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Designing a Color Filter with High Overall Transmittance for Improving the Color Accuracy of Digital Cameras

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Abstract

Previously improved color accuracy of a given digital camera was achieved by carefully designing the spectral transmittance of a color filter to be placed in front of the camera. Specifically, the filter is designed in a way that the spectral sensitivities of the camera after filtering are approximately linearly related to the color matching functions (or tristimulus values) of the human visual system. To avoid filters that absorbed too much light, the optimization could incorporate a minimum per wavelength transmittance constraint.

In this paper, we change the optimization so that the overall filter transmittance is bounded, i.e. we solve for the filter that (for a uniform white light) transmits (say) 50% of the light. Experiments demonstrate that these filters continue to solve the color correction problem (they make cameras much more colorimetric). Significantly, the optimal filters by restraining the average transmittance can deliver a further 10% improvement in terms of color accuracy compared to the prior art of bounding the low transmittance.

1. Introduction

Digital cameras measure color of the real world scenes by using three color channels, known as Red, Green and Blue. When the RGB sensitivities of a camera are within a linear transform from the CIE XYZ color matching functions [1], we say the camera meets the so-called Luther condition [2] and it is colorimetric [3].

However, we are not aware of any typical cameras (for example, in smartphones or single-lens reflex cameras) that are colorimetric [4, 5]. Rather, in typical signal processing pipelines, the RGBs measured can only be approximately corrected to the corresponding XYZ tristimulus values (or equivalently sRGB [6]). Invariably, a simple 3×3 matrix is used for color correction.

Recently Finlayson and Zhu [7] presented a method that designed a color filter that when placed in front of the camera, makes the camera more colorimetric. The idea of placing a prefilter and a camera is illustrated in Figure 1a. Explicitly, when we place a filter in front of a camera, the effective camera responses functions are equal to the original camera sensitivities multiplied by the spectral transmittance of the filter on a per wavelength basis. For example, given the spectral sensitivity curves of a camera (shown in Figure 1b) and the spectral transmittance distribution of an optimal filter obtained from the Luther-condition optimization in [7] (plotted in Figure 1c), we can obtain the new effective camera sensitivity set by per-wavelength multiplication as shown in Figure 1d.

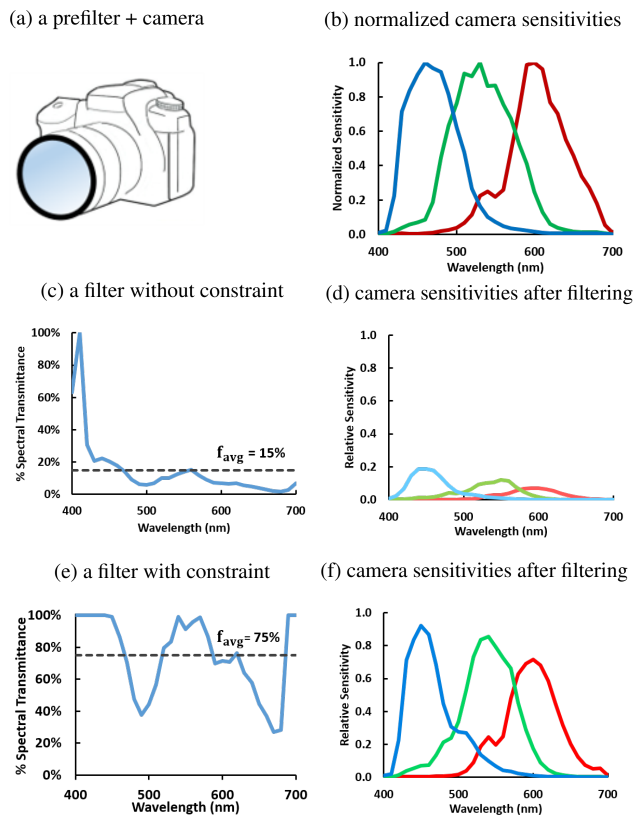

Figure 1: (a) Illustration of the setting of a 'prefilter + camera', (b) the spectral sensitivity curves of a Canon 40D camera normalized at the maximum of each color channel, the spectral transmittance distribution of optimal filters (c) without constraint and (e) with a constraint of $f_{avg} \geq 75\%$ (the dotted lines show the overall transmittance of the filter). In (d) and (f) are the new effective camera sensitivities after using the filters given in (c) and (e) respectively.

