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Boosting Color Similarity Decisions Using the CIEDE2000_PF Metric

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Abstract Color comparison is a key aspect in many areas of application, including industrial applications, and different metrics have been proposed. In many applications this comparison is required to be closely related to human perception of color differences, thus adding complexity to the process. To tackle this, different approaches were proposed through the years, culminating in the CIEDE2000 formulation. In our previous work, we showed that simple color properties could be used to reduce the computational time of a color similarity decision process that employed this metric, which is recognized as having high computational complexity. In this letter we show mathematically and experimentally that these findings can be adapted and extended to the recently proposed CIEDE2000 PF metric, which has been recommended by the CIE for industrial applications. Moreover, we propose new efficient models that not only achieve lower error rates, but also outperforming the results obtained for the CIEDE2000 metric.

Keywords Computer Vision · Segmentation · CIEDE2000 · CIEDE2000_PF · Color Similarity

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1 Introduction

Automatic color comparison in static images or video frames is a necessary process in many scenarios, including scientific and industrial applications. Moreover, it is often of utmost importance for the color differences to be closely related to how humans perceive these differences. The CIEDE2000 formula [12] (international standard ISO CIE 11664-6:2014) was defined for this goal; it quantifies the perceptual distance between colors in a way similar to how humans perceive the differences. Due to its discriminating power, the metric has been adopted in many scenarios, especially in industry applications. In dentistry it is used to compare teeth whitening efficacy [18, **?**] and cement shades [3]. It is also used to study the coating process of pharmaceutical tablets [15]. Computer vision applications for dehazing [1], segmentation [17] and comparison of contrast enhanced images [23] have also been proposed, illustrating the usefulness and recent usage of the metric.

It has been shown that the application of power functions could theoretically improve even further the ability of the CIEDE2000 metric to quantify color differences in conformity with human visual perception [9]. However, the application of these corrections have only very recently been recommended by CIE for industrial applications [20]. This was further confirmed in a recent study on ink jet print resistance that compared the results obtained using the traditional CIE formulas: CIE76 (ΔE^*_{ab}) [21], CIE94 (ΔE^*_{94}) [13] and CIEDE2000 [12] with their associated power function modifications. It demonstrated that not only CIEDE2000 outperformed the more traditional metrics, but the application of the power function to the metric further improved the agreement between calculated and perceived color differences [2]. However, it is important to note that the power function modification introduced in the formula increases its already vast computational complexity, which in turn may impair its use in more demanding applications or with hardware limitations.

This letter demonstrates that it is possible to apply a strategy for color similarity decision based on the CIEDE2000_PF [20] metric, that can significantly reduce the computational cost while maintaining consistent results. The current proposal is an extension of the methodology initially described in [19] for the CIEDE2000 metric. It consists of a cascade processing pipeline that receives a pair of colors and, at each stage, decides upon dissimilarity of the colors with regards to a CIEDE2000_PF based decision boundary. We demonstrate mathematically and empirically that it is also possible to derive models relating decision boundaries in the CIEDE2000_PF metric using the simple color properties proposed in [19]. Moreover, we derived new models that prove to be more efficient than the previously proposed ones, resulting in an even better performance gain when comparing to the original CIEDE2000 metric. In our experiments we also show that the usage of a cascade strategy is also recommended for color similarity decision based on this formula and that its usage coupled with the new models show improved performance on a real application, when comparing with the results obtained for the base CIEDE2000 metric.

The remainder of this letter is organized as follows. Section 2 presents the underlying hypothesis of this work, extending the formulation to the CIEDE2000_PF metric, as well as some key concepts. Section 3 illustrates a set of low complexity color-based properties to be used and shows mathematically that they can be applied. These properties are then coupled into a color similarity decision methodology that is detailed in Section 4. Then, an assessment of the proposal is shown in Section 5. Finally, the conclusions of our work are presented in Section 6.

