Models of an intelligent image transformation system for cyanotype reproduction*

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Abstract

This paper presents an intelligent tone transformation model for generating digital negatives suitable for cyanotype photographic reproduction. The proposed approach introduces an adaptive generalized sigmoid transformation specifically tailored to the requirements of the cyanotype process, combining an analytically interpretable tone model with intelligent parameter adaptation based on global image features. The model is based on a generalized sigmoid tone function with independent control of shadows, highlights, and tone balance through parameters γ, β, and k. Unlike manual tone adjustment in graphic editors, the proposed method formalizes the construction of the tone curve and ensures reproducibility of results. An interpretable parameter selection mechanism is implemented, combining global image statistics with rule-based logic and neural-assisted regression for mapping image features to sigmoid parameters. The approach is implemented in MATLAB: Simulink and demonstrated as an interpretable decision-support prototype for digital negative preparation in alternative photographic workflows.

Keywords

sigmoid tone transformation, intelligent image processing, tone model, neural-assisted mapping, cyanotype reproduction [1]

1. Introduction

Cyanotype is one of the oldest analog photographic processes, based on the ability of iron salts to form blue water-insoluble compounds under the influence of ultraviolet radiation. Nowadays, cyanotype is called an "alternative process" in photography, it is an unusual hand-printing technique that allows one to create retro prints, which has found its use today as a photographic art. According to the recent research [1], the global market for cyanotype master classes is showing steady growth, with a recorded 7,1 % annual rate from 2025 to 2033, which reflects the high demand for alternative photographic processes worldwide. This growth trajectory is primarily due to the revival of interest in analog and experimental photography, the integration of cyanotype techniques into art education, and the increasing adoption of hybrid and online learning platforms.

The development of digital imaging and printing technologies has enabled the generation of photographic negatives using standard computer-based image processing tools and their subsequent output on transparent media using conventional printers. As a result, cyanotype has evolved from a purely analog photographic process into a hybrid digital–analog workflow, in which the tonal characteristics of the final print are largely determined at the stage of digital image preparation. However, while modern information technologies provide flexible tools for image editing and printing, they do not inherently account for the photochemical specificity and

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nonlinear tonal response of the cyanotype process, leaving tone reproduction highly dependent on manual intervention and empirical adjustments.

To ensure a full tone print range, it is necessary to use a high-quality digital negative that provides sufficient optical density in the shadows and controlled transparency in the highlights [2]. Unlike traditional silver-gelatin negatives, digital negatives are printed on a transparent film using printers and are controlled by constructing a tone curve of brightness transformation. In modern graphic editors used in computer publishing systems to prepare images for printing (in particular, Adobe Photoshop and its analogues), tone correction is one of the basic and most important stages of the image processing [3, 4].

Tone correction is performed manually and therefore does not guarantee optimal results in terms of preserving details in the highlights and shadows, transmitting halftones and reproduction stability during printing. The optical density of the toner or ink layer on the negative directly determines the intensity of UV-light penetration, and accordingly, the reaction degree of the photosensitive layer on the paper. Cyanotype is characterized by high contrast and a sharp transition from shadows to highlights, which necessitates the development of intelligent methods for enhancing the contrast of the negative through nonlinear transformations in the 0-1 input signal range [5]. Under these conditions, the use of information technologies becomes a necessary tool for the intellectualisation of the digital negative generation process, enabling systematic control of tonal transformations instead of purely manual adjustment. The integration of analytical image models and adaptive data-driven techniques allows the preparation of digital negatives to be transformed into a reproducible, controllable and standardised workflow..

2. Literature review

In the domestic scientific school formed around the Ukrainian Academy of Printing, a distinct group of studies has focused on the development of mathematical models for tone transformation of digital images, accompanied by analyses of contrast sensitivity, discretization effects, and suitability for printing processes. A common methodological principle underlying these works is the representation of tone transformation as a one-dimensional gradation characteristic, where the input brightness level is mapped through an analytical function and evaluated via its derivatives, curve shape, and behavior in shadow and highlight regions. This approach enables a rigorous mathematical assessment of tone transfer properties; however, it inherently restricts the analysis to a single brightness channel, which limits its applicability in practical systems for digital negative preparation.

