The Optimizated CIELAB Colour Model For All-Analog Photoelectronic High Speed Vision-Task Chip (ACCEL) by Creative Computing Approach

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***Abstract*—The finding of this study created a design plan for improving the traditional Bayesian optimization algorithm logic by inserting Hidden Markov Chain and human preference, to avoid Bayesian algorithm self-trap in local. Additionally, this paper created a novelty model as the example case to help explaining the new logic. This paper stands on the creative computing approach to enrich the classical pure measurements (CIELAB colour standard) with visual intensity parameters. The new optical intensity colour model services the chip carrier, which is a high-speed vision-task photons chip design published in Nature at 25 Oct 2023[1]. The result model structure is expected to apply for the photons-based computer chip in the perspective of vision intensity optimization, such as future optically based virtual reality human-computer interaction applications.**

***Keywords*—Bayesian optimization, hidden Markov chain, creative computing, CIELAB model, computer photons chip**

I. Introduction

When the early scientists try to create a flying machine, they already have the electricity and advanced mathematical theory, but it was not enough to make the machine fly. Then, the scientists boldly borrowed the structures of the birds, and even borrow the structure of fish which looks unrelated, to create the electronic flying model. With the validation of the math metrics, the flying machine was built surprisingly successful. This power of creativity still shining in scientific research world, because the ontological philosophy points out that many laws and theorems are interlinked in essence.

This paper is borrowing the law of economics, transforming the Cobb-Douglas production function into the digital colour model for computer. And Proposing a design plan for improving Bayesian optimization algorithm to avoid self-trap by adding Hidden Markov Chain [2].

The reason why improving the Bayesian optimization (BO) by adding hidden Markov chain is because the traditional Bayesian optimization is tended to falling into the local trap, which is not the overall optimized value in the specific case such as colour searching in visual intensity [3].

To solve this problem, we introduced a design plan by adding Hidden Markov Chain (HMC) to clarify the zones, and adding the human preference filters. Therefore, "BO + Human filter loop + HMC" is a new attempt direction to solve unsupervised parameter optimization [4].

II. Background of Terminologies

In overall, this paper is a creative computing model design, by combining the economic structure with the digital colour space, to reconstruct and to leverage the Bayesian algorithm. The following shows the key terminologies in this study.

A. Transformational Creativity Concept

According to the literatures, transformational creativity in computing includes transforming the conceptual space to produce ideas in new styles of algorithm design. Bring the theories or formulars from different fields in computer science to generate novelty idea for improving the computing algorithms is the example of transformational creativity [5].

B. Cobb-Douglas Production Function

The Cobb-Douglas production function was originally created by the American mathematician C.W. Cobb and the economist Paul H. Douglas when they jointly explored the relationship between input and output. It is an economic mathematical model used to predict the production of industrial systems or large enterprises in countries and regions and to analyse the way to develop production, referred to as the production function [6].

The Cobb-Douglas production function takes the following form:

$$Q = AL^{\alpha}K^{\beta} \tag{1}$$

（Note： "Q" represents total output; "A" represents total factor productivity; "L" represents input of labour; "K" represents input od capital; "α"represents the elasticity coefficient of labour output; "β" represents the elasticity coefficient of capital output.）

From this model, it can be seen that the main factors that determine the development level of the industrial system are the number of labour inputs, fixed assets and comprehensive technology level (including the level of operation and management, the quality of labour, the introduction of advanced technology, etc.). Depending on the combination of α and β, it comes in three types:

a) α+β>1, increasing returns to scale, indicating that according to the existing technology, it is advantageous to increase output by expanding the scale of production.

b) α+β<1, the return to scale is decreasing, indicating that according to the existing technology, it is not worth the loss to increase output by expanding the scale of production.

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c) α + β = 1, the scale remuneration remains unchanged, indicating that the production efficiency will not increase with the expansion of production scale, and only by improving the technical level will the economic benefits be improved.

C. CIELAB Colour Space in Computer

The International Commission of Illumination (CIE) developed the L*a*b* colour model in 1976. CIELAB is the classical old standard colour space for computer systems. CIELAB its processing speed is as fast as RGB mode and several times faster than CMYK mode. In CIELAB space, each colour can be represents as a point (L, A, B) within a three-dimensional coordinate axes. L value represents the lightness, which is between 0 and 100. L=0 represents near black, L=100 represents white. The A value is Redness degree, it actually between red and green. A=100 is near red, and A=80 is green. The B value is yellowness degree, which indicates the colour between yellow and blue, B=100 is near yellow, B=80 is near blue [7].

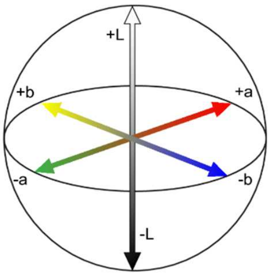

Fig 1. The Standard CIELAB Space in Computer

In the Fig above, L lies between 0 and 100, and a and b lie between -110 and 110. The white point for CIELAB is fixed at (0.9642, 1, 0.8249), which is the D65 standard.