2 Hypothesis Definition

Recently, it was validated by CIE [20] standardization body that the power function implications presented in [9] can indeed improve the performance of CIE color difference formulae. Additionally, it was also reported that the application of the power function to the CIEDE2000 is now the most recommended formula to be used in industry. In this section we present our underlying hypothesis and some key concepts. We will refer to the new recommended formula through the remainder of the letter as CIEDE2000_PF (ΔE_{PF}), and its definition can be seen in Eq. 1.

$$\Delta E_{PF} = 1.43(\Delta E_{00})^{0.7}, \tag{1}$$

where the ΔE_{00} is the original CIEDE2000 formula [12] and the numeric constants are the proposed power function changes presented in Table 1 of [20]. The hypothesis put forward in this letter is that the methodology and color properties thoroughly studied and detailed in [19] for the original CIEDE2000 metric can also be extended for this new formula. Thus, we define our main hypothesis as follows: For a given color-based property P and a user defined maximum value of CIEDE2000_PF ($t_{\Delta E}$), we argue that at least one mapping function f exists, which translates a CIEDE2000_PF distance cut-off value to a corresponding cut-off on the color property. A mathematical formulation of this hypothesis can be seen in Eq. 2.

$$\begin{gathered}\forall t_{\Delta E} \in \mathbb{R}^+, \forall C_1, C_2 \in \mathbb{C}_{RGB}, \\ P(C_1,C_2) > f(t_{\Delta E}) \implies \Delta E_{PF}(C_1,C_2) > t_{\Delta E},\end{gathered} \tag{2}$$

where C_1 and C_2 are two input colors in the RGB color space represented as $\mathbb{C}_{RGB}$. The usage of colors in the RGB color space is inspired by the adoption of this color space in the input images of multiple computer vision applications, as well as the typical color space used to store pictures obtained from handheld devices.

We know that, by definition, if $x > y, x \geq 0$ and $y \geq 0$, then $x^\gamma > y^\gamma, \gamma > 0$ is also true. With this insight, we can further generalize Eq. 2 to:

$$P^i > f(t_{\Delta E})^i \implies \Delta E^j_{PF} > t^j_{\Delta E}, \forall_{t_{\Delta E}>0}, i \geq 0, j \geq 0. \tag{3}$$

This is also valid for a lower bound function $\Delta E'$, since $\Delta E' \leq \Delta E_{PF}$. This means that implication 2 can be rewritten as:

$$\begin{gathered}\text{if } P > f(t_{\Delta E}) \implies \Delta E' > t_{\Delta E}, \forall_{t_{\Delta E}\geq 0} \\ \text{then } \Delta E_{PF} > t_{\Delta E}\end{gathered} \tag{4}$$

Consequently, a lower bound for the CIEDE2000_PF metric can also be applied. By analyzing the original CIEDE2000 formula, we can observe that the term $\frac{\Delta L}{K_L S_L}$ is itself a lower bound function of the whole formula, as proven in [19]. Therefore, we can extend this lower bound to the new formula as:

$$\Delta E'_{PF} = \left(\sqrt{\left(\frac{\Delta L}{K_L S_L}\right)^2}\right)^{0.7}, \tag{5}$$

where ΔL is the lightness difference between two colors, S_L represents a weighting function and K_L is a weighting factor associated with the lightness component. As used in other studies [20, ?], we also set the correction terms (parameter K in the color formulae) to 1 for our experiments. However, we will make use of them in the mathematical formulations to show that their influence is accounted for. In the above lower bound function for the CIEDE2000_PF formula, the constant 1.43 was disregarded as its value is above 1.0 and can therefore simplify further proofs as the property of $\Delta E_{PF} \geq \Delta E'_{PF}$ is also guaranteed.

