Emulating Emulsion: A Compact Physically-Based Model for Film Colour

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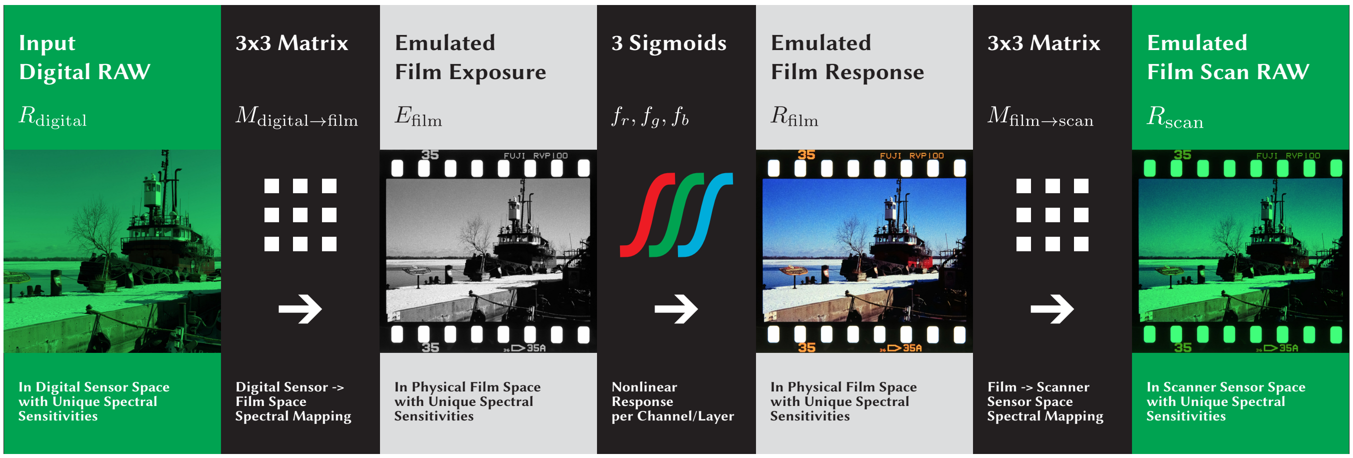

Figure 1: The proposed model emulates the film imaging process by mapping a digital RAW image R_{digital} to a film scan RAW R_{scan}. This is achieved through a sequence of operations that approximates inverting the digital capture pipeline, simulating the scene as if photographed on film, and then applying a virtual film scanning step.

ACM Reference Format:
Hyun Jo Jang, Hakki Karaimer, and Michael Brown. 2025. Emulating Emulsion: A Compact Physically-Based Model for Film Colour. In *Special Interest Group on Computer Graphics and Interactive Techniques Conference Posters (SIGGRAPH Posters '25), August 10-14, 2025.* ACM, New York, NY, USA, 2 pages. https://doi.org/10.1145/3721250.3743014

1 Introduction

Colour-positive photographic film is prized for its distinctive hues and pleasing tones, but many film stocks are discontinued, and their full pipeline (film exposure followed by digital scanning) is absent from modern workflows. Current digital emulation approaches often fall short: calibration methods using matrices and nonlinear functions from captured pairs [Kim et al. 2012] omit the scanning stage. End-to-end LUT fitting such as in [David 2013] emulate colour well but often introduce interpolation artefacts and lack transparency. Recent neural network-based models such as FilmNet's CNN [Li et al. 2023] demand extensive training data and also compromise on interpretability. While differentiable methods can learn general parametric photofinishing [Tseng et al. 2022], we demonstrate substantial simplification by explicitly modelling film-specific properties. We integrate the full film pipeline into a compact, 30-parameter analytic form, achieving LUT-level accuracy without artefacts and exposes interpretable parameters, while fitted efficiently from a single film roll.

2 Method

Our proposed model maps a digital RAW image R_{digital} to an emulated RAW image of the film scan R_{scan}, as a three-stage analytic pipeline (Figure 1):

(1) **Spectral remapping $M_{\text{digital}\rightarrow\text{film}}$.** A 3×3 matrix converts linear RAW triplets captured by any digital sensor R_{digital} into the energy that would have reached each of the three dye layers of the target film E_{film}. Grassmann's law states that a 3×3 matrix is sufficient to compensate for spectral sensitivity differences.

(2) **Three nonlinear response functions f_c ($c \in \{r, g, b\}$).** They are applied channel-wise to E_{film}, yielding the film's optical density response R_{film}. Each response function is modelled with a four-parameter sigmoid applied in log-exposure space, matching the "characteristic curves" published in manufacturer data sheets [Eastman Kodak Company 2006].

(3) **Film Scanner encoding $M_{\text{film}\rightarrow\text{scan}}$.** A second 3×3 matrix converts optical density, illuminated by a calibrated backlight (D50, $1000 cd/m^2$), into the scanner's RAW space R_{scan}.

