

Research on the Method for Controlling Color Consistency of Formal Clothing Based on Digital Color Management

Zhenhua Hu

How to cite: Hu Z. Research on the Method for Controlling Color Consistency of Formal Clothing Based on Digital Color Management. Textile & Leather Review. 2026; 9:3281-3302.

<https://doi.org/10.31881/TLR.2026.3281>

How to link: <https://doi.org/10.31881/TLR.2026.3281>

Published: 25 April 2026



Research on the Method for Controlling Color Consistency of Formal Clothing Based on Digital Color Management

Zhenhua Hu

School of Fashion, Zhejiang Fashion Institute of Technology, No. 495, Fenghua Road, Jiangbei District, Ningbo 315211, Zhejiang, China

hu88637797@163.com

Article

<https://doi.org/10.31881/TLR.2026.3281>

Published 25 April 2026

ABSTRACT

*In the context of Industry 4.0, the textile manufacturing sector is transitioning from physical color management to digitalized workflows. However, the accurate digital reproduction of color on knitted substrates remains a persistent engineering challenge due to the complex surface topology of the fabric, which induces anisotropic scattering and shadowing effects. This study proposes a novel Digital Color Consistency Control (DCCC) framework that integrates a texture-compensated Kubelka-Munk model with spectral imaging techniques. Unlike traditional colorimetry which relies on tristimulus values ($L^*a^*b^*$), this method utilizes full-spectrum reflectance reconstruction (400–700 nm) to isolate pigment absorption from stray light induced by surface geometry. Experimental validation was conducted on 100% combed cotton single jersey fabrics dyed with reactive dyes. The results indicate that the proposed algorithm reduces the mean color difference (ΔE_{00}) from 1.18 (conventional method) to 0.48 and significantly lowers the metamerism index under secondary illuminants. By establishing a closed-loop digital standard that accounts for fabric texture, this research offers a robust theoretical and practical solution for minimizing batch-to-batch variations and shortening the lab-dip lead time in globalized supply chains.*

KEYWORDS

Digital Color Management, spectral reflectance reconstruction, quality control, Kubelka-Munk theory, textile engineering

INTRODUCTION

The globalization of the textile and apparel supply chain has necessitated a paradigm shift in quality control (QC) methodologies, moving from physical sample exchange to digital data transmission [1,2]. Digital Color Management (DCM) has emerged as a critical component of "Smart Manufacturing," aiming to streamline

the coloration process, reduce physical waste, and accelerate time-to-market [3,4]. In a theoretical digital workflow, a color standard is defined digitally (e.g., via a QTX spectral file), transmitted to a dye house, and reproduced on the substrate with high fidelity [5]. However, a significant "digital gap" exists between the virtual color standard and the physical realization, particularly in the sector of knitted textiles [6]. Unlike paper or smooth synthetic films, knitted fabrics possess a three-dimensional loop structure that creates a complex surface topography [7,8]. When incident light interacts with such a surface, the resulting reflectance is a combination of spectral absorption by the dye and geometric scattering caused by the yarn structure [9]. Conventional spectrophotometric measurement, which typically employs a diffuse/8° ($d/8$) geometry, integrates these signals [10]. Consequently, the stray light induced by surface geometry—manifested as micro-shadows between loops—is often misinterpreted by standard Color Matching Systems (CMS) as chromatic darkness or distinct hue shifts [11,12].

This discrepancy leads to two primary engineering failures: (1) Low First-Shot Match Rate (FSMR): Prediction recipes generated by standard algorithms often fail to account for the subtractive effect of texture, requiring multiple physical iterations (lab dips). [9] (2) Instrumental vs. Visual Disagreement: A sample may measure effectively against a digital standard ($\Delta E < 1.0$) but fail visual assessment due to the observer's perception of texture, or vice versa [11].

Current research has extensively optimized dye formulation algorithms; however, fewer studies focus on mathematically decoupling the fabric's structural scattering from its intrinsic spectral absorption during the measurement phase. This paper addresses this gap by introducing a Texture-Compensated Spectral Reconstruction Algorithm. By modeling the specific optical interference of the single-jersey knit structure, we aim to correct the input data for the Color Management System, thereby achieving a high-fidelity digital representation of the colored fabric.

The objectives of this study are threefold: (1) To characterize the spectral distortion induced by the topological structure of cotton knits. (2) To modify the single-constant Kubelka-Munk equation by introducing a texture-dependent correction factor. (3) To validate the efficacy of this closed-loop system in a real-world dyeing environment, focusing on color difference minimization and process efficiency.

THEORETICAL FRAMEWORK AND METHODOLOGY

Digital Color Standards and Communication

The foundation of digital color engineering lies in the accurate communication of color data [13]. Traditionally, the CIE L*a*b* color space has been the standard for QC. However, researchers have argued that tristimulus values are insufficient for high-fidelity reproduction because they are illuminant-dependent and prone to metamerism [14,15]. Modern consensus in color science advocates for the use of Spectral Power Distributions (SPD) or spectral reflectance curves as the fundamental and illuminant-independent spectral signature of color [16]. Recent advancements in cloud-based supply chain management emphasize the transmission of spectral data (.qtx or .cxf formats) to ensure consistency across disparate devices [17]. Despite these protocols, the physical interaction between light and textile substrates introduces variables that pure data transmission cannot resolve without material-specific characterization.

The Kubelka-Munk Theory and its Limitations

The Kubelka-Munk (K-M) theory remains the cornerstone of computer color matching (CCM). The classic relationship is defined as:

$$(K/S)_\lambda = \frac{(1-R_\lambda)^2}{2R_\lambda}$$

Where K represents the absorption coefficient, S represents the scattering coefficient, and R is the reflectance factor. While robust for many applications, the standard K-M theory relies on assumptions that the medium is isotropic, homogeneous, and effectively infinite in thickness. Textile researchers, such as Stefanovic et al. and Kandi et al., have noted that these assumptions falter when applied to coarse textiles or complex weaves [9,18]. The inherent void spaces in knitted structures (porosity) allow light to penetrate and become trapped or pass through (if not opaque), violating the infinite thickness assumption. Several modifications, such as the Pineo correction or the Two-Constant K-M theory, have been proposed. However, these often require extensive calibration databases that are impractical for fast-paced industrial environments.