TABLE 1. EXPERIMENT DATA FROM HTTPS://CIELAB.XYZ/PDF/ [8]

CIE 1931 standard colorimetric observer						
λ, nm	L	A	B	$\bar{x}(\lambda)$	$\bar{y}(\lambda)$	$\bar{z}(\lambda)$
380	0.04000	5.37000	-12.11000	0.00137	0.00004	0.00645
400	0.36000	52.37000	-58.76000	0.01431	0.00040	0.06785
420	3.61000	174.69000	-150.47000	0.13438	0.00400	0.64560
440	16.99000	213.89000	-143.12000	0.34828	0.02300	1.74706
460	29.41000	139.56000	-121.70000	0.29080	0.06000	1.66920
480	44.09000	-27.57000	-95.40000	0.09564	0.13902	0.81295
500	63.59000	-254.31000	-0.93000	0.00490	0.32300	0.27200
520	87.49000	-244.38000	87.22000	0.06327	0.71000	0.07825
540	98.19000	-157.06000	138.72000	0.29040	0.95400	0.02030
560	99.81000	-73.60000	164.72000	0.59450	0.99500	0.00390
580	94.74000	14.26000	160.23000	0.91630	0.87000	0.00165
600	83.49000	71.14000	142.45000	1.06220	0.63100	0.00080
620	68.09000	117.78000	117.05000	0.85445	0.38100	0.00019
640	48.88000	107.56000	84.24000	0.44790	0.17500	0.00002
660	29.66000	80.71000	51.14000	0.16490	0.06100	0.00000
680	13.83000	53.78000	23.84000	0.04677	0.01700	0.00000
700	3.71000	28.83000	6.39000	0.01136	0.00410	0.00000
720	0.95000	7.63000	1.63000	0.00290	0.00105	0.00000
740	0.22000	1.82000	0.39000	0.00069	0.00025	0.00000
760	0.05000	0.44000	0.09000	0.00017	0.00006	0.00000

2.4 All-analog Chip (ACCEL) As CIELAB Carrier

In the Theory and Intelligent Technology Laboratory of Tsinghua University, an optoelectronic fusion chip was published in Nature at 25 Oct 2023 . Tsinghua University uses "a fully analog chip that combines "electronics and light" to describe the characteristics of this optoelectronic fusion chip, and uses the English initials of this sentence to name the chip " ACCEL "[1].

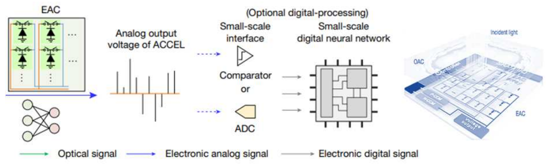

Fig 2. Optical Principle Based Signal Processing in Chip

All-analog Chip (ACCEL) is the CIELAB Carrier because it is based on the spectral principles servicing in computing visual effects. This paper is to renew and improve the CIELAB in creative computing approach, to make it develop with the more advanced computer screen and preparing for the related future potential technology changes. The following sections and the finding result in this paper shows more details and illustrations about how to improve CIELAB.

III. A TRANSFORMATIONAL CREATIVITY CASE

A. Philosophical Base

According to the philosophical ontology, the essence logic of models can be the same [9]. This paper is borrowing the law of economics, and transforming the Cobb-Douglas production function into the digital colour model for computer. Economic principles reflect social phenomena, but the logic of some principles can actually be applied to non-economic phenomena.

B. Bayesian Optimization is the Benchmark

Bayesian optimization is a sequential design strategy for global optimization of black-box functions which does not assume any functional forms. It is usually employed to optimize expensive-to-evaluate functions. The objective function is unknown. Bayesian strategy is to treat it as a random function and place a prior over it. The posterior distribution is used to construct an acquisition function (it often referred to as infill sampling criteria) that determines the next query point. The objective function Q (L, A, B)= Q_t can be sampled at [10]:

$$Q_t = argmax_Q\ U(Q|D_{1:t-1}) \tag{2}$$

Argmax is a function concept, which is a function that takes parameters (set) of a function. Argmax (f(x)) is the variable point x (or set of x) corresponding to the maximum value of f(x). Here $D_{1:t-1}$=(Q_1, U_1), …, (Q_{t-1}, U_{t-1}), and the U in functions is the acquisition function. Find the next sampling CIELAB colour code point Q_t by optimizing the acquisition function over the GP for t=1,2,…,repeat: $Q_t = argmax_Q\ U(Q|D_{1:t-1})$. Then Obtain a possibly noisy sample from the objective function Q (L, A, B) = Q_t, so there is a possibly noisy sample y:

$$y_t = Q(L_t, A_t, B_t) + \alpha_t \tag{3}$$

Then we can add the sample to previous samples $D_{1:t-1}$.

$$D_{1:t} = D_{1:t-1}, (Q_t, y_t) \tag{4}$$

The formular is for updating the GP usage, which is Q:

$$Q_t = argmax_Q\ U(Q|D_{1:t-1}) \tag{5}$$

3.3 Expected Improvement in Traditional Bayesian

Here assuming the expected improvement is defined as:

$$EI(Q) = Emax(Q(L, A, B) - Q(L^+, A^+, B^+), 0) \tag{6}$$

Here the formular $Q(L^+, A^+, B^+)$ is the value of the best sample so far. L^+, A^+, B^+ is the location of that sample:

$$Q^+ = Argmax_{Q_i \epsilon Q_{1:t}} f(Q_i) \tag{7}$$

Then, the expected improvements can be evaluated analytically under the GP mode:

$$\mathrm{EI}(Q) = \begin{cases} (\mu(Q) - f(Q^+) - \xi)\Phi(Z) + \sigma(Q)\varphi(Z) & , if\ \sigma(Q) > 0 \\ 0 & , if\ \sigma(Q) \leq 0 \end{cases} \tag{8}$$