3 Property Definition and Relation

In this chapter we demonstrate mathematically that mapping functions can be obtained for three simple color properties, thus validating the main hypothesis presented in Eq. 2. These color properties can be defined as follows:

$$\forall C_1, C_2 \in \mathbb{C}_{RGB},$$

$$\mathscr{A}(C_1,C_2) = \arccos\left(\frac{C_1 \cdot C_2}{\|C_1\|\|C_2\|}\right) \tag{6}$$

$$\mathscr{M}(C_1,C_2) = \|C_2 - C_1\| \tag{7}$$

$$\mathscr{L}(C_1,C_2) = |L(C_2) - L(C_1)| \tag{8}$$

The first equation, $\mathscr{A}$, refers to the angle between two colors on the sRGB color space, the second, $\mathscr{M}$ is the module of the difference vector between the colors and the last property represented by $\mathscr{L}$, refers to the absolute difference between the lightness of the colors. As a result, the last property requires a partial color conversion to the CIELAB color space in order to obtain the lightness component. The reader is referred to [10] for additional details about the color conversion procedure.

Starting with the lightness property, we hypothesize that its mapping function f can be non-linear and of the form:

$$f(t_{\Delta E}) = (mt_{\Delta E})^{\gamma} + w \tag{9}$$

We want to prove that:

$$\Delta L > (mt_{\Delta E})^{\gamma} + w \implies \Delta E'_{PF} > t_{\Delta E} \tag{10}$$

Expanding the lower bound (Eq. 5), we obtain:

$$\Delta E'_{PF} = \left(\frac{|\Delta L|}{K_L S_L}\right)^{0.7} \tag{11}$$

Applying Eq. 10, we get:

$$\Delta E_L = \left(\frac{|(mt_{\Delta E})^{\gamma} + w|}{K_L S_L}\right)^{0.7}, \tag{12}$$

$$\Delta E_L < E'_{PF} \tag{13}$$

If we select γ, m and w such that:

$$\begin{cases} w = 0 \\ \gamma \geq \frac{1}{0.7} \\ \frac{m}{(K_L S_L)^{0.7}} > 1 \end{cases} \tag{14}$$

We get that:

$$\Delta E_L > t_{\Delta E} \tag{15}$$

$$\therefore \Delta E_L > t_{\Delta E} \implies \Delta E_{PF} > t_{\Delta E} \tag{16}$$

For the angle and module property, we need to account for color conversion, as ΔE_{PF} makes use of the CIELAB color space and these properties use the sRGB color space. To obtain this conversion, it is necessary to first convert to the XYZ color space and then from XYZ to CIELAB. The reader is referred to [10] for more details regarding the color conversion process. An important property of this intermediate conversion is that the lightness property of the CIELAB makes use of only the Y component of XYZ. Therefore, we can also apply the lower bound strategy and simplify the process. Applying this notion, we define in Eq. 17 a lower bound for the lightness property.

$$L'(y_r) = \frac{116}{3} y_r, \tag{17}$$

where y_r is obtained from the intermediate conversion between CIELAB to XYZ and defined as:

$$y_r = \alpha R + \beta G + \nu B \tag{18}$$

where $\alpha = 0.2126729/255$, $\beta = 0.7151522/255$ and $\nu = 0.072175/255$. These constants are normalizing constants obtained from the D65 white point standard. For a more detailed explanation of the formulation of this lower bound, the reader is referred to [19].

As $\Delta L' \leq \Delta L$ we can make use of this new formula for the lightness difference calculation:

$$\Delta E_{PF} > \Delta E''_{PF} = \left(\frac{|\Delta L'|}{K_L S_L}\right)^{0.7} \tag{19}$$

So, as with the lightness property, we wish to prove that there exists a function f such that:

$$\mathscr{M} > f(t_{\Delta E}) \implies \Delta E''_{PF} > t_{\Delta E}, \forall_{t_{\Delta E} \geq 0} \tag{20}$$