In [7], a filter is found such that the new sensitivity functions of the 'filter+camera' system after an optimal linear transform is closest to the XYZ color matching functions in the least-squares sense (thereby optimizing the Luther condition). In Figure 1d, clearly we can see that the camera using such a filter produces much lower sensitivity responses. Although we can increase the exposure time or set a higher ISO value to compensate for the loss of light, unfortunately a camera with low sensitivity functions will sometimes result in high noise levels (i.e. lower signal-to-noise ratio).

In a recent work, the noise issue in the prefilter design has been studied by Vrhel [9]. Vrhel's work shows that the filters with higher overall transmittance values perform better in terms of Signal-to-Noise Ratio (SNR). For the color filter, it is a trade-off between the colorimetric measurement potential of a camera and the amount of noise that is present in captured images (for a given intensity of light). It is of great practical interest to design color filters which can transmit more of the incoming light while delivering improved colorimetric performance for digital cameras.

To avoid solving for a filter that has low transmittance, previous work [8] showed how to design filters that were required to transmit a low-bound percentage of light at all wavelengths (e.g. the filter transmittance has to be greater than 20% at any wavelength). Again, there is a trade-off here: the higher the low bound, the less well a filter can make a camera colorimetric.

In this paper we look at the filter transmittance in a different way. Rather than placing a lower bound at each wavelength, we instead focus on the overall transmittance (on average how much of an incident uniform white light can be transmitted by a filter). We place the constraint that the average light power transmitted by the filter must be greater than a target percentage (e.g. 50%). We formulate our problem subject to this transmittance constraint.

Significantly, compared to the boundedness constrained optimization [8], our new overall transmittance approach of filter design returns filters that deliver a further 10% improvement in color accuracy. Not only does this teach that the form of the optimization has a profound impact on the filters we solve but also that there is a good deal of latitude in how filters might be designed. This argues well for the fabrication of filters that might make cameras more colorimetric.

Experiments demonstrate that we can find highly transmissive filters that provide comparable colorimetric improvement for a camera compared to the prior art of unconstrained optimal filters.

2. Background

Color Image Formation

The color of a pixel formed in a digital camera mainly depends on three physical factors, i.e. the spectral power distribution of the illuminant $E(\lambda)$, the reflectance factor of the object surface $S(\lambda)$, and the spectral response curves of the camera, $Q_k(\lambda)$ for each color channel. The color of a pixel, under Lambertian surface model, can be modelled as

$$\rho_k = \int_{\omega} E(\lambda)S(\lambda)Q_k(\lambda)d\lambda, \quad k \in \{R,G,B\} \tag{1}$$

where the variable λ is defined in the visible wavelength domain ω and $Q_k(\lambda)$ is the spectral sensitivity curve of channel k in the camera, usually red-, green- and blue-channels.

It is useful to recast the continuous integration into the discrete representation using matrices and vectors. Typically, for imaging application, it is sufficient to sample a spectrum measured within the visible wavelength range between 400 nm and 700 nm for every 10 nm sampling interval.

For a collection of m surface color stimuli under a given illuminant, the camera responses can be concisely readdressed as

$$\mathbf{P} = \mathbf{S}^T diag(\mathbf{E})\, \mathbf{Q} \tag{2}$$

where the camera RGB values $\mathbf{P}$ is an $m \times 3$ matrix, the object reflectance $\mathbf{S}$ is a $31 \times m$ matrix, the illuminant $diag(\mathbf{E})$ is a 31×31 diagonal matrix, and $\mathbf{Q}$ is a 31×3 matrix denoting the camera sensitivities over red-, green-, and blue-channels. The superscript ^{T} denotes the matrix transpose.

Similarly, the color values observed by a standard observer can be quantified as

$$X = \mathbf{S}^T diag(\mathbf{E})\, \mathbf{X} \tag{3}$$

where X is an $m \times 3$ matrix representing the observer color tristimuli and $\mathbf{X}$ is a 31×3 matrix denoting the CIE 1931 2° XYZ color matching functions [1].