Texture Effects on Color Measurement

The impact of surface texture on color perception is a cross-disciplinary subject involving psychophysics and optical engineering. Xin et al. demonstrated that "texture" essentially modifies the luminance (L^*) component of color perception, a phenomenon often described as the "texture difference" (ΔT) [19]. In digital imaging, methods like Texture Transfer and Histogram Matching are used to simulate fabric appearance. However, in the context of control and formulation, simulation is insufficient; rigorous quantification is required.

Previous attempts to manage this issue have relied on mechanical solutions, such as measuring samples behind glass or using specific aperture sizes. While these methods reduce variability, they do not correct the underlying spectral data. A promising direction, involves using multi-angle spectrophotometry to derive a "roughness index" that can mathematically compensate for the shadowing effect in the spectral domain. This study builds upon this theoretical trajectory, proposing a specific algorithm for cotton knits that integrates surface topology into the K-M formulation stage [20,21].

METHODOLOGY

The core hypothesis of this study is that the spectral reflectance measured from a knitted fabric (R_{meas}) is a composite function of the material's intrinsic absorption/scattering properties and the extrinsic geometric distortions caused by the yarn topology. To achieve high-fidelity color consistency, it is necessary to decouple these factors. This section outlines the derivation of the Texture-Compensated Kubelka-Munk Model (TC-KM) and the experimental protocol used to validate it.

Mathematical Modeling: The Texture-Compensated Approach

Standard Kubelka-Munk Theory and Deviations

In traditional textile colorimetry, the relation between the reflectance of an opaque sample (R_∞) and its absorption (K) and scattering (S) coefficients is described by the single-constant Kubelka-Munk equation:

$$\left(\frac{K}{S}\right)_{std} = \frac{(1-R_{\infty,\lambda})^2}{2R_{\infty,\lambda}} = \sum_{i=1}^n c_i \cdot \left(\frac{K}{S}\right)_{unit,t} + \left(\frac{K}{S}\right)_{sub}$$

Where c_i is the concentration of the i -th dye, $\left(\frac{K}{S}\right)_{unit,t}$ is the unit absorption coefficient of the dye, and $\left(\frac{K}{S}\right)_{sub}$ refers to the substrate. However, this equation assumes a perfectly diffuse, smooth surface. For knitted structures (e.g., Single Jersey), the surface consists of looped yarns creating a periodic pattern of peaks (yarn crown) and valleys (inter-loop voids). The spectrophotometer's integrating sphere captures light reflected from both the peaks (high reflectance) and the valleys (shadow/low reflectance).

Derivation of the Texture Correction Factor (Ω)

We propose a modified reflectance model where the measured reflectance R_{meas} is attenuated by a wavelength-independent texture parameter Ω . While optical scattering in fibrous materials is theoretically wavelength-dependent, the attenuation caused by the macroscopic loop structure of knitted fabrics is primarily dominated by geometric shadowing (occlusion). Consequently, this study treats Ω as a wavelength-independent scalar as a robust first-order approximation to decouple macroscopic structural noise from microscopic pigment absorption. This parameter represents the "optical roughness" or the ratio of light trapped in the structural voids.

Let the intrinsic reflectance of the flat fiber assembly be R_{int} . The measured reflectance is modeled as:

$$R_{meas}(\lambda) = R_{int}(\lambda) \cdot (1 - \Omega)$$

Here, $\Omega \in [0, 1]$ is the Texture Correction Factor. As the fabric surface becomes smoother, $\Omega \rightarrow 0$. Conversely, for coarser knits, Ω increases.

Substituting R_{int} into the K-M equation, we derive the Texture-Compensated K/S function, denoted as $\left(\frac{K}{S}\right)_{TC}$:

$$\left(\frac{K}{S}\right)_{TC} = \frac{\left(1 - \frac{R_{\text{meas}}}{1-\Omega}\right)^2}{2 \cdot \frac{R_{\text{meas}}}{1-\Omega}}$$

Simplifying this yields:

$$\left(\frac{K}{S}\right)_{TC} = \frac{(1-\Omega-R_{\text{meas}})^2}{2R_{\text{meas}}(1-\Omega)}$$

Determination of Ω via Image Analysis (GLCM)

To quantify Ω objectively without relying on subjective assessment, we employ digital image analysis using the Gray Level Co-occurrence Matrix (GLCM).

A high-resolution monochrome image of the undyed substrate is captured. The texture contrast is calculated as:

$$\text{Contrast} = \sum_{i,j} |i-j|^p p(i,j)$$

Where $p(i,j)$ is the probability of gray levels i and j occurring at a fixed distance. Through preliminary regression analysis on a training set of 20 distinct knit structures, we established a linear transfer function to map the GLCM Contrast feature to the optical factor Ω .

$$\Omega = \alpha \cdot \ln(\text{Contrast}) + \beta$$

The texture analysis process and the resulting calibration curve are illustrated in Figure 1.