Tone transformation is also widely considered in the broader context of digital image enhancement, where brightness remapping is usually performed using linear inversion, gamma correction, histogram-based methods, manual tone curves, and nonlinear tone-mapping operators. Among these approaches, tone curves remain one of the most interpretable tools because they modify the tonal distribution of an image without changing its spatial structure [6]. Tone-curve optimization studies also show that brightness remapping can be formulated as a controlled mathematical problem rather than only as a manual editing operation [7]. However, in the case of digital negatives for cyanotype reproduction, simple inversion or global gamma correction is insufficient, because the final print is affected by the nonlinear photochemical response of the cyanotype layer, ultraviolet exposure, and the optical density of the printed transparent film [4, 5].

Studies [8] demonstrate that sinusoidal functions are effective for enhancing dark image regions by allowing control over the position of maximum curve steepness through frequency and phase shift parameters. These models provide smooth transitions and stable contrast behavior, but they are primarily oriented toward digital image processing tasks and do not explicitly address the constraints imposed by specific reproduction technologies. Further development of this direction is presented in [9], where a normalized exponential tone transformation is proposed for dark regions, accompanied by contrast sensitivity analysis using the derivative of the gradation characteristic. Nevertheless, this approach also remains confined to a one-dimensional formulation without explicit linkage to the physical properties of a particular printing or photographic process. In [10], a power-linear tone transformation retaining an S-shaped characteristic is introduced, with reduced steepness at the beginning of the tone scale to avoid highlight collapse. Although the author demonstrates that proper discretization can mitigate posterization effects, the model lacks experimental validation in a concrete technological context, which limits its practical relevance.

In the international research context, S-shaped tone curves are widely regarded as a universal tool for controlled dynamic range compression. For example, [11] proposes HDR image compression based on a multi-peak S-shaped tone curve, confirming the analytical robustness of sigmoid functions as tone-mapping operators. Modern HDR enhancement studies also show that tone mapping can be combined with other image-processing tasks, including denoising and perceptual quality optimization [12, 13]. A further shift from fixed nonlinear operators toward adaptive tone control is presented in [14], where tone mapping is formulated as a real-time tone curve estimation problem driven by image characteristics. This paradigm aligns with the broader concept of intelligent tone transformation, in which the shape of the tone curve is determined automatically rather than selected manually. Similarly, [15] demonstrates dynamic sigmoid mapping for underwater image enhancement, where sigmoid parameters are adapted to scene content to regulate contrast and detail visibility.

The adaptive selection of tone-transformation parameters has also been developed in learning-based image enhancement. Recent curve-estimation approaches use neural models to construct nonlinear brightness mappings, including Bezier-based tone adjustment and zero-reference deep curve estimation [16]. Serrano-Lozano et al. proposed a learning-based enhancement approach in which tone curves are estimated for semantically meaningful colour components [17]. In addition, iterative curve-estimation models have been applied to real-time underwater image enhancement, confirming the relevance of curve-parameter adaptation under complex imaging conditions [18]. These studies are methodologically important for the present work because they demonstrate a transition from fixed tone operators to image-dependent parameter estimation. At the same time, most of these approaches are designed for perceptual improvement of digital images and are not directly linked to the technological requirements of contact printing or photochemical reproduction.

Recent studies in intelligent visual data processing further confirm the relevance of adaptive enhancement strategies. Maksymiv and Rak [19] proposed an adaptive video enhancement approach based on blind degradation estimation, demonstrating that correction of visual data can be guided by automatically estimated degradation characteristics rather than by fixed processing parameters. Although their study focuses on video enhancement, its general idea of image-dependent adaptive correction is methodologically relevant to the present work, where global image statistics are used to select the parameters of a sigmoid tone transformation for cyanotype digital-negative preparation.

Overall, contemporary studies indicate a clear evolution from fixed nonlinear tone curves, such as sinusoidal and exponential functions, toward adaptive sigmoid-based models whose shape is influenced by image features. However, the majority of these approaches focus on digital visualization tasks and assess tone curves primarily from the perspective of perceptual contrast enhancement. The technological constraints of photochemical reproduction processes are rarely considered explicitly, and parameter selection often remains heuristic, lacking clear physical or process-related interpretation.

