method after measuring the printed test color charts*

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