The Luther Condition

The Luther condition requires that the camera sensitivities are within a linear transform from the CIE XYZ color matching functions. Mathematically, we write

$$\mathbf{X} = \mathbf{Q}\, \mathbf{M} \tag{4}$$

where $\mathbf{M}$ is a full rank 3×3 matrix mapping camera sensitivities to the visual color matches.

If the camera sensitivity curves meet the Luther condition, we can easily prove that their tristimulus color responses are also linear apart:

$$\mathbf{S}^T diag(\mathbf{E})\, \mathbf{X} = \mathbf{S}^T diag(\mathbf{E})\, \mathbf{Q}\, \mathbf{M} \;\Rightarrow\; X = \mathbf{P}\, \mathbf{M} \tag{5}$$

which makes the camera a colorimeter, i.e. the triplet color values produced by the camera can be linearly related to that of the visual tristimulus values.

Linear Color correction

The Luther condition places a very strong constraint on the sensitivity functions of a camera and in practice, most cameras do not satisfy the Luther condition. But, a 3×3 linear color correction matrix can be found that best maps the RGB responses to the human visual tristimuli.

The best linear mapping matrix is solved as a least-square regression:

$$\mathbf{M} = \mathbf{P}^{+}\mathbf{X} = (\mathbf{P}^T\mathbf{P})^{-1}\mathbf{P}^T X \tag{6}$$

where the superscript $^+$ and $^{-1}$ denote respectively the Moore-Penrose inverse [10] and the matrix inverse.

3. Filter Design

The Modified Luther Condition

Let $\mathbf{V} = [\mathbf{v}_1, \mathbf{v}_2, \mathbf{v}_3]$ denote a special linear combination of $\mathbf{X}$ whose columns are orthonormal basis vectors, i.e. $\mathbf{V}^T\mathbf{V} = \mathbf{I}_3$ ($\mathbf{I}_3$ is the identity matrix). Matrix $\mathbf{V}$ can be calculated from $\mathbf{X}$ by the QR factorization or singular value decomposition [15]. Mathematically, we write $\mathbf{X} = \mathbf{VH}$ where $\mathbf{H}$ is a full rank 3×3 matrix.

By substituting into Equation (4), we can rewrite the Luther condition as

$$\mathbf{VH} = \mathbf{QM} \;\Rightarrow\; \mathbf{V} = \mathbf{QMH}^{-1} \tag{7}$$

where the superscript $^{-1}$ denotes the matrix inverse and $\mathbf{MH}^{-1}$ forms a new 3×3 matrix. This equation teaches us that the camera sensitivities $\mathbf{Q}$ of which meets the Luther condition should also be within a linear transform from the orthonormal basis $\mathbf{V}$.

In this paper, we will choose to find a filter and a linear transform that approximately maps $\mathbf{Q}$ to $\mathbf{V}$ (see the optimization shown in Equation (12)) because previous work [12] has shown that optimizing the least-squares Luther condition with respect to the orthonormal basis is equivalent as finding the filter that optimizes the Vora-Value [13].

The Vora-Value is a measure of goodness of the set of camera sensitivities with respect to the human visual space. By definition, it calculates the geometric closeness of two vector spaces spanned by the camera sensitivity functions (in our case the filtered camera sensitivities) and the XYZ color matching functions. The Vora-Value is independent of the basis in which the sensors are described.

In the previous work [12], we found that the filter solved for optimizing the Luther condition using the orthonormal basis of the XYZ color matching functions (simultaneously optimizing the Vora-Value) could provide better results than the original formation of the Luther condition as in Equation (4). In fact, by orthonormalization, we encourage the Luther optimization to optimize for the Vora-Value. Hence we use the modified Luther condition as our optimization criterion in this paper.

Filter Constraints

Physically, for a color filter, the filter transmittance must be non-negative and no greater than 1 as

$$0 \leq f(\lambda) \leq 1, \quad \lambda \in \omega \tag{8}$$

where $f(\lambda)$ denotes the filter transmittance at a given wavelength λ, defined on the domain of the visible spectrum ω.

Practically, a prefilter will inevitably absorb part of the incoming light. Sometimes we can adjust the capture setting of a camera, such as longer exposure time and higher ISO, so as to match the light level of that when no filter is placed. But, in scenes where there is movement we need to use a short exposure and then the captured filtered image will be affected by relatively more noise (compared to without using the filter). How much extra noise there is depends on how much light is absorbed by the filter. In the example in Figure 1c), the camera absorbs most of the light and so the noise problem may be significant.