By expanding Eq. 19:

$$\begin{aligned} \sqrt{\left(\frac{\Delta L'}{K_L S_L}\right)^2} &= \sqrt{\left(\frac{\frac{116}{3}(y_{r2} - y_{r1})}{K_L S_L}\right)^2} \\ &= \left(\frac{116}{3K_L S_L}\right)\sqrt{[\alpha(R_2 - R_1) + \beta(G_2 - G_1) + \nu(B_2 - B_1)]^2}, \end{aligned} \tag{21}$$

where α, β and ν are the normalization constants depicted in Eq. 18. Since $\nu < \alpha < \beta$:

$$\sqrt{\left(\frac{\Delta L'}{K_L S_L}\right)^2} > \left(\frac{116\nu}{3K_L S_L}\right)\sqrt{\mathscr{M}^2 + Z} \tag{22}$$

$$\begin{aligned} Z = {} & 2(R_2 - R_1)(G_2 - G_1) \\ & + 2(R_2 - R_1)(B_2 - B_1) \\ & + 2(G_2 - G_1)(B_2 - B_1) \end{aligned} \tag{23}$$

Similarly to the process for lightness, we apply Eq. 20 and get a new lower bound of ΔE_{PF} (ΔE_M). For visual simplification purposes, we also adopt a variable substitution $D = 116v/3K_LS_L$, and obtain:

$$\Delta E_M = \left(D\sqrt{(mt_{\Delta E}^{\gamma}+w)^2+Z}\right)^{0.7} = \left(D\sqrt{(mt_{\Delta E}^{\gamma})^2+2mwt_{\Delta E}^{\gamma}+w^2+Z}\right)^{0.7} \tag{24}$$

If we select m, γ and w such that:

$$\begin{cases} 2mwt_{\Delta E}^{\gamma}+w^2+Z \geq 0 \\ \gamma > \frac{1}{0.7} \\ Dm > 1 \end{cases} \tag{25}$$

We get that:

$$\Delta E_M > t_{\Delta E} \tag{26}$$

$$\therefore \Delta E_M > t_{\Delta E} \implies \Delta E_{PF} > t_{\Delta E} \tag{27}$$

Analogous to the module property, we can model our hypothesis for the angle property as:

$$\mathscr{A} > f(t_{\Delta E}) \implies \Delta E''_{PF} > t_{\Delta E}, \forall_{t_{\Delta E} \geq 0} \tag{28}$$

Since the angle also makes use of the sRGB color space, we modify Eq. 22 by applying the cosine rule we obtain:

$$\Delta E_A = \left(D\sqrt{||C_1||^2+||C_2||^2-2||C_1||\,||C_2||\cos\mathscr{A}+K}\right)^{0.7} \tag{29}$$

Since the colors are defined in the sRGB color space, then their angle varies between 0 and at most $\frac{\pi}{2}$. Therefore, the cosine of these vectors varies between 0 and 1. Due to this, we can simplify the equation by taking a majorant of the cosine in this restricted domain. For this we use the function $1-\frac{4}{\pi^2}\mathscr{A}^2$, which effectively follows the imposed restrictions for a majorant of the cosine in the domain $[0, \frac{\pi}{2}]$. Applying this function results in:

$$\Delta E_A > \left(D\sqrt{\|C_1\|^2+\|C_2\|^2-2\|C_1\|\,\|C_2\|+Q}\right)^{0.7} \qquad Q = \frac{8}{\pi^2}\|C_1\|\,\|C_2\|\mathscr{A}^2+Z \tag{30}$$

Since $\|C_1\|^2+\|C_2\|^2-2\|C_1\|\,\|C_2\| \geq 0$, we can further simplify Eq. 30:

$$\Delta E_A > \left(D\sqrt{\frac{8}{\pi^2}\|C_1\|\,\|C_2\|\mathscr{A}^2+Z}\right)^{0.7} \tag{31}$$

As with the module, we apply Eq. 28 and obtain a new lower bound:

$$\Delta E'_A = \left(D\sqrt{\left(\frac{8}{\pi^2}||C_1||\,||C_2||(mt_{\Delta E}^{\gamma}+w)^2+K\right)}\right)^{0.7} \tag{32}$$