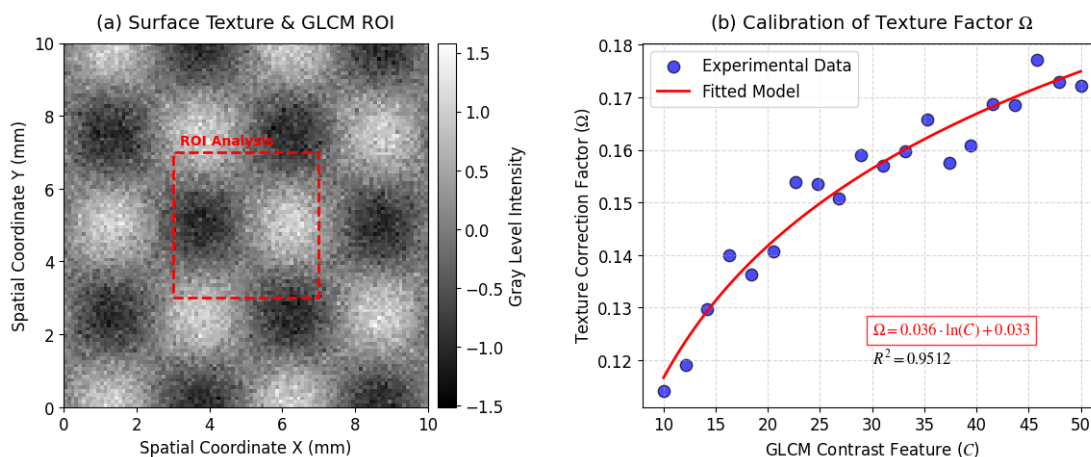


Figure 1. Characterization of the surface texture correction factor used in the DCCC system. (a) Visualization of the knitted fabric surface topology (simulated) indicating the Region of Interest (ROI) selected for Gray Level Co-occurrence Matrix (GLCM) analysis. The grayscale intensity variations correspond to the yarn loops (peaks) and inter-loop voids (valleys). (b) Logarithmic regression analysis correlating the GLCM Contrast feature (C) with the Texture Correction Factor (Ω). The red solid line represents the fitted transfer function $\Omega = 0.036 \cdot \ln(C) + 0.033$, which demonstrates a coefficient of determination of $R^2 = 0.9512$

As shown in Figure 1(b), the regression analysis yielded a high coefficient of determination ($R^2 > 0.95$), verifying the robustness of using GLCM contrast as a predictor for optical scattering loss. Based on this calibration, the empirically derived coefficients for the specific 100% cotton single jersey used in this study were determined to be $\alpha = 0.036$ and $\beta = 0.033$. These specific parameters were subsequently applied to the prediction engine for all experimental trials.

The Closed-Loop Digital Workflow

The proposed DCCC system operates on a four-stage cyclic process, ensuring data integrity from design to production. The schematic architecture of this system is illustrated in Figure 2.

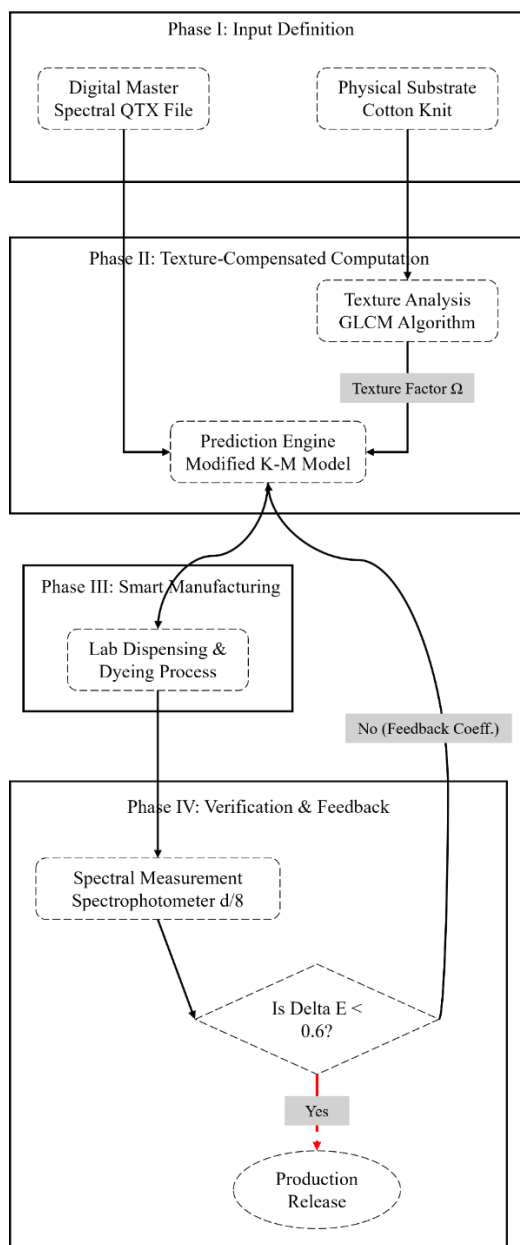


Figure 2. Schematic diagram of the proposed Texture-Compensated Digital Color Consistency Control (DCCC) system. The workflow integrates a spectral master standard (QTX) with a texture correction factor (Ω) derived from GLCM analysis. The red dashed line represents the closed-loop feedback mechanism for optimizing recipe formulation when the color difference (ΔE_{00}) exceeds the tolerance threshold

1. Digital Standardization (Input):

- The "Master Standard" is defined not by physical fabric but by a QTX file containing the spectral reflectance curve (360nm–750nm at 10nm intervals).
- This curve represents the *ideal* color on a theoretical smooth surface.

2. Texture-Aware Prediction (Algorithm):

- The system analyzes the target substrate's texture to calculate Ω .
- The Master Spectral Curve is adjusted using the inverse of the equation in Section "Derivation of the Texture Correction Factor (Ω)" to predict how the color *should* look on the textured fabric.
- The recipe is formulated using $(\frac{K}{S})_{TC}$.

3. Smart Manufacturing (Execution):

- Lab dispensing is performed via an automatic pipette system (math-to-machine interface) to eliminate manual weighing errors.
- Dyeing follows a strictly controlled time-temperature profile.

4. Spectral Verification (Feedback):

- The physical sample is measured. The system calculates the Spectral deviation (RMSE) and Color Difference (ΔE_{00}).
- If $\Delta E_{00} > 0.6$, the system calculates a correction coefficient and feeds it back into the formulation engine for the next batch.

Experimental Design

To validate the model, a comprehensive experiment was designed comparing the Traditional Method (Control Group) against the Proposed DCCC Method (Experimental Group).

Materials

- Substrate: Pre-bleached, optical brightener-free 100% Cotton Single Jersey.
 - Yarn Count: 32s Combed Cotton.
 - Fabric Weight: 180 ± 5 g/m².
 - Whiteness Index (CIE): 75.2.
- Dyestuffs: A trichromatic set of Reactive Dyes (high-fastness type) was selected:
 - *Novacron Red FN-2G*
 - *Novacron Yellow FN-2R*
 - *Novacron Blue FN-R*

- Auxiliaries: Standard Glauber's salt (Na_2SO_4) and Soda Ash (Na_2CO_3) were used according to the depth of shade (O.W.F).