Here Phi is an irrational mathematical constant, approximately 1. 618.., and is often denoted by the Greek letter φ. where μ(x) and σ(x) are the mean and the standard deviation of the GP posterior predictive at x, respectively. Φ and φare the CDF and PDF of the standard normal distribution respectively. The first summation term in Equation EI(Q) is the exploitation term and second summation term is the exploration term [10].

$$Z = \begin{cases} \frac{\mu(Q) - f(Q^+) - \xi}{\sigma(Q)} & , if\ \sigma(Q) > 0 \\ 0 & , if\ \sigma(Q) \leq 0 \end{cases} \tag{9}$$

ξ in Equation EI(Q) determines the amount of exploration during optimization. with increasing ξ values, the importance of improvements predicted by the GP posterior mean μ(x) decreases. A recommended default value for ξ is 0.01.

C. Explanation of the Research Gap

The Bayesian Optimization principle has some flaws, one of the most well-known flaws is it's the greedy algorithm and tend to fall into local optimum. This paper is focus on this most famous flaw, and proposing a design for improve the traditional Bayesian Optimization, to avoid it falling into local optimum. The Monte Carlo method can be used to find many random numbers to detect whether it falls into a local optimum in the Bayesian network, but it requires a large amount of calculation. Another new improving approach is to calculate the mutual information between nodes in the network, retain the direct links of nodes with larger mutual information, and then conduct a complete search on the simplified network to find a globally optimized structure.

This study created a design plan for improving the traditional Bayesian optimization algorithm logic by inserting Hidden Markov Chain and human preference, to avoid Bayesian algorithm self-trap in local. Because mathematically, a Bayesian network is a weighted directed graph, which is an extension of the Markov chain.

D. Set A Prior Function for Bayesian Optimization

In this paper we use the structure of Cobb-Douglas production function and transform it into a prior function. It originally takes the following form: $Q = AL^{\alpha}K^{\beta}$.

In the original function, "Q" represents total output, it also can be represent as the output of the intensity effect in this study as the assumption, logically it can be the output of computer command; Therefore, Q = (L, A, B). In economics logic of Cobb-Douglas production function, "A" represents total factor productivity. However, the total factor productivity concept is not only apply for economic concept, it also can be apply for the similar concept of the total factor in producing, such as producing lightness. Therefore, A can be the total brightness factor productivity in producing colour. The "L" in economic Cobb-Douglas production function represents input of labour. Labour is the obvious factor, which quickly increase the heat of the economy, in some synaesthesia related literatures labour was defined as warm tone for the economic growth. Therefore, it has a subtle link with the colour of the warm red and green in synaesthesia [15]. In the creative approach, the labour factor can be assumes as Redness degree in synaesthesia viewpoint. "K" represents input of capital; It refers to the density of the colour, which is the cool tone. Cool tone defines the density of the colour, here the colour blue to yellow is the cool tone. Therefore, K is the B in CIELAB. "α" represents the elasticity coefficient of labour output; In this paper, "α"represents the elasticity coefficient of warm tone. "β" represents the elasticity coefficient of capital output）. This paper assumes "β" represents the elasticity coefficient of cool tone. Therefore, according to the assumptions above, function can be rewrite as a CIELAB structure:

$$Q = f(\mathrm{L}, \mathrm{A}, \mathrm{B}) = \mathrm{L}\mathrm{A}^{\alpha}\mathrm{B}^{\beta} \tag{10}$$

In the formular (2), L is the brightness value, A is the colour tone between red and green. B is the colour tone between yellow and blue. "α"represents the elasticity coefficient of warm tone. "β" represents the elasticity coefficient of cool tone. This formular will serve as the basis for assuming a priori functions in Bayesian optimization process. "Q" is the so-called black box, that is, user input a set of hyperparameters and get an output value. "∂", "β"are the hyperparameters search space. L is between 0 and 100, and A and B are all between -110 and 110. The input and output can be 3 separate matrices or a three-dimensional tensor.

In this paper. We assume α + β = 1. In Cobb-Douglas production function, when α + β = 1, the scale remuneration remains unchanged, the production efficiency will not increase with the expansion of production scale. In this situation, improving the technical level will the economic benefits be improved. In this paper, "β" and "α" is refer to the elasticity coefficient of warm and cool tone of the colour under light intensity [14]. In the situation "β" and "α" is unknown, the function can be either convex or not convex. Therefore, formular (2) can be rewrote as:

$$Q = f(\mathrm{L}, \mathrm{A}, \mathrm{B}) = \mathrm{L}\mathrm{A}^{\alpha}\mathrm{B}^{1-\alpha} \tag{11}$$

When the function is convex and the domain is also convex, we can handle it through convex optimization that has been widely studied, but it is not necessarily convex, and in machine learning it is usually an expensive black-box function, which requires lot of resources. In another word, it will need a relative slow and inefficient processing. So we use improved Bayesian optimization to deal with this problem.