Motivated by these limitations, the present study seeks to bridge the gap between analytical tone-curve modeling and the specific requirements of cyanotype reproduction. The proposed approach introduces a generalized sigmoid tone transformation with independently controllable shadow, highlight, and balance parameters, whose selection is guided by global statistical features of the input image. By embedding the tone transformation within an interpreted intelligent framework, the model formalizes the decision-making process traditionally performed intuitively by practitioners and aligns it with the physical characteristics of the cyanotype process..

3. Mathematical model of image transformation

This section formulates an analytical tone transformation model for digital negative generation in the cyanotype process. The model is defined as a parametric nonlinear operator acting on normalized image brightness and serves as the mathematical core of the proposed intelligent system.

For this, the sigmoid transformation of the image is used, which, according to the mathematical model, has the following interpretation in the form of the sigmoid function:

$$f(L) = \frac{1}{1 + g(L)} \tag{1}$$

where *g(L)* is a monotone function [20].

To capture changes in shadows and highlights, a parametric power tone inversion function is used:

$$g(L) = k\frac{(1-L)^{\beta}}{L^{\gamma}} \tag{2}$$

Substituting (3) into (2), the function is obtained:

$$f(L) = \frac{1}{1 + k\frac{(1-L)^{\beta}}{L^{\gamma}}} \tag{3}$$

Finally, after simplification, a sigmoid dependency is obtained for cyanotype reproduction:

$$f(L) = \frac{L^{\gamma}}{L^{\gamma} + k(1-L)^{\beta}} \tag{4}$$

$$L_{negat} = 1 - L_n(L), \quad L \in [0,1] \tag{5}$$

where: L is a normalized value of the pixel input brightness (0 – black, 1 – white); $Ln(L)$ is a result of sigmoid transformation after tone correction; L_{neg} is a value in negative (inverted brightness map); γ is a parameter of influence on "shadows", how the dark range is enhanced or expanded; β is a parameter of influence on "highlights", the suppressing degree in the highlights on the negative; k is a coefficient of shift of the curve operating point, it determines the balance of shadows/highlights.

The proposed formulation results in a smooth, monotonic, and continuously differentiable tone curve, making it suitable for both analytical contrast sensitivity analysis and adaptive parameter selection. Although the model is defined as a one-dimensional brightness operator, its parameters possess clear technological interpretation and can be systematically adapted based on global image characteristics. This property enables the integration of the analytical tone model into an interpreted intelligent framework, which is addressed in the following section through rule-based and neural-assisted parameter estimation. Thus, a modified sigmoid function is obtained, which describes the tone transformation during the formation of a digital negative. Power operators in the numerator and denominator allow an independent control of shadows (γ) and highlights (β), and the coefficient k shifts the curve operating point, which is important for increasing the contrast in the highlight zone, characteristic of the cyanotype process. The following implementation of the task will be carried out using the Matlab-Simulink software package.

4. Intelligent tone transformation model and experimental results

4.1. Model architecture of an image sigmoid transformation

For the practical formation of digital negatives, a single-channel sigmoid transformation model is used, identical in mathematical dependency (4). The implementation in the MATLAB: Simulink environment (Ramp–Sigmoid–Negative–Derivative model) provides an analytical analysis of the curve properties, while the MATLAB script applies the same model to real images and generates negative files for printing on transparent films. Fig. 1 presents a block diagram of the model that implements the image tone transformation using a sigmoid function.