If we select m, γ and w such that:

$$\begin{cases} \frac{8}{\pi^2}||C_1||\,||C_2||(2mt_{\Delta E}^{\gamma}w+w^2)+K \geq 0 \\ D\sqrt{\frac{8}{\pi^2}||C_1||\,||C_2||}\,m > 1 \\ \gamma > \frac{1}{0.7} \end{cases} \tag{33}$$

We get that:

$$\Delta E'_A > t_{\Delta E} \tag{34}$$

$$\therefore \Delta E_A > t_{\Delta E} \implies \Delta E_{PF} > t_{\Delta E} \tag{35}$$

Through the usage of lower bound functions of the CIEDE2000_PF metric we showed that it is possible to obtain mapping functions for each of these properties. Since the definition of a lower bound function (minorant) states that the function is always bellow or equal to the target function in its domain, we can validate our main hypothesis (Eq. 2) as follows:

$$P > f(t_{\Delta E}) \implies \Delta E'_{PF} > t_{\Delta E} \tag{36}$$

$$\Delta E' > f(t_{\Delta E}) \implies \Delta E_{PF} > f(t_{\Delta E}) \tag{37}$$

$$(P > f(t_{\Delta E}) \implies (\Delta E'_{PF} > t_{\Delta E}) \wedge (\Delta E' > f(t_{\Delta E})) \implies (P > f(t_{\Delta E}) \implies (\Delta E_{PF} > t_{\Delta E}) \tag{38}$$

4 Proposed Processing Strategy for Color Similarity Decisions

In Section 2 we demonstrated mathematically that the findings put forward in [19] for the simple color properties and the original CIEDE2000 formula can also be applied to the new CIEDE2000_PF formula. We assess the applicability of a similar cascade for this new formula to obtain an efficient color similarity decision. Fig. 1 depicts an illustration of the proposed pipeline.

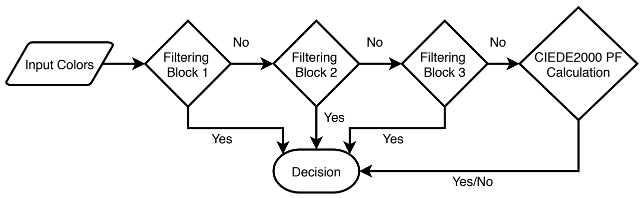


Fig. 1: Cascade Pipeline for Color Similarity Decision.

Each filtering block represents the analysis of a property, that provides a binary decision about color difference

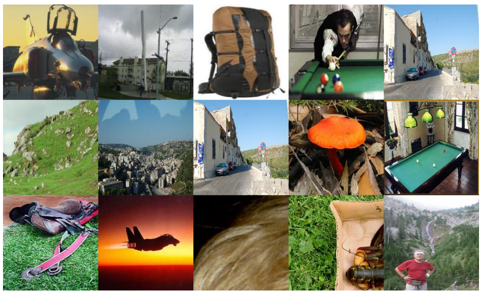


Fig. 2: Mosaic representing images sampled from the Caltech 256 dataset.

given an initial cut-off of CIEDE2000_PF and the corresponding property cut-off, obtained from the mapping function. The main idea behind the cascade decision is that, by first computing simple color properties that have a direct mapping function between the properties limits and the CIEDE2000_PF metric, we can decide that two colors are too distant without even computing the metric. Thus effectively reducing the computational complexity of the decision. Although we proved mathematically that a mapping function exists, approximations were introduced to simplify the process. Therefore, the derived formulae are not optimized. As such, we took a data-driven approach to derive efficient mapping functions for these properties through the training of regression models.

To train these models we used 5 million color comparisons resulting from uniformly sampling colors from images of the Caltech 256 dataset [8]. An example of images from this dataset can be seen in Fig. 2. For these pairs we calculated the three proposed properties, as well as the CIEDE2000_PF distance. Given that the power function applied to the CIEDE2000 formula imposes an additional non-linearity, we opt to use gradient boosting [7], as it is a very successful and applied model [14].