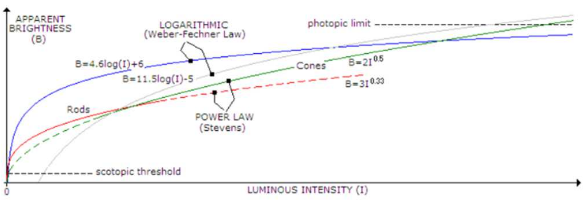

Fig 3. Optical Findings from *https://www.telescope-optics.net/eye_intensity_response.htm* [11]

The Fig 3 is from the public optical finding, their plots based on Weber-Fechner (logarithmic) and Steven's (power) laws of psychophysical (sensual) response applied to luminous intensity. The rate of eye response to changes in luminous intensity is over a limited range of intensities, which is farther from origin it can be. In general, it described by either logarithmic or power response. This paper uses Steven's (power) laws of psychophysical (sensual) response. Red is illustrating rods function, with 0.33 exponent. Green is illustrating cones function, with 0.5 exponent. Rods are responsible for vision at low light levels (scotopic vision). Cones are active at higher light levels (photopic vision), it is capable in colour vision and it’s responsible for high spatial acuity. Therefore, the formular is expanding as the following:

$$\mathrm{L_{intensity}}(\text{scotopic vision})=\mathrm{B(rod)}=3L^{0.33} \tag{12}$$

$$\mathrm{L_{intensity}}\ (\text{photopic vision})=\mathrm{B(cone)}=2L^{0.5} \tag{13}$$

$$\mathrm{Q_{vision\ intensity\ Output}} = L_{intensity}\ A^{\alpha}B^{1-\alpha} \tag{14}$$

$$Q=\begin{cases}3L^{0.33}A^{\alpha}B^{1-\alpha},\ in\ Low\ light\ background\\ 2L^{0.5}A^{\alpha}B^{1-\alpha},\ in\ \text{High light background}\end{cases} \tag{15}$$

Here in formular (15), the Q is the vision intensity Output. In low light background means the colour is in the scotopic vision environment or background. Scotopic refers to rod vision and corresponds to an adaptation level below 0.01 cd/m2. The peak sensitivity of the rods is at 507 nm, in the blue-green part of the visible spectrum. In high light background means the colour is in photopic vision environment or background. Photopic vision is the vision of the eye under well-lit conditions (luminance levels from 10 to 108 cd/m2). For the simplification, here is decent assumption of α + β = 1, and α = β = 0.5, therefore the warm tone and cool tone are treated unbiased and equal. Therefore, the formular can be as the following:

$$\mathrm{U_{vision\ intensity}} = \begin{cases}3L^{0.33}\sqrt{|AB|},\ \text{scotopic}\\ 2L^{0.5}\sqrt{|AB|},\qquad \text{photopic}\end{cases} \tag{16}$$

The mapping of this prior function shows as the following:

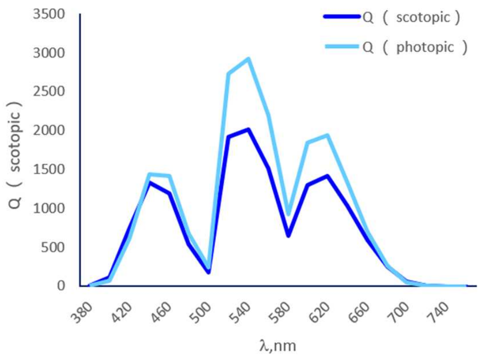

Fig 4. The Mapping of This Prior Function

TABLE 2. LOGISTIC DISTRIBUTION OF VISION INTENSITY MODEL

		QS	QP
Series or Sequence Length		20	20
Number of Missing Values in the Plot	Negative or Zero Before Log Transform	0	0
	User-Missing	0	0
	System-Missing	0	0

The cases are unweighted.

Estimated Distribution Parameters

		QS	QP
Logistic Distribution	Location	5.3463	5.3209
	Scale	1.426	1.647

The cases are unweighted.

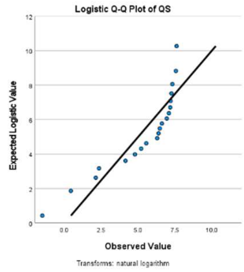

Fig 5. Logistic Plot of QS (Scotopic Vision Intensity)

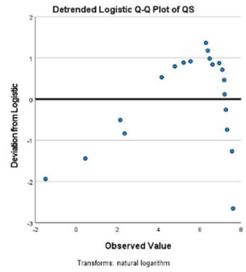

Fig 6. Logistic Plot of QS (Scotopic Vision Intensity)

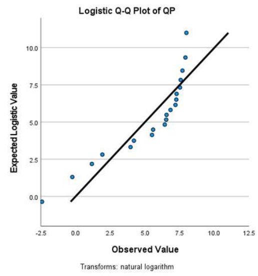

Fig 7. Logistic Plot of QP (Photopic Vision Intensity)

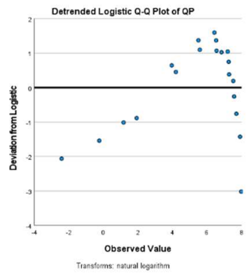

Fig 8. Logistic Plot of QP (Photopic Vision Intensity)

3.6 The Logic Plan for Improvements

The Bayesian optimization algorithm makes full use of the previous information. The Bayesian optimization algorithm learns the shape of the objective function and finds the parameters that improve the objective function to the global optimal value. Specifically, the way it learns the shape of the objective function is to first assume a search function based on the prior distribution, and then using this information to updating the prior distribution of the objective function each time. The new sampling point is used to test the objective function. Finally, the algorithm tests the point where the global maximum is , by given the posterior distribution it is most likely to occur.