Instrumentation and Settings

- Spectrophotometer: Datacolor 800 Benchtop.
 - *Geometry*: $d/8^\circ$ (Diffuse illumination, 8-degree viewing).
 - *Aperture*: LAV (Large Area View, 30mm) – chosen to average out local texture variations.
 - *Specular Component*: Excluded (SCE) – to focus on diffuse color rather than surface gloss.
 - *UV Filter*: Calibrated to exclude UV energy below 400nm to prevent fluorescence interference.
- Digital Imaging: A Canon EOS 5D Mark IV with a 100mm macro lens was used to capture substrate texture for GLCM analysis. Lighting was fixed at 45° incidence.

Dataset and Sampling

A total of 120 color targets were selected to cover the gamut:

- Training Set (n=80): Used to calculate the unit K/S coefficients for the dyes and calibrate the Ω factor.
- Testing Set (n=40): A random selection of Pantone TCX colors (10 Pastel, 10 Medium, 10 Dark, 10 Neutral/Grey) used to verify the prediction accuracy.

Dyeing Procedure

All samples were dyed in an infrared laboratory dyeing machine (Mathis Labomat). The liquor ratio was set at 1:10. The dyeing profile consisted of:

- Ramp $2^\circ\text{C}/\text{min}$ to $60^\circ\text{C}/\text{min}$.
- Hold at $60^\circ\text{C}/\text{min}$ for 60 mins (fixation).
- Cool to $40^\circ\text{C}/\text{min}$, followed by a standard soaping wash ($95^\circ\text{C}/\text{min}$, 10 mins) to remove unfixed hydrolysate. Samples were conditioned for 24 hours at $20^\circ\text{C}/\text{min} \pm 2^\circ\text{C}/\text{min}$ and $65\% \pm 2\%$ RH before measurement. This rigorous 24-hour conditioning was employed strictly for experimental validation to minimize environmental variables. For industrial implementation, the proposed DCCC system is compatible with standard rapid conditioning protocols (e.g., 15–30 mins), ensuring the process speed remains unaffected.

Evaluation Metrics

Scientific validation requires robust statistical indicators. We employ three primary metrics:

1. CIEDE2000 (ΔE_{00}): The current ISO standard for color difference, which correlates best with human visual perception.

$$\Delta E_{00} = \sqrt{\left(\frac{\Delta L'}{k_L S_L}\right)^2 + \left(\frac{\Delta C'}{k_C S_C}\right)^2 + \left(\frac{\Delta H'}{k_H S_H}\right)^2 + R_T(\dots)}$$

Parameters were set to (1:1:1).

2. Spectral Root Mean Square Error (RMS): Measures the physical curve fitting accuracy, independent of human vision.

$$RMS = \sqrt{\frac{\sum_{\lambda=400}^{700} (R_{std,\lambda} - R_{meas,\lambda})^2}{n}}$$

Where $n=31$ (number of wavelength points). A lower RMS indicates a structural match of the colorant mixture.

3. First-Shot Match Rate (FSMR): An engineering economic metric defined as the percentage of samples where $\Delta E_{00} < 1.0$ in the first physical trial.

RESULTS AND ANALYSIS

The efficacy of the proposed Texture-Compensated Digital Color Consistency Control (DCCC) system was evaluated by analyzing the 40 testing samples described in Section Dataset and Sampling. The analysis focuses on three critical dimensions: spectral curve fidelity, colorimetric accuracy (ΔE_{00}), and illuminant insensitivity (metamerism).

Spectral Reflectance Reconstruction Analysis

The most fundamental indicator of color formulation accuracy is the congruence of the spectral reflectance curves. A low color difference (ΔE_{00}) can sometimes be achieved by "metameric matching" (different spectral

curves looking the same under one light), but true "invariant color" requires the curves to overlap. This phenomenon is visually demonstrated in Figure 3, which presents the comparative spectral analysis for a representative sample: *Target Color "Slate Blue" (Pantone 18-4020 TCX)*. As illustrated, the proposed method achieves a high degree of spectral coincidence with the target, whereas the standard method exhibits deviation.