In this paper we wish to tackle the problem of the derived filter absorbing too much light. In previous work [8], filters were found that met a low bound on transmittance. Here we solve for the filter that, in total, transmits a prescribed percentage of the total light (or more).

We define the average transmittance percentage as:

$$\frac{\int_{\omega} 1 \cdot f(\lambda)\, \mathrm{d}\lambda}{\int_{\omega} 1\, \mathrm{d}\lambda} \tag{9}$$

where we calculate the ratio between the amount of a uniform white light (which has a value of 1 at any wavelength) a filter transmits over the visible spectrum against that when no filter is used.

Equivalently, in the discrete domain, the average percentage transmittance is written as

$$\frac{1}{31}\mathbf{f} \cdot \mathbf{1} \tag{10}$$

where $\cdot$ is the inner product between two vectors and 31 is the number of sampling points between 400 nm and 700 nm.

We would like to make sure the average transmittance is larger than a criterion amount f_{avg}:

$$\frac{1}{31}\mathbf{f} \cdot \mathbf{1} \geq f_{avg}. \tag{11}$$

The Luther-condition based Filter Optimization

Given the filter transmittance vector $\mathbf{f}$ and the camera spectral sensitivity functions $\mathbf{Q}$. When we place a filter in front of the camera, the filtered camera sensitivity functions can be modeled as $diag(\mathbf{f})\mathbf{Q}$. Mathematically, by adopting the formula in Equation (7) and incorporating the filter constraints in Equations (8) and (11), we reformulate the Luther-condition based filter optimization as

$$\underset{\mathbf{f},\mathbf{M}}{\arg\min} \quad \| diag(\mathbf{f})\mathbf{QM} - \mathbf{V} \|_F^2, \qquad s.t. \;\; 0 \leq \mathbf{f} \leq 1 \;\text{ and }\; \frac{1}{31}\mathbf{f} \cdot \mathbf{1} \geq f_{avg} \tag{12}$$

where $\| \; \|_F^2$ denotes the square of the Frobenius norm (i.e. the sum of the squares of all elements in the matrix). $\mathbf{M}$ is a 3×3 matrix to be determined.

Solving the Minimization

The filter optimization presented in Equation (12) has no closed-form solution. Fortunately, the filter matrix $\mathbf{f}$ and the correction matrix $\mathbf{M}$ can be solved iteratively using a technique called the *Alternating Least-Squares* (ALS) regression. Promisingly, the ALS method is guaranteed to converge (although not necessarily to the global optimum) [14].

Initially, we solve for $\mathbf{M}$ by assuming a uniform filter $\mathbf{f} = [1, 1, \cdots, 1]$. Given this newly solved $\mathbf{M}$, we update for the filter solution. That is to say, we solve for matrix $\mathbf{M}$ by holding the filter $\mathbf{f}$ fixed and alternatively using the newly solved matrix $\mathbf{M}$ to solve for the filter $\mathbf{f}$ and the process will continue updating both matrices in turn until it converges to a predefined error threshold.

Given a known filter vector, the correction matrix can be solved by

$$\mathbf{M} = \left(diag(\mathbf{f})\mathbf{Q}\right)^{+}\mathbf{V} \tag{13}$$

where $^{+}$ denotes the Moore-Penrose inverse [10].

Given a known $\mathbf{M}$, the filter under constraint can be easily converted to a Quadratic problem subject to linear constraints and solved by the Quadratic programming [15].

4. Experiments and Results

The filter optimization is tested out on two representative digital cameras from two well recognized camera manufacturers, a Canon 40D and a Nikon D5100 digital single-lens reflex cameras,

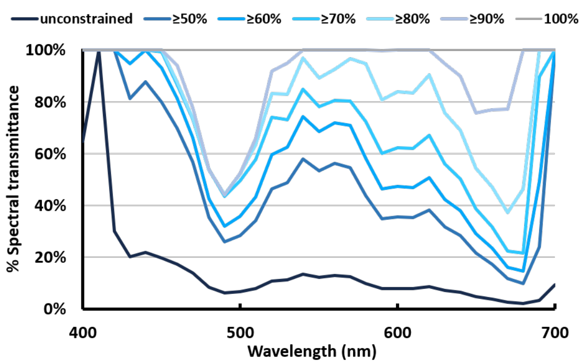

Figure 2: Spectral transmittance distributions of optimized filters under different average transmittance constraints for Canon 40D.