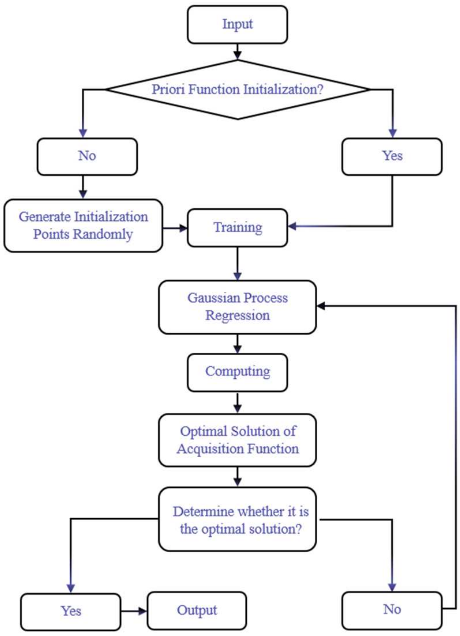

Fig 9. Traditional Bayesian (Before Improving)

This paper does not follow the traditional steps. The improved logic shows as the following flow. To give an example: a business user who want to chooses the best intensity of colour for products colours in advertisement (bright yellow, red, black), based on the conditional keywords (relaxed, happy, professional). In this example, the visible state is the colour output, however the hidden state is the keyword added by the users, which is the filter for human preference intervention.

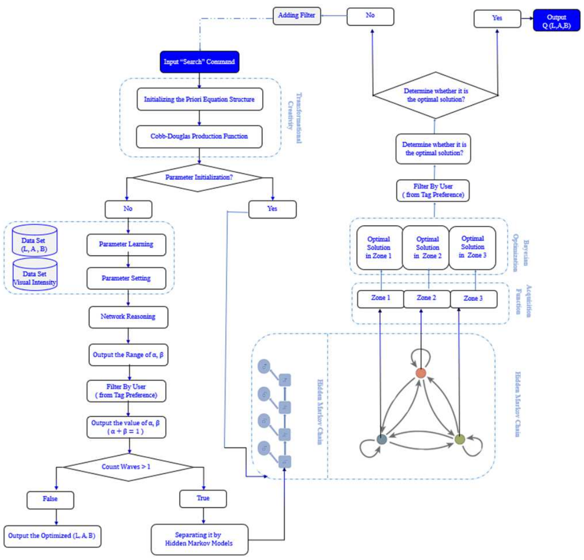

Fig 10. The Logic for Improving Bayesian Local Trap

Hidden Markov Chain is from the Hidden Markov Models (HMM). The hidden Markov model is an extension of the Markov chain: the state at any time t is invisible. But the Hidden Markov model will output a symbol o_t at each time t, and o_t is only related to U_t. For each zone, there has the Probability P.

$$P\ (o_1, o_2, o_3, \dots |S_1, S_2, S_3, \dots) = \prod_t P\ (o_t|S_t) \quad (17)$$

$$P\ (S_1, S_2, S_3, \dots) = \prod_t P\ (S_t|S_{t-1}) \quad (18)$$

Then we have the strong chain relationship to avoid local trap for the next Bayesian optimizing process,

$$P\ (S_1, S_2, S_3, \dots o_1, o_2, o_3, \dots |) = \prod_t P\ (S_t|S_{t-1}) * P\ (o_t|S_t) \quad (19)$$

The model parameters can generate the sequence; then, calculating the probability of this model, as well as all possible paths generated and the probabilities of generating these paths. Finally, a new set of model parameters is calculated, and based on the new model parameters, we continue to search for better model parameters until the output probability of the objective function is maximized. This process is called Expectation-Maximization (EM). EM with filters can ensure that the algorithm converges a preferred local optimal point, but it cannot guarantee the global optimal point in theory. But with segmentations, combining Bayesian with artificial filtering layers, the preferred optimal value can be obtained [12].

IV. DIVERSE OPTIMIZATION RESULTS AT EACH ZONES

The value of the best sample so far. L^+, A^+, B^+ is the location of that sample:

$$Q = \prod_t P\ (S_t|S_{t-1}) * P\ (o_t|S_t)\ Argmax_{Q_i \epsilon Q_{1:t}} f(Q_i) \quad (20)$$

The following shows when P=1, which means it included all zones.