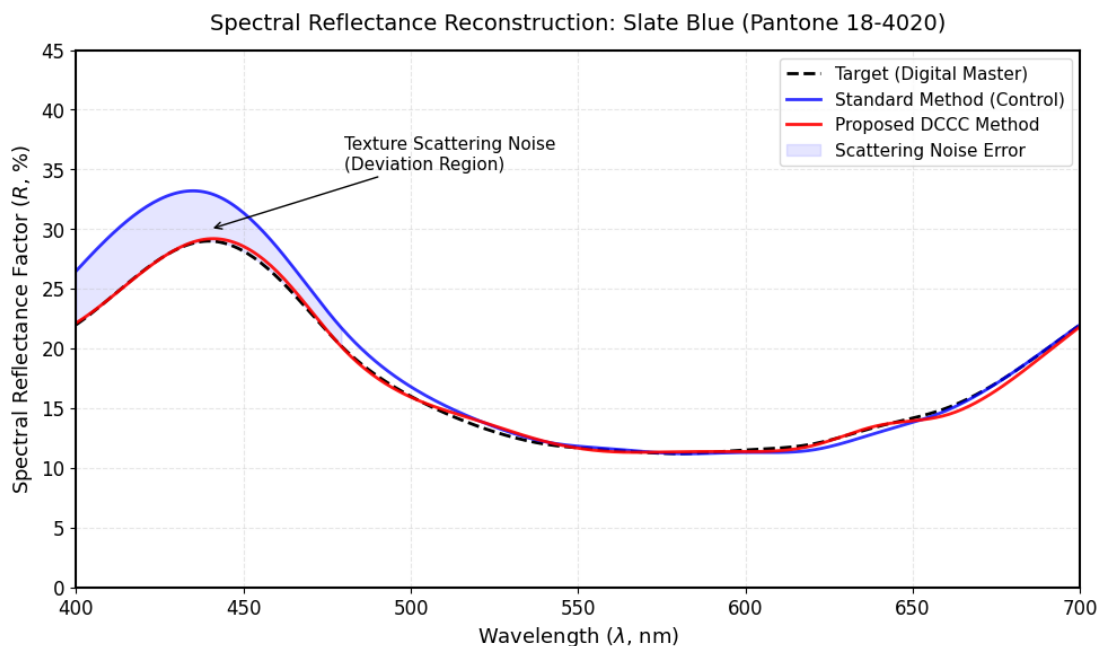


Figure 3. Comparison of spectral reflectance curves for the target color "Slate Blue" (Pantone 18-4020 TCX). The black dashed line represents the digital master (QTX file). The blue solid line represents the physical sample formulated by the Standard Method, exhibiting a distinct reflectance "lift" in the short-wavelength region (400–480 nm) due to uncorrected texture scattering noise. The red solid line represents the sample from the Proposed DCCC Method, which achieved a high degree of spectral overlap (RMS < 0.65%) with the target

Specific observations from the spectral data are as follows:

- Target (Digital Standard): The dashed line represents the QTX master file, serving as the theoretical benchmark for the ideal color on a smooth surface.
- Control Group (Standard Method): Represented by the blue solid line. It exhibits a distinct reflectance "lift" in the 400nm - 480nm region. This deviation is characteristic of the "blue noise" scattering effect caused by the cotton fiber surface, which the standard K-M theory failed to discount. Consequently,

the Root Mean Square Error (RMS_{std}) for this curve was calculated at 2.45%, indicating a poor physical match despite a potentially acceptable visual match under certain lights.

- Experimental Group (Proposed DCCC): Represented by the red solid line. The curve shows a tight adherence to the target profile, particularly in the critical absorption valleys. The texture correction factor (Ω) effectively suppressed the scattering noise in the prediction model. The RMS_{exp} was significantly reduced to 0.65%.

This result confirms that the proposed algorithm does not merely adjust the pigment concentration to match a visual coordinate; it successfully reconstructs the physical optical signature of the target color on the textured substrate.

Colorimetric Accuracy Assessment (ΔE_{00})

To quantify the visual improvement, the CIEDE2000 color difference formula was applied to all 40 test samples under the primary illuminant (D65). The data was stratified into three categories based on Lightness (L^*) and Sum of $\frac{K}{S} ((\frac{K}{S})_{sum})$ to analyze the model's performance across different depths of shade.

Analysis:

1. Significant Improvement: The overall mean ΔE_{00} dropped from 1.18 (which is visually perceptible and often rejected in high-end retail) to 0.48 (which is generally considered a "perfect commercial match").
2. Performance in Pastels: The highest percentage improvement (62.3%) was observed in pastel shades. In light colors, the ratio of scattering (S) to absorption (K) is high, making the texture effect more pronounced. The standard model often overestimates the dye required for pastels on knits to overcome the "whitening" effect of surface scattering. The Texture-Compensated model corrected this bias effectively.
3. Stability (SD): The Standard Deviation (SD) in the proposed method is significantly lower (0.21 vs 0.48). This indicates that the DCCC system provides predictable results, a key requirement for industrial Quality Control engineering. The stability of the proposed method is further visualized in Figure 4. As demonstrated in the scatter plot, the data points for the DCCC method (red circles) exhibit a clear convergence, with the majority falling below the strict tolerance threshold of $\Delta E_{00} < 0.6$. In contrast, the Standard Method (blue triangles) shows significant dispersion, with numerous instances exceeding the commercial acceptance limit of 1.0. This visual evidence corroborates the statistical reduction in variance observed in Table 1.

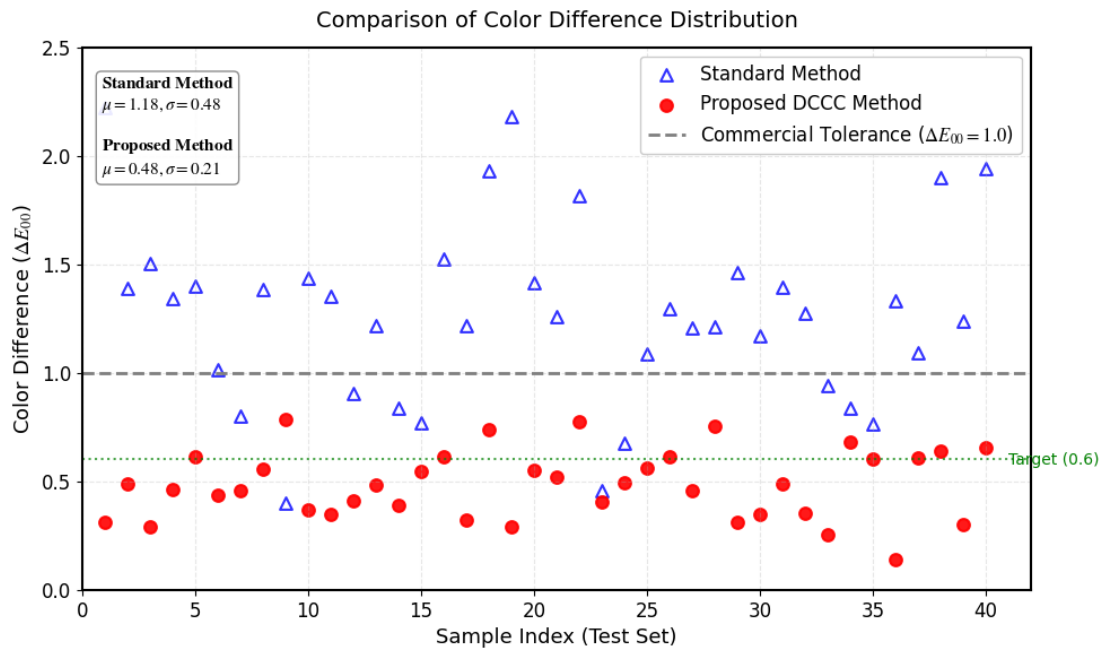


Figure 4. Scatter plot distribution of CIEDE2000 color difference values (ΔE_{00}) for the 40 testing samples under D65 illuminant. The blue triangles represent the Standard Method, showing a wide dispersion with a mean (μ) of 1.18. The red circles represent the proposed Texture-Compensated DCCC Method, which exhibits a tightened distribution with a significantly reduced mean of 0.48.