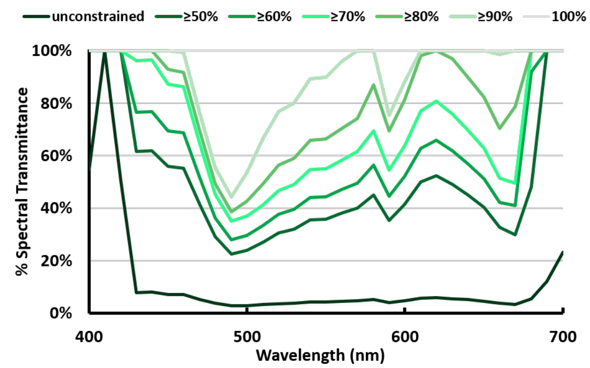

Figure 3: Spectral transmittance distributions of optimized filters under different average transmittance constraints for Nikon D5100.

with measured spectral sensitivities [16]. We solve for the best filters for each of the testing cameras with gradually levelling up the constraints of the average transmittance: from greater than 50%, 60%, 70%, 80%, 90%, to 100% (100% equivalently means no filter is used) respectively. In the experiments, the algorithm starts with an initial uniform filter of $\mathbf{f} = f_{avg} * [1, 1, \cdots, 1]^T$, then solves for a new 3×3 correction matrix **M**; given this newly solved **M**, we recalculate the filter solution. The process goes on solving these two unknown matrices in an alternative way. Empirically, the algorithm converges quickly (here we use the stopping criterion: the cost function error between two consecutive iterations is less than $1e-08$). It usually takes less than 1 second to compute a converged solution set of the optimal filter and the mapping matrix.

Table 1: ΔE^*_{ab} statistics of the color corrected native camera, the color corrected camera with the unconstrained filter, filters under different average constraint levels (f_{avg}), and filters under the low transmittance bounds (f_{min}) for a Canon 40D camera

	Mean	Median	95%	Max
Native camera	1.72	1.03	5.12	28.39
no constraint ($f_{avg} = 15\%$)	0.38	0.20	1.23	9.86
$f_{avg} \geq 50\%$	0.44	0.24	1.43	11.73
$f_{avg} \geq 60\%$	0.54	0.30	1.74	13.83
$f_{avg} \geq 70\%$	0.73	0.38	2.33	18.18
$f_{avg} \geq 80\%$	0.97	0.56	3.12	20.82
$f_{avg} \geq 90\%$	1.27	0.78	4.06	21.82
$f_{min} \geq 24\%$ ($f_{avg} = 50\%$)	0.55	0.31	1.80	12.52
$f_{min} \geq 43\%$ ($f_{avg} = 70\%$)	0.86	0.50	2.74	17.68
$f_{min} \geq 77\%$ ($f_{avg} = 90\%$)	1.41	0.81	4.30	24.45

The spectral transmittance distribution of the optimized filters under these conditions are shown in Figures 2 and 3 for Canon and Nikon cameras respectively. For reference, we also plot the best Luther filter when no transmittance constraint is applied, i.e. we run the original optimization as in [7] (see the dark line with a sharp peak at the short wavelength end). Evidently, the unconstrained filters for both cameras present much lower overall transmittance (the transmittances over most of the wavelengths are less than 20% with the mean transmittance of 15% for the Canon camera and 12% for the Nikon camera respectively).