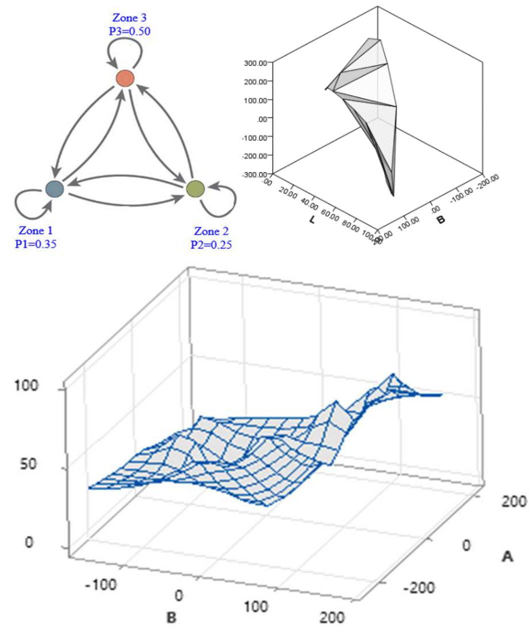

Fig 11. All Zone (380nm-760nm)

When the credible interval is 95%, choosing the number of the Monte Carlo Sample 30000.

Bayesian One-way Repeated Measures ANOVA for Zone (380nm-500nm) shows the optimized visual intensity value Q in scotopic background is 2011.90, while the optimized visual intensity value Q in photopic background is 2925.27.

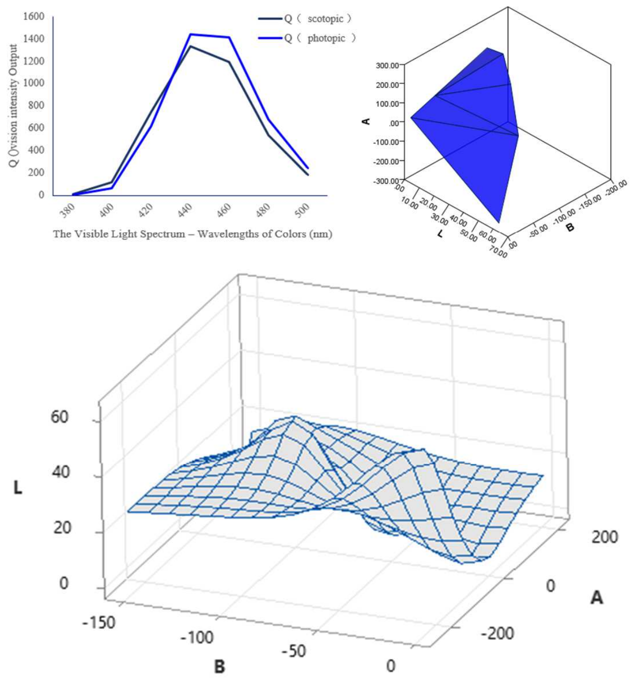

Fig 22. Zone 1 (380nm-500nm)

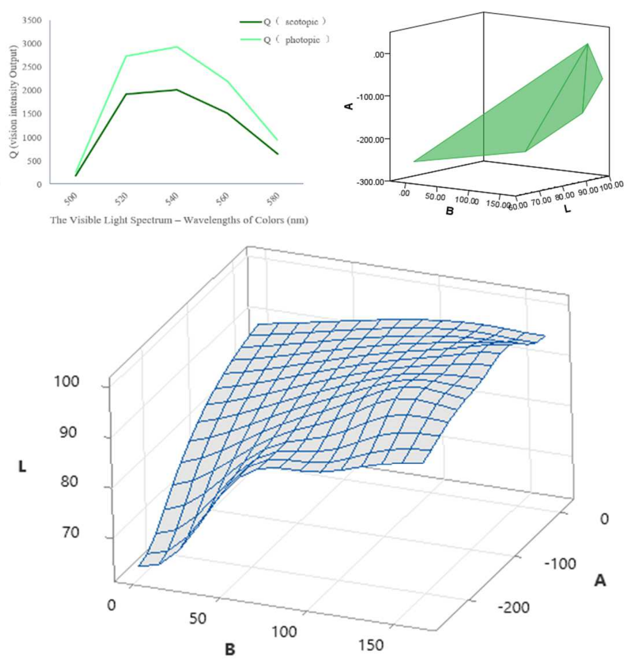

Fig 13. Zone 2 (500nm-580nm)

TABLE 3. BAYESIAN ONE-WAY REPEATED MEASURES ANOVA FOR ZONE 1 (380NM-500NM)

Case Processing Summary

	N	Percent
Included	7	100.0%
Excluded	0	0.0%
Total	7	100.0%

Descriptive Statistics of Within-Subject Factor Levels

Dependent Variables	Mean	Std. Deviation	N	Min	Max
QS	600.0742	10987.71770	7	8.36	1336.69
QP	656.1744	12397.97438	7	3.23	1442.35

Bayes Factor and Test of Sphericity

		Mauchly's Test of Sphericity			
	Bayes Factor[a]	Mauchly's W[b]	Approx. Chi-Square	df	Sig.
Within-Subject Effect	2.150E+152	1.000	.000	0	.

a. Method: BIC approximation. Testing model versus null model.

b. The Mauchly's Test uses an equally-spaced polynomial contrast to test the null hypothesis that the error covariance matrix of the orthonormalized transformed dependent variables is proportional to an identity matrix.

Compare with the traditional Bayesian which does not have the hidden Markov chain. For the Zone 1 (380nm-500nm), the new optimized visual intensity value Q in scotopic background is 1336.69 instead of 2011.90. When the user prefers the tags in 380nm-500nm, the traditional one does not have filters in process, therefore old Bayesian optimized visual intensity value Q in scotopic background is 2011.90, which is mathematically higher but not the logically optimized value. The new optimized visual intensity value Q in photopic background is 1442.35 compare to the original value 2925.27. The value drops but it is the optimized in logic, and it fit for the required preferences of the users in the specific case.