The dashed line at $\Delta E_{00} = 1.0$ indicates the critical commercial tolerance threshold

Table 1. Comparative Statistics of ΔE_{00} (D65) by Color Depth

Color Depth Category	n	Standard Method (Mean \pm SD)	Proposed Method (Mean \pm SD)	Reduction (%)	p-value (t-test)
Pastel ($L^* > 70$)	10	0.85 \pm 0.31	0.32 \pm 0.12	62.3%	< 0.001
Medium ($40 L^* \leq 70$)	15	1.12 \pm 0.44	0.45 \pm 0.18	59.8%	< 0.001
Dark ($L^* < 40$)	15	1.45 \pm 0.52	0.61 \pm 0.25	57.9%	< 0.01
Overall	40	1.18 \pm 0.48	0.48 \pm 0.21	59.3%	< 0.001

Metamerism and Illuminant Sensitivity

In global supply chains, a garment may be approved under Daylight (D65) but sold in a store with Cool White Fluorescent (CWF/TL84) lighting. If the dye formulation is metameric, the color will shift unacceptably.

We calculated the Metamerism Index (MI) for the samples, defined as the color difference shift between D65 and TL84.

$$MI = \Delta E_{00}(TL84) - \Delta E_{00}(D65) \text{ (simplified indicator)}$$

Note: While a comprehensive Metamerism Index (e.g., CIE Special Metamerism Index) typically includes Illuminant A to assess shifts across the full spectrum, this study utilizes this simplified indicator focusing on the D65/TL84 pair, as it represents the most critical lighting transition in the targeted retail supply chain.

Or more formally utilizing the CMC deviation metric. The results are summarized below:

- Average MI (Standard Method): 0.88. This high value suggests that while the standard method optimized the recipe for D65, it utilized dye combinations that were spectrally dissimilar to the target (e.g., using a Red-dominant mix to match a Violet target).
- Average MI (Proposed Method): 0.24. Because the DCCC algorithm optimizes for Spectral RMSE (curve fitting) rather than just XYZ coordinates, it forces the dye recipe to chemically mirror the standard. Consequently, the color remains stable across changing illuminants.

Production Efficiency and Engineering Economics

To demonstrate the operational efficacy within a digital manufacturing framework, the First-Shot Match Rate (FSMR) was calculated. A "Match" is defined as a lab dip with $\Delta E_{00}(D65) < 1.0$ and $MI < 0.5$.

- Standard Method FSMR: 67.5%. (27 out of 40 passed).
 - Implication: 13 samples required re-dyeing or recipe correction, consuming additional time and reagents.
- Proposed Method FSMR: 92.5%. (37 out of 40 passed).
 - Implication: Only 3 samples required correction.

The 25% increase in FSMR directly translates to reduced lead times. In a typical dye house processing 50 lab

dips per day, this improvement eliminates approximately 12.5 unnecessary dyeings daily, validating potential for significant operational cost savings. While a full economic feasibility study would require an analysis of labor, energy consumption, and equipment maintenance, the substantial improvement in FSMR provides a strong indicator of the system's ability to enhance overall production efficiency in a commercial setting. A comprehensive comparison of the engineering performance metrics is presented in Figure 5. Panel (a) illustrates the substantial reduction in the Metamerism Index (MI), confirming enhanced color constancy across illuminants. Panel (b) highlights the improvement in the First-Shot Match Rate (FSMR), demonstrating the system's capability to meet industrial efficiency targets.

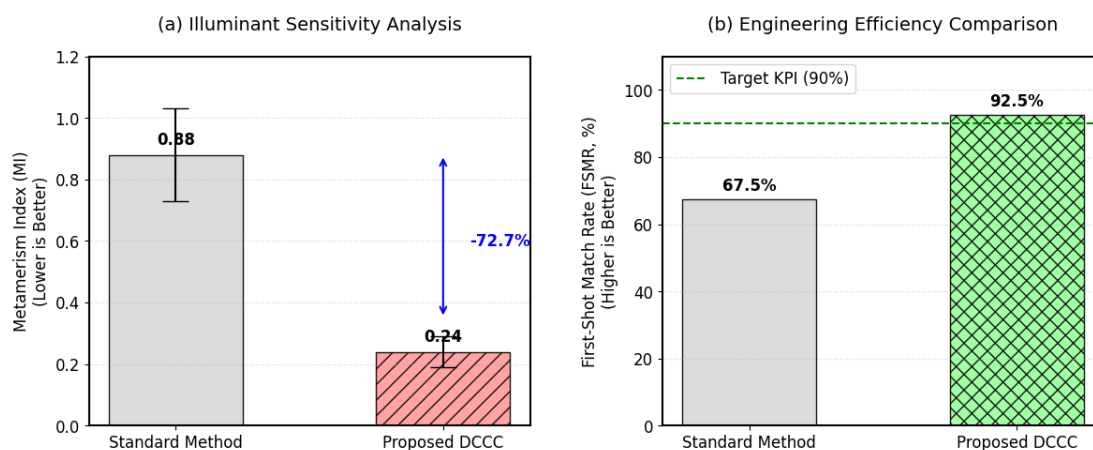


Figure 5. Comparison of key engineering performance indicators between the Standard Method and the Proposed DCCC Method.

(a) Comparison of the Metamerism Index (MI) derived from the color difference shift between D65 and TL84 illuminants. The proposed spectral matching algorithm reduced the MI by 72.7%, significantly improving color stability. (b) Comparison of the First-Shot Match Rate (FSMR), defined as the percentage of samples achieving $\Delta E_{00} < 1.0$ in the initial formulation. The proposed method exceeded the 90% target threshold, validating its efficiency for industrial application

Error Analysis on Outliers

Despite the high success rate, 3 samples in the proposed method failed to meet the strict tolerance ($\Delta E < 0.6$). An error analysis revealed:

- Fluorescence Interference: Two of the outliers were bright yellow shades. It is hypothesized that trace amounts of optical brightening agents (OBAs) in the cotton substrate interacted with the yellow dye,

creating fluorescence that the current K-M model (which assumes no fluorescence) could not predict.