Table 2: ΔE^*_{ab} statistics of the color corrected native camera, the color corrected camera with the unconstrained filter and filters under average constraints (f_{avg}), and filters under the low transmittance bounds (f_{min}) for a Nikon D5100 camera

	Mean	Median	95%	Max
Native camera	1.66	0.90	5.30	27.66
no constraint ($f_{avg} = 12\%$)	0.81	0.48	2.70	11.87
$f_{avg} \geq 50\%$	0.85	0.53	2.85	14.98
$f_{avg} \geq 60\%$	0.86	0.53	2.88	13.41
$f_{avg} \geq 70\%$	0.92	0.57	3.03	12.87
$f_{avg} \geq 80\%$	1.07	0.66	3.60	16.07
$f_{avg} \geq 90\%$	1.28	0.77	4.19	18.83
$f_{min} \geq 26\%$ ($f_{avg} = 50\%$)	0.92	0.57	3.10	13.47
$f_{min} \geq 43\%$ ($f_{avg} = 70\%$)	0.96	0.60	3.20	14.32
$f_{min} \geq 75\%$ ($f_{avg} = 90\%$)	1.41	0.80	4.46	22.29

More importantly, for the two tested cameras, the derived filters have similar shapes and, significantly, they have (dented) peaks at about 490 nm and 680 nm spectrum. From the figures, we also see that the transmittance values at these two peak wavelengths are resistant to change compared to values at other wavelengths when we increase the average transmittance level. The figures demonstrate that the transmittance values at these peaks are critical for satisfying the Luther condition and consequently for the performance of color measurement accuracy.

We also evaluate the performance of cameras after using a filter in the color measurement experiment in terms of the perceptual color errors (here we use the color difference metric in the CIELAB color space [1]). The color correction experiments are performed for a set of 102 illuminants and 1995 reflectance spectra [18]. We calculate the RGBs and XYZs of all reflectance spectra under each illuminant according to Equations (2) and (3), and find the best 3×3 correction matrices mapping RGBs to the ground-truth XYZs before converted into CIELAB color space [19] to calculate the difference between the reference and test color values. Then the overall mean, median, 95-percentile and max of ΔE^*_{ab} are averaged over the all test lights.

The color measurement results are given in Table 1 for Canon 40D and Table 2 for Nikon D5100 cameras. As the baseline, we calculate the color errors of the **Native** camera when no filter is used, given in the first row. For comparison purpose, we also show results of the best Luther filter in the second row when no transmittance constraint is applied (its mean transmittance value is given in the parentheses).

As expected, greater threshold of the average transmittance will lead to less effective color accuracy. However, comparing the results of 2nd and 3rd rows in Table 1, we see that a filter having an average transmittance value of 50% has very close color accuracy compared to the unconstrained filter whose average transmittance is only 15%. The same trend occurs in the Nikon camera as we see a filter having an average transmittance value of 60% has similar performance of an unconstrained filter with the mean transmittance of 12%. Even a filter having an average transmittance value as high as 90% can significantly reduces color errors by about a quarter compared to the results of the **Native** camera.

We also present filter results of the prior art when we apply a lower bound on the filter transmittances. See the last three rows of Table 1 and Table 2. Here, $f_{min} \geq 24\%$ means that the filter transmittance at all wavelengths must be no less than 24%. When the lower bound is set to 24%, then the prior art optimization returns a filter that has an overall transmittance of 50%. Thus, by choosing the lower bound constraint carefully, we can compare the colorimetric efficacy of the prior art filter optimization and the approach we advocate in this paper.

We see that our new method offers a further 10% increase in color accuracy, for both cameras (when compared at the same overall transmittance level).

5. Conclusion

In this paper, we extend the Luther condition optimization to improve a key property of the optimized filter – the overall transmissivity – by enforcing the filter to transmit at least half of the incident light. The objective is to lessen the impact of noise in camera signals while maintaining the colorimetric accuracy. We tested on two representative digital cameras in the color measurement test. Experimental results show that a filter transmits 50% of the incident light can reduce nearly two-thirds to three-quarters of the color errors compared to the **native** camera when no filter is used. Promisingly, we can achieve comparable color accuracy improvement using much higher transmissive filters (e.g. a filter transmit 70% of the light) compared to the case of an *unconstrained* Luther-filter (a filter transmit 15% of the light). Moreover, the current method can deliver a further 10% improvement in terms of color accuracy compared to the prior art of restraining the minimum transmittance.

For the further study, it is of great interest in investigating the relation between the overall transmittance percentage of the filter and the signal-to-noise (SNR) ratio in the color measurement application. Or more effectively, we can adopt the SNR as the optimization criterion of the filter design as in [9]. Additionally, it is useful to take the smoothness of the filter into account (as studied in [20,21]) since it plays an important role when turning our optimal filter into fabrication.

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