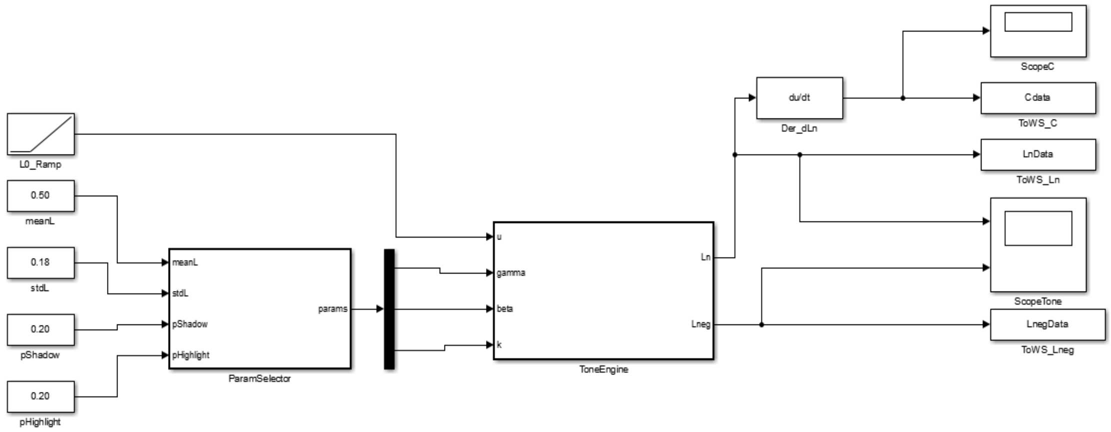

Figure 1: A single-channel Simulink model of a sigmoid transformation for a negative formation.

The developed model implements the intelligent tone transformation of the brightness signal based on a generalized sigmoid function, the parameters of which are adaptively selected according to the statistical characteristics of the image. The model allows not only the tone curve itself but also its local contrast to be analysed.

The main blocks of the model are:

1. The intelligent *ParamSelector* block implements a rule-based adaptive mechanism for selecting the parameters of the sigmoid function, which includes: compensation of the average brightness through the parameter γ (steepness change in dark tones); control of the "shoulder" of highlights through β; balance between highlights and shadows through the coefficient k; correction for high scene variability (*stdL*). Thus, ParamSelector plays the role of an intelligent tone curve regulator.
2. The next element of the model is *ToneEngine*, which implements a generalized sigmoid function of the form (4), based on adaptive parameters γ, β and k.

For the analysis of local contrast, the Continuous Derivative (dLn/dt) block is used, which calculates the derivative of the tone curve. The intelligent model selection is implemented through:

1. Influence of *meanL* $\longrightarrow \gamma$

- dark scene (*meanL* < 0.5) ⟶ decrease in γ ⟶ increase in shadows;
- light scene ⟶ increase in γ ⟶ compression of shadows.

Influence of *pHighlight* $\longrightarrow \beta$

- many bright areas ⟶ increase in β ⟶ soft bright shoulder;
- few bright areas ⟶ decrease in β ⟶ aggressive highlights.

2. Influence of p*Highlight* – *pShadow* $\longrightarrow k$

- dominance of highlights ⟶ increase in k ⟶ balance towards shadows;
- dominance of shadows ⟶ decrease in k ⟶ avoidance of "collapse".

Correction by stdL, with a high stdL, the parameters are softened to avoid the contrast oversaturation.

In the proposed model, the detection of image features and making an intelligent decision on the formation of a negative are considered as a holistic sequential process, as close as possible to the real logic of digital image preparation. The model intentionally avoids pixel analysis and local operators, since in traditional alternative photo processes the result is controlled not at the level of individual pixels, but through a general assessment of the tone structure of the scene and its compliance with the capabilities of the emulsion and the exposure process.

The initial stage is based on the assumption that the brightness histogram contains sufficient information to make a correct technological decision. The average brightness is interpreted as an integral characteristic of the scene illumination and determines whether the image is shifted towards shadows or highlights. In the context of negative preparation, this feature plays the role of an analogue of exposure assessment, since it allows one to predict which areas of the tone range need to be enhanced and which ones need to be suppressed.

The standard deviation of brightness is used as a measure of the overall contrast and the scene complexity. Additionally, the fractions of shadows and highlights are introduced, which quantitatively describe the asymmetry of the histogram and the presence of dominant zones in the tone distribution. These parameters have direct technological meaning. Based on the formed features, an intelligent decision is made, which is implemented in the form of an adaptive selection of the parameters of the generalized sigmoid tone function.

After making a decision, the parameters of the sigmoid function are used to construct an adaptive tone curve that describes the transition from the brightness of the original to the normalized values of the positive image. This curve reflects a compromise between preserving details, controlling contrast, and technological limitations of the photo process. The formation of the negative is carried out by inverting the obtained tone response.