For these models, a 10-fold cross validation approach was followed. The average RMSE obtained was: 5.91×10^{-5} for Angle, 4.26×10^{-14} for Module and 7.06×10^{-6} for Lightness. Comparing these errors with the ones obtained in [19] show that much more precise models can be obtained by employing gradient boost. These impressive results allow for the application of the trained models without a need for correction offsets, suggesting a further improve in performance. Additionally, these results show the feasibility of obtaining mapping functions for the CIEDE2000_PF metric.

5 Evaluation and Results

In order to evaluate the applicability and performance gain of using the cascade processing pipeline and the associated mapping models, we defined two segmentation algorithms. The first algorithm serves as an additional validation step for the models and the cascade developed. The second algorithm, is based on a real application. This assessment not only validates the mapping models, but also explores the possibility of applying the cascade processing pipeline on a real scenario, where a color similarity decision is required. It is important to note that the three proposed color properties have different computation costs and its possible that two or three properties can filter the same color pairs, as such, it is important to also account for the order in which the properties are placed in the cascade. This results in 15 possible configurations for the cascade processing pipeline. The tests were performed in a desktop computer equipped with an Intel i7 4471 processor @3.5Ghz, which is the same hardware as the tests performed in [19].

The first algorithm requires as input: a cut-off for the CIEDE2000_PF distance (previously introduced as $t_{\Delta E}$); input colors to be searched for; and a dataset of images for which the colors need to be found. The purpose of the experiments with this algorithm is to validate if the usage of the proposed cascade strategy, associated color properties and models can indeed be applied to a color similarity decision task with no loss in accuracy of the decision, while providing a much faster decision than using the CIEDE2000_PF formula. The assessments performed with this algorithm were two-fold. First we evaluated the performance of each of the possible cascades and checked if any error was encounter. Then we validated these findings in a randomized experiment with multiple and differentiated datasets. This way, any bias that could be introduced in the first assessment can be nullified.

For the first step of assessments for the first algorithm, we selected as unique colors the ones presented in the color bank [4] and gave as input images from the Caltech 256 [8] dataset. Regarding the cut-off values, the values of 3, 5, 7 and 10 were originally selected for the CIEDE2000 metric in [19], due to their relation to the human notion of similarity. For instance, a distance of 3 corresponds to a noticeable color difference, while 10 corresponds to an ample difference (see Table 1 of [24] for a more detailed correlation between distance values). Since we are now using the new CIEDE2000_PF metric, we opt to use the same values but transformed with the application of the power function. This results in the new cut-off values for the CIEDE2000_PF metric of: 3.085, 4.412, 5.583 and 7.167.

As a baseline to compare the performance impact of the proposed models and cascades, we first compute the time required to process all the data using only the CIEDE2000_PF formula. To facilitate the presentation of the results, we consider the properties Module, Angle and Lightness as, respectively, M, A and L. Therefore the cascade MAL represents the use of Module, followed by Angle and lastly by Lightness. The idea is that: for a color pair we compute the mod-

Table 1: Summary of the cascade results using Boosting models.

	Relative Gains for CIEDE2000_PF cut-offs			
Cascade Struct.	3.085	4.412	5.583	7.167
A	63,40%	56,16%	52,96%	44,18%
AL	82,68%	77,06%	73,70%	64,80%
ALM	84,31%	79,43%	76,52%	66,27%
AM	93,40%	88,34%	85,43%	73,63%
AML	93,58%	89,67%	86,81%	76,26%
L	81,02%	76,19%	71,70%	65,43%
LA	84,89%	81,91%	78,97%	72,58%
LAM	86,63%	83,83%	81,34%	74,31%
LM	87,15%	84,32%	81,43%	72,90%
LMA	86,98%	84,32%	81,89%	74,77%
M	**97,25%**	92,09%	88,09%	73,84%
MA	**97,16%**	92,30%	89,09%	76,97%
MAL	**98,04%**	**94,58%**	**91,73%**	**82,49%**
ML	**97,81%**	**93,44%**	89,57%	76,73%
MLA	**97,93%**	**94,02%**	**90,73%**	**82,73%**

Table 2: Summary of the cascade results using the best cascades for different Datasets.