TABLE 4. BAYESIAN ONE-WAY REPEATED MEASURES ANOVA FOR ZONE 2 (500NM-580NM)

Case Processing Summary

	N	Percent
Included	5	100.0%
Excluded	0	0.0%
Total	5	100.0%

Descriptive Statistics of Within-Subject Factor Levels

Dependent Variables	Mean	Std. Deviation	N	Min	Max
QS	1256.2196	18473.45280	5	181.62	2011.90
QP	1812.6732	26790.37420	5	245.27	2925.27

Bayes Factor and Test of Sphericity

		Mauchly's Test of Sphericity			
	Log Bayes Factor[b]	Mauchly's W[c]	Approx. Chi-Square	df	Sig.
Within-Subject Effect	1871.919[a]	1.000	.000	0	.

a. The Bayes Factor cannot be calculated due to a numerical under- or overflow. Switching to log.

b. Method: BIC approximation. Testing model versus null model.

c. The Mauchly's Test uses an equally-spaced polynomial contrast to test the null hypothesis that the error covariance matrix of the orthonormalized transformed dependent variables is proportional to an identity matrix.

At the zone 2 (500nm-580nm), the traditional Bayesian which does not have the hidden Markov chain has the same optimized Q with the new one. The new optimized visual intensity value Q in scotopic background is 2011.90 when the user prefers the tags in 500nm-580nm, the traditional one does not have filters in process, the old Bayesian optimized visual intensity value Q in scotopic background produces the same value in this occasion which is just the cross mathematically coincide. The optimized visual intensity value Q in photopic background is also the same as the original value 2925.27. The value is the same but it is totally different in logic.

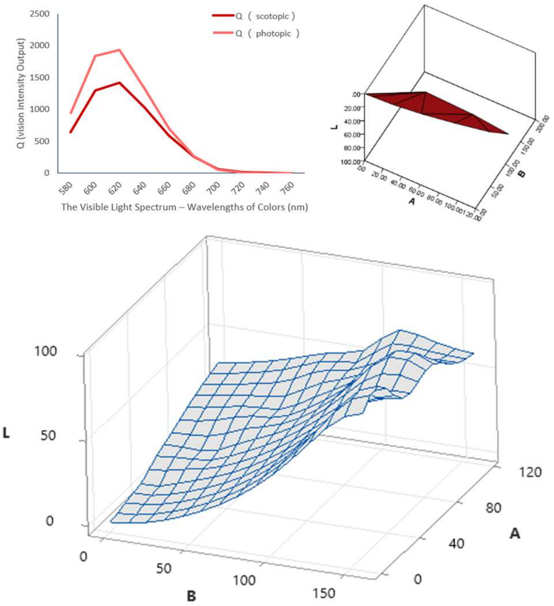

Fig 14. Zone 3 (580nm-760nm)

Case Processing Summary

	N	Percent
Included	10	100.0%
Excluded	0	0.0%
Total	10	100.0%

Descriptive Statistics of Within-Subject Factor Levels

Dependent Variables	Mean	Std. Deviation	N	Min	Max
QS	493.8283	14241.71759	10	.22	1418.27
QP	654.0127	19726.30798	10	.09	1937.73

Bayes Factor and Test of Sphericity

	Log Bayes Factor[b]	Mauchly's Test of Sphericity			
		Mauchly's W[c]	Approx. Chi-Square	df	Sig.
Within-Subject Effect	1584.693[a]	1.000	.000	0	.

a. The Bayes Factor cannot be calculated due to a numerical under- or overflow. Switching to log.

b. Method: BIC approximation. Testing model versus null model.

c. The Mauchly's Test uses an equally-spaced polynomial contrast to test the null hypothesis that the error covariance matrix of the orthonormalized transformed dependent variables is proportional to an identity matrix.

TABLE 5. BAYESIAN ONE-WAY REPEATED MEASURES ANOVA FOR ZONE 3 (580NM-760NM)

Compare with the traditional Bayesian which does not have the hidden Markov chain, for the Zone 3 (580nm-760nm), the new optimized visual intensity value Q in scotopic background is 1418.27 instead of 2011.90, when the user prefers the tags in 580nm-760nm, the traditional one does not have filters in process. The previous Bayesian optimized visual intensity value Q in scotopic background is 2011.90, which is a mathematically higher value but not the logically optimized value. The logically optimized visual intensity value Q in photopic background is 1937.73 compare to the original value 2925.27. 1937.73 fit more for the required preferences of the users in the specific case when the tags in 580nm-760nm.

V. CONCLUSION OF KNOWLEDGE CONTRIBUTION

In all, this paper proposed a new algorithm design plan and created a novelty digital colour model as the attempt direction to solve unsupervised parameter optimization.

First, this paper improved the Bayesian optimization (BO) by adding hidden Markov chain. This paper created a new algorithm design plan by adding hidden Markov chain (HMC) to identify the probability of the each zones. Furthermore, this paper added the human will filters, to make "BO + Human filter loop + HMC" a direction for solving unsupervised parameter optimization [13].