As a result, the model implements an interpreted intelligent system in which the sensory level is represented by statistical features of the image, the cognitive level is represented by an adaptive rule-based selection of the tone function parameters, and the executive level is represented by the formation of an optimized negative.

4.2. Implementation of a sigmoid transformation in the model

In the adaptive parameter selection stage, a regression neural network with a single hidden layer is employed to approximate a continuous nonlinear mapping f: $R^4 \rightarrow R^3$, which relates a vector of global image features to the parameters of the generalized sigmoid tone function. The network architecture is intentionally kept compact, as its role is not high-capacity learning, but the demonstration of an interpretable mechanism for image-dependent parameter estimation.

The input feature vector is defined as $X=[meanL,\ stdL,\ p_{shadow},\ p_{highlight}]^T$, where meanL represents the average image brightness and serves as an analogue of global exposure estimation, stdL characterizes the overall contrast and scene complexity, while p_{shadow} and phighlight quantify the asymmetry of the brightness histogram through the relative fractions of pixels in dark and bright regions. For a normalized grayscale image $L(x,y) \in [0,1]$, the global feature vector is calculated on the basis of the brightness distribution of all image pixels.

The mean brightness meanL is determined as the arithmetic average of normalized pixel values and characterizes the general exposure tendency of the source image. The standard deviation stdL describes the global tonal variability and is used as an indicator of contrast complexity. The shadow fraction pshadow is defined as the relative number of pixels with $L < 0.2$, whereas the highlight fraction phighlight is defined as the relative number of pixels with $L > 0.8$. Thus, the input vector does not describe individual local details, but represents the global tonal structure of the image, which is consistent with the practical logic of digital-negative preparation for contact printing.

For each training example Xi, a corresponding target parameter vector $Y_i = [\gamma, \beta, k]^T$ is specified, reflecting the desired shape of the sigmoid tone curve for a given type of scene. In images dominated by bright regions, higher values of the highlight suppression parameter β and the balance parameter k are assigned in order to limit excessive ultraviolet transmission and shift the operating point of the tone curve. Conversely, for predominantly dark scenes, the parameter configuration is adjusted to avoid loss of shadow detail and premature tonal collapse. The resulting training sets are organized in matrix form, with feature vectors and parameter vectors represented column-wise in accordance with standard neural network toolchains.

In the present implementation, the target parameter vectors were assigned according to expert-defined tonal scenarios rather than obtained from a large empirical database. Four basic tonal scenarios were used to calibrate the mapping: dark-dominant, highlight-dominant, low-contrast, and balanced image structures. For each scenario, the values of γ, β, and k were selected according to their technological interpretation. The parameter γ controls the expansion or compression of shadow information, β controls the suppression of highlight regions in the negative, and k shifts the operating point of the sigmoid curve between shadows and highlights. Therefore, the target vectors represent interpretable tone-curve configurations rather than arbitrary numerical labels. The regression network was trained to approximate the mapping f: X ⟶ Y, where X = [meanL, stdL, pshadow, phighlight]T is the input feature vector and Y = [γ, β, k]T is the output parameter vector of the generalized sigmoid transformation. The training objective was to minimize the mean squared error between the predicted and target parameter vectors.

After training, the network estimates the parameters γ, β, and k for an input image according to its global tonal statistics. At the current stage, this estimation should be regarded as prototype-level adaptive support rather than as a fully validated generalization model. Full assessment of generalization requires a larger dataset of images, optical-density measurements of printed negatives, exposure tests, and validation on real cyanotype prints. Nevertheless, even in the present prototype form, the proposed scheme formalizes the process “image features ⟶ tone-curve parameters ⟶ digital negative”. For example, Fig. 2 presents the results of transforming a digital image by the developed model.