	Relative Gains for CIEDE2000_PF cut-offs			
Cascade Struct.	3.085	4.412	5.583	7.167
Caviar Dataset				
ML	98,03 %	92,55 %	86,25 %	67,27 %
MAL	98,07 %	93,82 %	89,14 %	75,72 %
MLA	98,10 %	93,86 %	89,15 %	75,23 %
PETS2006 Dataset				
ML	98,34 %	91,70 %	85,48 %	66,09 %
MAL	98,38 %	92,85 %	87,83 %	74,18 %
MLA	98,43 %	92,93 %	88,00 %	73,88 %
Coil-100 Dataset				
ML	98,65 %	95,63 %	92,20 %	81,05 %
MAL	98,62 %	96,27 %	94,10 %	86,77 %
MLA	98,67 %	96,30 %	94,01 %	86,36 %
FiM Dataset				
ML	96,80 %	91,34 %	86,65 %	72,77 %
MAL	97,10 %	92,67 %	89,20 %	79,75 %
MLA	97,13 %	92,72 %	89,13 %	79,34 %
Open Images Dataset				
ML	95,88 %	88,75 %	82,97 %	67,52 %
MAL	96,14 %	90,12 %	85,54 %	74,27 %
MLA	96,18 %	90,20 %	85,51 %	73,76 %

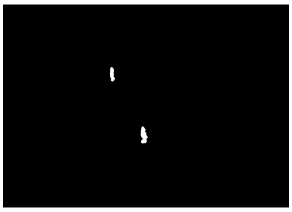
ule, if the value obtained is above the threshold for this property, then we skip the following calculations for this pair as its CIEDE2000_PF value is above the limit. If the value is below the limit we check the next property in the cascade. If no property has a value above its corresponding limit, then we calculate the CIEDE2000_PF value and evaluate. A summary of the time reduction obtained from processing the data with the various cascade hypothesis is presented in Table 1. As expected from the training of the models, a low training error resulted in precise models, which lead to a superior performance increase when comparing with the results obtained in [19]. It is also important to notice that, once more, the best strategies are clearly the MAL and MLA cascades.

For the second part of the assessments of the first algorithm, we selected the best performing cascade strategies, namely ML, MLA and MAL, and validated that their performance gains are unrelated to the initial selected base colors and selected dataset. For this, we randomly selected unique colors from images of the Caltech256 [8] dataset and then applied the above procedure to the following datasets: Caviar [6], PETS2006 [25], Coil-100 [16], Photo in Motion (FiM) [22] and Open Images [11]. For each dataset we selected different unique base colors, guaranteeing that the distribution of the colors was uniform, so that colors are well distributed. Table 2 details the temporal gains obtained for these datasets using the three best cascade setups identified, namely, ML, MLA and MAL. As observed in this table, it is a general consensus in these datasets that the performance of a color similarity decision can be greatly improved by making use of our proposed cascade architecture and models. Furthermore, the cascades MAL and MLA are also prove to be the ones with most impact.

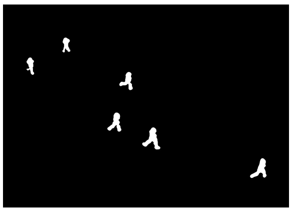
Our second testing algorithm targets a real practical computer vision application of the cascade pipeline. For this, we defined a soccer player segmentation algorithm, that segments each frame to identify the players of each team and places a bounding box over them. To assess this algorithm we used the ISSIA soccer dataset [5], which consists of multiple soccer videos of two teams, with associated groundtruth for the player location and team. The main colors of the teams are set as input for the process and the detection of the players and identification of the corresponding team is made automatically. In order to compare the results obtained with our previous work, we set the CIEDE2000_PF cut-off limit for this experiment to 5.583, which corresponds the power-transformed cut-off limit of 7 in the CIEDE2000 formula. This experiment intends to observe the practical applicability of the proposed models and cascade and to compare the results obtained with the ones on the cascade for the CIEDE2000 metric. An example of the segmentation resulting from applying the proposed method is depicted in Fig. 3.