Comparing Issues	Bayesian optimization	Algorithm Design of This Paper
Local Trap	Probability "p" trap in Local (P=1)	A Design plan for reducing local trap probability "P" by Hidden Markov chain
Human filter loop	No human subjective filtering layers	Set human subjective tags as filtering layers when iterating

TABLE 6. THIS PAPER IMPROVED THE BAYESIAN OPTIMIZATION

Secondly, this paper stands on the creative computing approach and enriched the classical pure measurements (CIELAB colour standard) with the visual intensity parameters. This paper uses Steven's (power) laws of psychophysical (sensual) response and data from Russia to improve the CIELAB for the visual intensity effect [11].

Comparing Issues	CIELAB	Improved CIELAB of This Paper
Vision Intensity	Not directly related to vision Intensity	Directly related to Vision Intensity
User Preferences	Does not reflect user colour preferences	Reflect user's colour preferences
Application	For traditional screen	Human-computer interaction wearable Computational devices

TABLE 7. THIS PAPER ENRICHED THE CIELAB COLOUR STANDARD

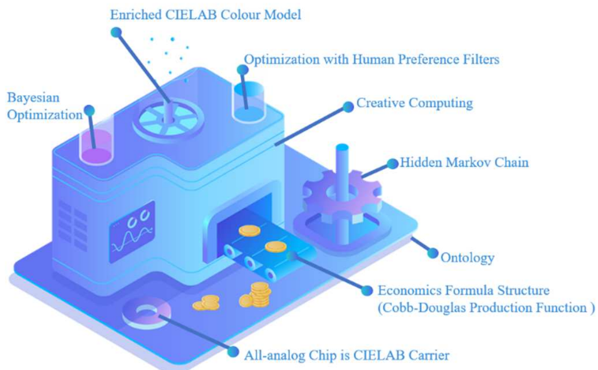

Fig 15. The Theories Creatively Melts Together

The result model structure is expected to apply for the photons-based computer chip in the perspective of vision intensity optimization, such as future optically based virtual reality human-computer interaction applications.

REFERENCES

[1] Y. Chen, M. Nazhamaiti, H. Xu, et al, "*All-Analog Photoelectronic Chip For High-Speed Vision Tasks", Nature,Vol.* 623, PP.48–57, New York, USA, 2023.

[2] S. Dayanik and K. Yamazaki, *"Detection And Identification Of Changes Of Hidden Markov Chains: Asymptotic Theory", Statistical Inference for Stochastic Processes*, *Springer Nature,* PP.1-41, Amsterdam, Netherlands, 2022.

[3] A. Siemenn, E.Ren, Z. Li, T. Buonassisi, *"Fast Bayesian Optimization Of Needle-In-A-Haystack Problems Using Zooming Memory-Based Initialization (Zombi)", NPJ Computational Materials, Springer Nature,* Vol. 9(1), PP.79, New York, USA, 2023.

[4] C. Can, E. Ergun, R. Soyer, "*Bayesian Analysis Of Proportions Via A Hidden Markov Model*", *Methodology and Computing in Applied Probability*, Vol.24(4), PP.3121-3139, 2022.

[5] M. Cheng, *"The Creativity of Artificial Intelligence in Art", Conference on Theoretical and Foundational Problems in Information Studies, MDPI In Proceedings,*Vol. 81, PP. 110, San Diego, USA, 2022.

[6] G. Hong-ye, *"Development of Western Micro and Macro Economics in the 20th Century", Journal of Renmin University of China, Vol.* 1 ,PP.4, Beijing, China, 2000.

[7] D. Tsivas, A. Vlyssides, *"Differentiation Of The Composting Stages Of Green Waste Using The CIELAB Colour Model", Journal of Chemical Technology & Biotechnology*, London, UK, 2023.

[8] Санчо,CIELAB XYZ, https://cielab.xyz/pdf/, Moscow, Russia, 2014.

[9] W. P. Grygiel, *"A Critical Analysis Of The Philosophical Motivations And Development Of The Concept Of The Field Of Rationality As A Representation Of The Fundamental Ontology Of The Physical Reality", Zagadnienia Filozoficzne Nauce, Copernicus Center PressSince,* Vol.72, PP. 87-108, Chicago, USA, 2022.

[10] R. Garnett, *Bayesian optimization*, *Cambridge University Press, London,UK,* 2023.

[11] V. Sacek, " *13.8. Eye Intensity Response, Contrast Sensitivity*", https://www.telescope-optics.net/eye_intensity_response.htm, Telescope Optics, Moscow, Russia, 2022.

[12] P. Kumar and A. R. Abhyankar, "*A Time Efficient Factorial Hidden Markov Model Based Approach for Non-Intrusive Load Monitoring*", *IEEE Transactions on Smart Grid,* Waterloo, Canada 2023.

[13] B. Catkin and V. Patoglu, *"Preference-Based Human-in-the-Loop Optimization for Perceived Realism of Haptic Rendering", IEEE Transactions on Haptics*, Houston, USA , 2023.

[14] A. Karliczek, *"The Evolution Of Colours or Colour as Self-Recognition", Colours & Cultures Interdisciplinary Explorations Couleurs & Cultures Explorations Interdisciplinaires*, PP.32, Berlin, Germany, 2022.

[15] M. Seaberg, *The Synesthesia Experience: Tasting Words, Seeing Music, and Hearing Colour, Red Wheel Weiser, New Page Books,* New York, USA, 2023.