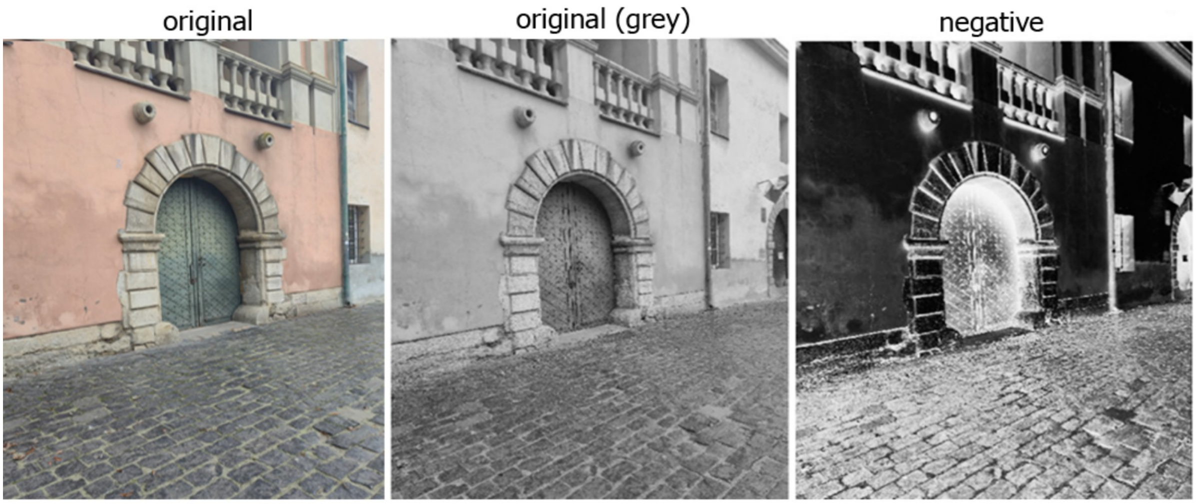

Figure 2: A digital grayscale image and a sigmoidally inverted negative image.

To clarify the practical behavior of the proposed model, a numerical example of sigmoid parameter selection is provided for the image shown in Fig. 2. The analyzed image is characterized by the following global statistical features: $meanL$ = 0,63, $stdL$ = 0,18, p_{shadow} = 0,09, and $p_{highlight}$ = 0,34, which corresponds to a predominantly bright scene with moderate overall contrast. According to the adaptive parameter selection logic implemented in the ParamSelector block, the estimated sigmoid parameters are γ = 0,75, β = 1,85 and k = 0,62. Substitution of these values into equation (4) results in a tone curve that moderately enhances shadow detail while strongly compressing highlight regions of the negative. This configuration limits excessive ultraviolet transmission in light areas and establishes a balanced tonal response suitable for cyanotype exposure.

The result of the image transformation is demonstrated in the histograms presented in Fig. 3.

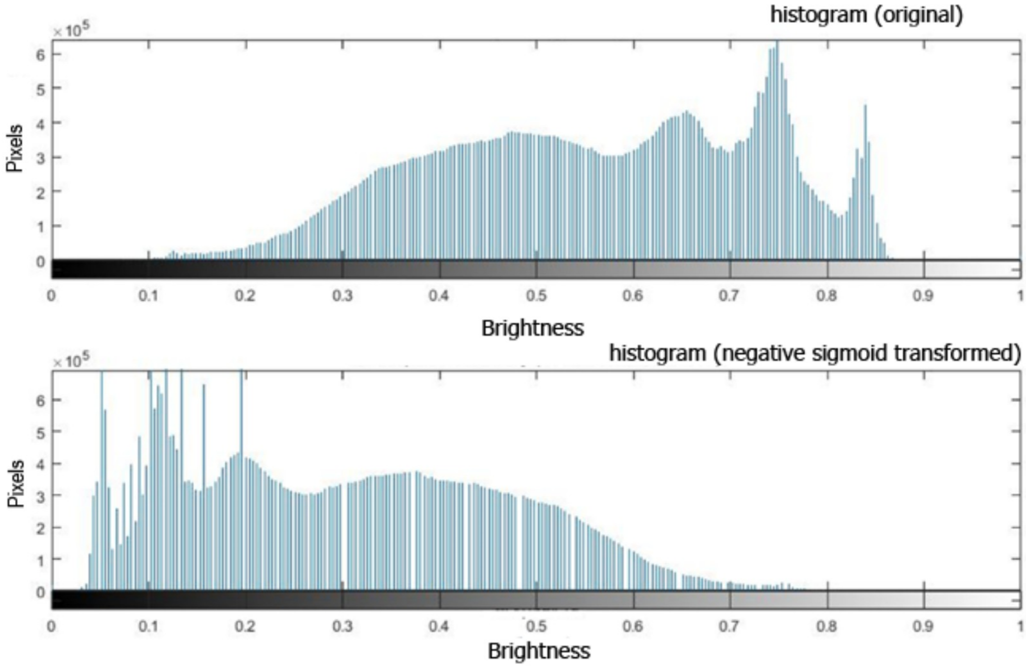

Figure 3: A histogram of the digital original image and the negative transformed one.