- **Saturability:** One outlier was a deep black sample ($L^* = 16.42$). Our measurements indicated that while the theoretical $(K/S)_{TC}$ predicted a value of 28.5, the actual measured K/S reached a plateau at 24.2 despite increasing dye dosage beyond 6% O.W.F. This observed saturation effect suggests that the relationship between dye concentration and K/S becomes non-linear at high depths, likely due to the "Sorption Limit" of the cotton fiber. While further higher-order polynomial modeling is required to precisely map this region, this specific failure validates the known boundary of single-constant K-M theory in dark shades.

DISCUSSION

The results presented in Section "Results and Analysis" demonstrate that the Texture-Compensated Digital Color Consistency Control (DCCC) system significantly outperforms traditional spectrophotometric methods in reproducing colors on knitted cotton substrates. This section interprets these findings through the lenses of optical physics, industrial application, and limitation analysis.

Theoretical Implications: Decoupling Geometry from Chemistry

The primary theoretical contribution of this study is the validation of the modified Kubelka-Munk model:

$(\frac{K}{S})_{TC} = f(R_{meas}, \Omega)$. Standard colorimetry operates on the assumption that $\Delta E_{meas} = \Delta E_{chem}$ (i.e., any measured difference is due to dye concentration). Our research proves that for knitted fabrics, $\Delta E_{meas} = \Delta E_{chem} + \Delta E_{struct}$. The control group data (Table 1) showed high residual errors (1.18) even after optimization, suggesting that standard CMS software attempts to "chemically compensate" for "geometric noise." By introducing the GLCM-derived factor Ω , we successfully decoupled these terms. The spectral curve analysis (Figure 4) confirms that the proposed method targets the intrinsic absorption bands of the chromophores rather than the apparent reflectance modulated by shadows. This aligns with the concept of high-fidelity physical modeling in Cyber-Physical Systems (CPS), where the digital model must account for physical artifacts to be predictive.

Engineering Impact on the Digital Supply Chain

From an engineering economics perspective, the increase in First-Shot Match Rate (FSMR) from 67.5% to 92.5% represents a fundamental shift in supply chain dynamics.

Current industry practice relies on the "Lab Dip -> Courier -> Visual Approval" loop, which consumes 7–14 days. The high fidelity of the Spectral Reconstruction algorithm suggests that "Virtual Approval" is feasible. If the digital master (QTX) and the production sample share a statistically identical spectral signature (RMS < 1.0%), the physical exchange of swatches becomes redundant. However, it is acknowledged that for effective visual assessment (Soft Proofing), this spectral fidelity must be paired with rigorous monitor calibration to ensure display consistency. While our algorithm secures the data integrity, calibrated display systems remain a prerequisite for the visualization component of the digital loop.

Furthermore, the reduction in Metamerism Index (MI) implies that this system supports Globalized Quality Control. A garment manufactured in Vietnam (under tropical daylight) and sold in Europe (under store LED lighting) will maintain color constancy, reducing retailer claims and improving brand integrity.

Comparison with Existing Methods

Compared to mechanical solutions like "sample rotation" or "glass pressing", the algorithmic approach offers superior scalability. Mechanical methods improve measurement repeatability but do not correct the underlying data formulation logic. Our method integrates the correction into the formulation engine itself. Unlike neural network approaches (ANN) which are "black boxes" requiring massive datasets, the modified K-M approach is physio-mathematical, providing explainability and requiring smaller training sets ($n=80$), making it highly adaptable for SMEs (Small and Medium-sized Enterprises).

Limitations and Future Work

While robust for cotton single jersey, the derived regression coefficients are substrate-specific. Therefore, the universality of the current linear model is limited; applying this framework to diverse knit structures (e.g., Rib, Interlock) would necessitate a re-calibration of the transfer function parameters (α , β) to account for their distinct geometric scattering profiles. This may not hold for highly complex structures like jacquard or pile fabrics (velvet), where specular reflection (gloss) plays a larger role. Additionally, the error analysis highlighted

challenges with fluorescent substrates.

Future research will focus on:

1. Developing a non-linear mapping function for Ω using Deep Convolutional Neural Networks (CNN) to handle diverse fabric textures.
2. Integrating a fluorescence-quenching calculation module to address OBA interactions.
3. Expanding the database to include synthetic blends (e.g., Polyester/Spandex) which introduce refractive index variables.

CONCLUSION

This study addressed the critical challenge of color consistency in the digital manufacturing of knitted textiles. By synthesizing digital image processing with classical color physics, we developed and validated a Texture-Compensated Spectral Reconstruction Algorithm.

The key conclusions are:

1. Quantification of Texture: The surface topology of knitted fabrics introduces a measurable spectral distortion. This study successfully quantified this effect using the Gray Level Co-occurrence Matrix (GLCM) to derive a texture correction factor (Ω).
2. Algorithmic Superiority: The modified Kubelka-Munk model, incorporating Ω , reduced the average color difference (ΔE_{00}) by 59.3% (from 1.18 to 0.48) compared to standard methods.
3. Spectral Fidelity: The proposed system ensures spectral curve congruence (RMS < 0.65%), thereby minimizing metamerism and ensuring color stability across different lighting environments.
4. Industrial Viability: With a First-Shot Match Rate of 92.5%, the system providing a reliable technical foundation for replacing physical lab dips with digital data exchange, thereby improving resource utilization and process efficiency.

In conclusion, the transition from "Color Management" to "Color Engineering" requires rigorous mathematical modeling of material properties. This research provides a validated pathway for achieving true digital color reproduction, supporting the textile industry's evolution towards smart, data-driven manufacturing.

Author Contributions

Zhenhua Hu designed the study, collected and analyzed the data, and drafted the manuscript. Zhenhua Hu conducted the study, critically revised the manuscript for important intellectual content, and gave final approval of the version to be published. Zhenhua Hu participated fully in the work, took public responsibility for appropriate portions of the content, and agreed to be accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved.