SIGGRAPH Posters '25, Vancouver, BC, Canada

ACM ISBN 979-8-4007-1549-5/2025/08
https://doi.org/10.1145/3721250.3743014

Formally,

$$R_{\text{scan}} = M_{\text{film}\to\text{scan}}\, f\left(M_{\text{digital}\to\text{film}}\, R_{\text{digital}}\right)$$

where f applies the three sigmoid functions f_c ($c \in \{r, g, b\}$) element-wise to the vector $M_{\text{digital}\to\text{film}}\, R_{\text{digital}}$:

$$R_{\text{film},c} = f_c(E_{\text{film},c}) = \frac{A}{1 + e^{-k(E_{\text{film},c} - x_0)}} + y_0$$

with four learnable parameters A, k, x_0, y_0. In total, this yields 9 ($M_{\text{digital}\to\text{film}}$) + 12 ($f$, 4 per f_c) + 9 ($M_{\text{film}\to\text{scan}}$) = 30 (36 including bias terms) parameters to optimise.

Parameters are jointly optimised via SciPy least-squares on 3168 RAW patch pairs from a 96-patch colour chart shot over a 36-exposure film roll, under 3 illuminants and 11 exposures. We minimise mean squared error between predicted and scanned RAW R_{scan}. Identity and zero initialisation is used.

3 Key Results

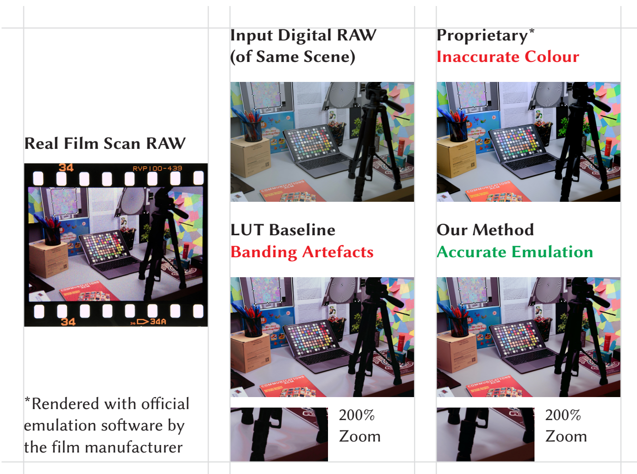

Figure 2: Qualitative results on a general test image. The film manufacturer's proprietary emulation distorts colour, the LUT baseline shows banding artefacts, and the proposed model shows accurate colour rendition with no artefacts.

Despite similar average colour chart patch-wise root mean-square error (RMSE) values between a LUT baseline constructed directly from the dataset and the proposed model (1.1% vs. 1.3%), visual inspection tells a clearer story. In (Figure 2), we show images of a general scene plus a 200% zoom of a smooth region. The film manufacturer's proprietary emulation feature for their digital cameras produce colours that deviate noticeably from the real film scan. The LUT baseline reproduces colour but introduces subtle banding wherever the 3D grid must interpolate between sparse points. The proposed model matches ground-truth digitised film closely in both hue and tone while remaining free of artefacts, confirming that a physics-guided formulation can achieve perceptual fidelity on par with an unrestricted LUT.

To verify that the learned parameters are indeed grounded in reality, we compare our post-optimisation sigmoids with curves in the film manufacturer's data sheet (Figure 3). The ordering and slope

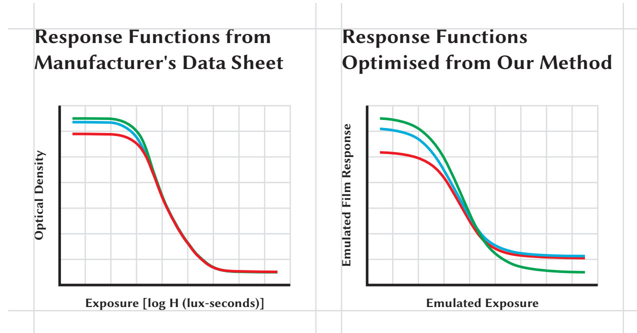

Figure 3: Comparison between the film manufacturer's published response functions and those we optimised. Note the strong alignment in shape and channel ordering, especially on the left-hand slope of each curve.

of the RGB channels coincide, demonstrating that the optimisation converges to physically plausible parameters rather than overfitting the colour chart data.

4 Applications

(1) **Production compatibility.** Because the model is continuous (two matrices and three sigmoids), we can generate LUTs of any resolution, which can be dropped seamlessly into existing production pipelines to emulate a faithful "Film look". Alternatively, a <1KB JSON is sufficient to encode all 30 parameters if artists opt to use the proposed model directly over LUTs.

(2) **Archival preservation.** Institutions and hobbyists can digitise the palette of an out-of-production film with a single existing roll, confident that every parameter maps to a verifiable physical quantity. This is especially valuable when long-term colour accuracy is more important than just stylistic approximation.

(3) **Creative authoring.** Camera or software vendors may expose the four sigmoid parameters as sliders ("toe", "shoulder", etc.), enabling artists to manipulate the emulation in ways that still respect the film's physical properties.

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