The presented histograms demonstrate the distribution of image brightness before and after applying the sigmoid tone transformation. The upper diagram shows the histogram of the original image, in which the pixel intensities are concentrated mainly in the mid-highlight area (0,45-0,85). This indicates that a significant part of the frame contains smooth transitions and few dark areas. The graph shows several peak clusters that correspond to locally dominant details of the scene, while dark tones are presented in a smaller number and shifted to the left part of the scale. After the transformation (lower diagram), the overall distribution pattern changes fundamentally: a significant part of the bright values of the original, which corresponded to light areas, is transferred to the range of dark tones of the negative.

This is the result of the action of function (4), which inverts the tone and makes the negative suitable for printing for cyanotype. The sigmoid curve compresses high brightness values and creates a characteristic "collapse" of the histogram in the 0,7-1,0 range, which corresponds to a dense darkening of light areas on the negative. This reduces UV-transmission and enhances the formation of the optical density of the future image on the print.

Fig. 4 presents the local contrast of the tone transformation, defined as the derivative of the adaptive tone curve $C(L)=dLn/dL$. It shows how the system sensitivity changes along the entire tone range. High values $C(L)$ in the shadows indicate a targeted enhancement of weak tone differences, which ensures the preservation of details in the dark areas of the negative. In the midtone zone, the sensitivity remains moderate and stable, ensuring a uniform transmission of the main visual information.

Thus, this curve serves as a visual indicator of the contrast distribution and explains the logic of the intellectual formation of the negative.

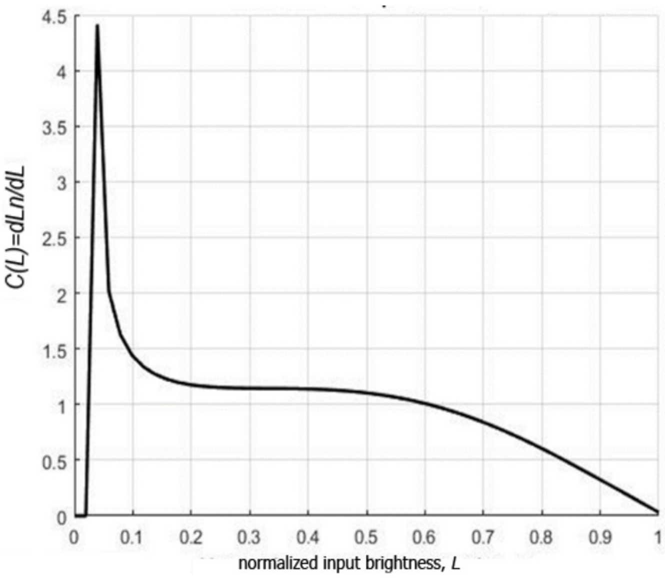

Figure 4: Local contrast of the tone transformation.

Conclusions

The paper substantiates the feasibility of using sigmoid tone transformations for the formation of digital negatives in the cyanotype process. It is shown that classical tone correction models used in printing and digital environments do not take into account the specifics of the photochemical process of alternative techniques and require a further adaptation although they provide some mathematical control. The proposed modified sigmoid function with power operators allows one to independently adjust the shadow and highlight ranges, as well as shift the curve operating point in accordance with the image nature. The implemented intelligent model based on global statistical features of the image formalizes the decision-making process, which in the alternative photography practice is usually performed intuitively.

The analysis of histograms and local contrast confirms that the proposed transformation provides the effective darkening of light areas of the negative, the enhancement of details in the shadows and the controlled distribution of contrast along the entire tone range. This creates the prerequisites for improving the stability, repeatability and quality of cyanotype prints. The results obtained indicate the prospects of using interpreted intelligent models of tone transformation for preparing digital negatives not only in cyanotype, but also in other alternative photo processes.