The assessment strategy for this application is two-fold. First we address the computation time requirements and secondly we compare the quality of the detection. For the latter we calculate the precision and recall for each processed frame. Table 3 illustrates the average processing time obtained for the entire dataset using only the CIEDE2000_PF metric and the best performing cascade strategy (MAL). Additionally we also compare the results obtained for the same cascade on the CIEDE2000 metric. From these results we can observe two important aspects. First, when comparing the computation time required not using the cascade between the two metrics we see that clearly the additional complexity introduced by the power function has a penalty in performance, resulting in a decrease in the frames per second processed by the CIEDE2000_PF metric. However, when applying the cascade strategy, the new metric outper-

(a) Original frame 429 from the stream 4 of the ISSIA dataset.



(b) Blobs detected belonging to the blue team.



(c) Blobs detected belonging to the white team.

Fig. 3: Detected blobs from the frame 429 of the stream 4.

Table 3: Average computation time for the ISSIA Dataset using the cascade MAL and no cascade for the CIEDE2000 metrics and the comparable results obtained for the CIEDE2000 metric in [19].

	CIEDE 2000		CIEDE2000_PF	
Cascade Struct.	Time(s)	FPS	Time(s)	FPS
No cascade	1511.42	1.99	1760.65	1.71
MAL	240.17	13.05	189.49	16.08

forms the base CIEDE2000. This happens mainly due to the improvements that were obtained in the mapping models, but also due to how the new metric relates to the color properties, resulting in more color pairs being filtered.

For the second evaluation, we look into the practical performance of detecting players in a soccer match and evaluated the precision and recall of the segmentation algorithm. In our previous work, the precision obtained was of 92.5% and the recall of 75.8%. Using the new metric we obtained a precision of 97.4% and a recall of 78.8%. These results show that by applying the new metric and associated cascades with comparable cut-off values we are able to not only obtain better computational performance but also better accuracy. This further illustrates the observations in [20] that the application of the power function to the CIEDE2000 metric augments its ability to compare colors more precisely and the fact that it can indeed be applied in practical applications.

6 Conclusion

This letter proposes an efficient strategy for deciding on the similarity of the colors based on the new formula, CIDE2000_PF, recommended by CIE, thus extending and improving our initial findings for the original CIEDE2000 metric. The color similarity decision process makes use of low complexity color properties with corresponding decision boundaries automatically defined through models that maps an original boundary in the CIDE2000_PF. This enables decisions consistent with the CIDE2000_PF but with significant computational performance gains, which increases applicability, for example, in scenarios with hardware limitation.

This proposal has two main contributions. First, it proves that a family of functions that enables the mapping of an original cut-off in the CIEDE2000_PF metric into a decision boundary for the proposed low complexity properties also exists. Second, it shows that by employing gradient boosting to the training of the mapping models, it is possible to not only obtain much more precise models, but also skip the offset correction that was introduced in our previous work. This lead to an improved performance while guaranteeing that no classification error occurred. By proving mathematically and empirically that a fast and efficient color similarity decision methodology can be defined for the newly recommended CIEDE2000_PF, we aim to show that industrial applications can be adapted to reduce their computational requirements. As future work, we envision the applicability of a similar strategy to input colors in color spaces other than RGB. Although it is always possible to convert these colors to the RGB color space and use the proven strategy, with an expected performance decrease due to the color conversion.

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Conflict of interest

The authors declare that they have no conflict of interest.

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