

Color Transfer in Digital Images: A Study of Covariance-Based Color Mapping

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Abstract

This report presents an implementation and evaluation of a covariance-based color transfer technique. Using MATLAB, the method transfers color characteristics from a target image to a source image by mapping color distributions through mean vectors and covariance matrices. Seven image pairs (s_0-t_0 to s_6-t_6) were tested, transforming source images to adopt target color styles. Results are analyzed via stitched outputs and reflections on effectiveness. The study also examines the drawbacks of reversing the transfer direction (target to source). While excelling in stylization, the technique struggles with extreme color distributions and computational complexity.

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1 Introduction

Color transfer enhances synthetic images or stylizes real ones by adopting the color properties of a reference image. This assignment implements a covariance-based method from Xiao and Ma (2006)[1], corrected for mathematical errors, to transform source images using target color characteristics. The process involves vectorization, statistical computation, SVD, and matrix transformation, executed in MATLAB. This report outlines the methodology, presents results for seven image pairs, and discusses strengths, limitations, and the implications of reversing the transfer direction.

2 Methodology

The algorithm comprises five steps, implemented in MATLAB:

2.1 Vectorization

Source ($I_s, m \times n \times 3$) and target ($I_t, p \times q \times 3$) images are loaded with `imread`, converted to double precision, and reshaped into $N \times 3$ matrices ($N = m \times n$ for source, $N = p \times q$ for target), with RGB channels as columns.

2.2 Statistical Computation

Mean vectors ($\mu_s = [rs, gs, bs]^T, \mu_t = [rt, gt, bt]^T$) and 3×3 symmetric covariance matrices (C_s, C_t) are calculated using `mean` and `cov`.

2.3 Singular Value Decomposition

SVD is performed on C_s and C_t via `svd`, yielding U_s, D_s, V_s (source) and U_t, D_t, V_t (target), where $U_s = V_s$ and $U_t = V_t$ due to symmetry.

2.4 Transformation Matrix

A 4×4 matrix F is constructed as:

$$F = M_t \times R_t \times W_t \times W_s \times R_s \times M_s \quad (1)$$

where:

- M_t : Translates by μ_t .
- M_s : Subtracts μ_s .
- R_t, R_s : Rotation matrices from U_t and U_s^{-1} .
- W_t, W_s : Scaling matrices from $\sqrt{D_t}$ and $1/\sqrt{D_s}$.

2.5 Application and Post-Processing

The source matrix S is augmented with ones, transformed by F , reshaped to $m \times n \times 3$, clipped to $[0, 255]$, rounded, and cast to `uint8`.

3 Experimental Setup

Seven image pairs (s0-t0 to s6-t6) from online sources were stored in **source** and **target** folders, supporting **.bmp** and **.jpg** formats. The MATLAB script generates transformed source images (**transformed_sX.jpg**) and stitched outputs (**stitched_sX_tX.jpg**: original source, target, transformed source).

4 Results

The following figures present the color transfer results for each pair, with each stitched image showing the original source (left), original target (middle), and transformed source (right):



Figure 1: Result for Pair s0-t0: Original Source (Left), Original Target (Middle), Transformed Source (Right)



Figure 2: Result for Pair s1-t1: Original Source (Left), Original Target (Middle), Transformed Source (Right)



Figure 3: Result for Pair s2-t2: Original Source (Left), Original Target (Middle), Transformed Source (Right)



Figure 4: Result for Pair s3-t3: Original Source (Left), Original Target (Middle), Transformed Source (Right)



Figure 5: Result for Pair s4-t4: Original Source (Left), Original Target (Middle), Transformed Source (Right)



Figure 6: Result for Pair s5-t5: Original Source (Left), Original Target (Middle), Transformed Source (Right)



Figure 7: Result for Pair s6-t6: Original Source (Left), Original Target (Middle), Transformed Source (Right)

5 Discussion

5.1 Effectiveness of the Method

The method does a great job of shifting the target colors onto source images. For example, in the case of s0-t0, the transformed source adopts the overall mood of the target image while preserving the structure of the original source. This pattern holds across different image pairs, though the effectiveness varies depending on how closely the color distributions align. When the source and target images have similar palettes, the transformation appears natural and seamless. However, significant differences in color distributions can introduce distortions.

5.2 Limitations and Challenges

While effective in many cases, the method has some limitations. It struggles when the source and target images have extreme differences in color distributions. For instance, if the source image is grayscale and the target is highly vibrant, the transformation may produce unnatural or jarring results. Another issue is computational efficiency. Since the process involves singular value decomposition (SVD) and multiple matrix transformations, it becomes increasingly slow for high-resolution images.

5.3 Reversing the Color Transfer Process

Reversing the transformation, where the target image is adjusted to match the source’s colors instead of the other way around, presents several challenges. The original intent of this method is to restyle source images using target color properties, and flipping the process can diminish the effectiveness of the approach. For example, if a vibrant target

image is forced to adopt the muted tones of a plain source, the result may appear dull and unappealing.

From a practical standpoint, color transfer is most useful when adapting new images to fit a specific visual theme, as seen in applications like film color grading. In such workflows, source images are typically adjusted to match a reference palette, not the other way around. As a result, reversing the transfer direction does not align well with real-world use cases.

6 Conclusion

This covariance-based color transfer method successfully stylizes source images to match target distributions across seven pairs. It shines in artistic applications but falters with extreme color differences and computational demands. Reversing the transfer direction compromises its purpose and practicality.

References

- [1] Xuezhong Xiao and Lizhuang Ma, “Color transfer in correlated color space,” *Proc. of ACM International Conference on Virtual Reality Continuum and its Applications*, pp. 305–309, 2006.