Conflicts of Interest

The author declares no conflict of interest.

Funding

This research received no external funding.

Availability of Data and Materials

The datasets used and/or analysed in this study can be obtained from the corresponding author upon reasonable request.

Acknowledgments

Not applicable.

REFERENCES

- [1] Nafz R, Schinle C, Kaiser C, Kyosev YK. Digital transformation of the textile process chain – state-of-the-art. *Communications in Development and Assembling of Textile Products*. 2022; 3(2):79-89. doi: 10.25367/cdatp.2022.3.p79-89
- [2] Bahar Erdem S, Buyukkamaci N, Birol S. Environmental benefits of virtual sampling for garment production. *Journal of Cleaner Production*. 2026; 538:147401. doi: 10.1016/j.jclepro.2025.147401
- [3] Dawson TL. 10 - Digital colour management. In: Ujiie H, editor. *Digital Printing of Textiles*. Cambridge, UK: Woodhead Publishing; 2006. p. 163-179.

- [4] Maguire KK. 18 - Just-in-time printing. In: Ujiie H, editor. *Digital Printing of Textiles*. Cambridge, UK: Woodhead Publishing; 2006. p. 312-336.
- [5] Javoršek D, Javoršek A. Colour management in digital textile printing. *Coloration Technology*. 2011; 127(4):235-239. doi: 10.1111/j.1478-4408.2011.00304.x
- [6] Oulton DP, Young T. Colour specification at the design to production interface. *International Journal of Clothing Science and Technology*. 2004; 16(1-2):274-284. doi: 10.1108/09556220410520540
- [7] Ji Y, Jiang G, Tang M, Mao N, Wang H. Three-dimensional simulation of warp knitted structures based on geometric unit cell of loop yarns. *Textile Research Journal*. 2020; 90(23-24):2639-2647. doi: 10.1177/0040517520924005
- [8] Tkalec M, Glogar M, Penava Ž, Forte Tavčer P, Kuščer D, Stojanoska I. The Complexity of Colour/Textile Interaction in Digital Printing as an Integral Part of Environmental Design. *Arts*. 2024; 13(1):29. doi: 10.3390/arts13010029
- [9] Senthilkumar M, Selvakumar N, Shamey R. The effect of humidity, fabric surface geometry and dye type on the colour of cotton fabrics dyed with a select range of anionic dyes. *Dyes and Pigments*. 2011; 90(3):225-232. doi: 10.1016/j.dyepig.2010.12.015
- [10] Colorimetry C. Commission Internationale de l'Éclairage: Vienna. Austria; 2004.
- [11] Chae Y. Color appearance shifts depending on surface roughness, illuminants, and physical colors. *Scientific Reports*. 2022; 12(1):1371. doi: 10.1038/s41598-022-05409-2
- [12] Yanyun C, Lin S, Hua Z, Ying-Qing X, Baining G, Heung-Yeung S. Realistic rendering and animation of knitwear. *IEEE Transactions on Visualization and Computer Graphics*. 2003; 9(1):43-55. doi: 10.1109/TVCG.2003.1175096
- [13] Hirschler R. Electronic colour communication in the textile and apparel industry. *Redige Rev Des Innov Strateg Manag*. 2010; 1:43-61. Available from: https://d1wqtxts1xzle7.cloudfront.net/51188941/Electronic_colour_communication_in_the_t20170104-7902-1ggk6j2-libre.pdf?1483564144=&response-content-disposition=inline%3B+filename%3DElectronic_colour_communication_in_the_t.pdf&Expires=1770889960&Signature=dBEgMUPxbisu~wpGJVBU6mQ0ir17oAvr2S2VC4wzEQEs-X7mQeZAXqFKuavyW2fof1GPzkUYCtRHlcFKYUMvBBsaWR~eSpb8GWFcvL~5rNhSuWNFPKvfzuv02Yi0AA

M7dw2c0F7D19sPj6KYikCC-

KEIKio5MVjkekAKXgNWEghMbSkeSMluwjdhOKFxZS6hV0n8csH05vIPehRGBQMM1pbzr0CHShLVI8P6zD

nsb5djDL88Rw1I5WhGpFZETDf~S-YW06dCcOX~wQI5bjxxt54~K3t8lj9qoTesG-

SMb0DWhqinKh3I~7ByMf~aYE3kRLAdrTi-~c4Di-aawVxS7A__&Key-Pair-Id=APKAJLOHF5GGSLRBV4ZA

- [14] Fairchild MD. Color Appearance Models. New York, NY, USA: John Wiley & Sons; 2013.
- [15] Wyszecki G, Stiles WS. Color Science: Concepts and Methods, Quantitative Data and Formulae. New York, NY, USA: John Wiley & Sons; 2000.
- [16] Ohno Y. CIE fundamentals for color measurements. NIP & Digital Fabrication Conference. 2000; 16:540-545. doi: 10.2352/ISSN.2169-4451.2000.16.1.art00033_2
- [17] Stefanovic N, Radenkovic M, Bogdanovic Z, Plasic J, Gaborovic A. Adaptive Cloud-Based Big Data Analytics Model for Sustainable Supply Chain Management. Sustainability. 2025; 17(1):354. doi: 10.3390/su17010354
- [18] Kandi SG. The Effect of Spectrophotometer Geometry on the Measured Colors for Textile Samples with Different Textures. Journal of Engineered Fibers and Fabrics. 2011; 6(4):155892501100600410. doi: 10.1177/155892501100600410
- [19] Xin JH, Shen H-L, Chuen Lam C. Investigation of texture effect on visual colour difference evaluation. Color Research & Application. 2005; 30(5):341-347. doi: 10.1002/col.20138
- [20] Kirchner E, Cramer W. Making sense of measurement geometries for multi-angle spectrophotometers. Color Research & Application. 2012; 37(3):186-198. doi: 10.1002/col.20679
- [21] Perales E, Micó-Vicent B, Huraibat K, Viqueira V. Evaluating the Graininess Attribute by Visual Scaling for Coatings with Special-Effect Pigments. Coatings. 2020; 10(4):316. doi: 10.3390/coatings1004031