From an engineering perspective, the proposed approach demonstrates that tone-curve design for alternative photographic processes can be formalized as an interpretable decision-support problem rather than treated only as a heuristic manual operation.

The generalized sigmoid model provides a transparent relationship between image statistics and the parameters responsible for shadow control, highlight compression, and tonal balance. This makes the process of digital-negative preparation more reproducible and more suitable for further automation.

At the current stage, the neural-assisted component should be regarded as a prototype mechanism for adaptive parameter estimation. Its purpose is to demonstrate the feasibility of mapping global image features to sigmoid tone-curve parameters within an interpretable workflow. Further research will focus on expanding the training and validation dataset, comparing the proposed model with additional baseline tone-correction methods, measuring the optical density of printed digital negatives, and validating tone reproduction on real cyanotype prints.

Declaration on Generative AI

During the preparation of this work, the authors used Grammarly in order to: grammar and spelling check; DeepL Translate in order to: some phrases translation into English. After using these tools/services, the authors reviewed and edited the content as needed and take full responsibility for the publication's content.

References

[1] *Cyanotype Photography Workshops Market Research Report 2033*, Growth Market Reports. URL: https://growthmarketreports.com/report/cyanotype-photography-workshops-market

[2] C. Ozawa, K. Yamamoto, K. Izumi, Y. Ochiai, *Alternative Photographic Processes Reimagined: The Role of Digital Technology in Revitalizing Classic Printing Techniques*, in: SIGGRAPH Asia 2023 Art Papers, December 12–15, 2023, Sydney, NSW, Australia, Association for Computing Machinery, New York, NY, USA, 9 pp. doi:10.1145/3610591.3616430.

[3] Adobe Inc., *Adjust Image Color and Tone with Curves*, Adobe Help Center. URL: https://helpx.adobe.com/photoshop/using/curves-adjustment.html

[4] *Preparing Digital Negative*, Special Edition Art Project, 2018. URL: https://specialeditionartproject.com/guides/SEAP%20Preparing%20Digital%20Negative%20v2018-1.pdf

[5] C. Grier, *Calibration for Alternative Photographic Processes: Introduction*, The Wet Print, 2020, 17 p. URL: https://thewetprint.com/wp-content/uploads/2021/05/Guide-0_Introduction.pdf

[6] J. Bennett, G. D. Finlayson, Simplifying tone curves for image enhancement, Color and Imaging Conference, 31 (2023), 20-25. doi:10.2352/CIC.2023.31.1.20.

[7] D. Huang, X. Zheng, J. Li, R. Zhan, J. Dong, Y. Wen, X. Mao, Y. Chen, Y. Chen, Tone mapping of HDR images via meta-guided Bayesian optimization and virtual diffraction modeling, Sensors, 25 (2025), 6577. doi:10.3390/s25216577.

[8] Y. Y. Serdyuk, M. M. Lutskiv, Analysis of sinusoidal transformation model of dark tone digital images, Technology Audit and Production Reserves, 4 (2025), 24-28. doi:10.15587/2706-5448.2025.334896.

[9] M. Lutskiv, et al., Simulation of normal exponential transformation of dark tone images, in: Proceedings of the 1st International Workshop on Intelligent & Cyber-Physical Systems (ICyberPhyS-2024), Khmelnytskyi, Ukraine, 2024. URL: https://ceur-ws.org/Vol-3736/paper5.pdf

[10] S. Kavyn, Development of a model of power-linear conversion of digital images for dark tones, Technology Audit and Production Reserves, 2 (2025), 32-36. doi:10.15587/2706-5448.2025.323535.

[11] J. Qiu, Z. Wang, H. Huang, High dynamic range image compression based on the multi-peak S-shaped tone curve, Optics Express, 31 (2023), 9841–9853. doi:10.1364/OE.484321.

[12] L. Hu, H. Chen, J. P. Allebach, Joint multi-scale tone mapping and denoising for HDR image enhancement, in: Proceedings of the IEEE/CVF Winter Conference on Applications of Computer Vision Workshops, 2022, pp. 729-738.

[13] X. Wan, Q. Wei, X. Xu, J. Zhong, W. Zhang, L. Shen, W. Ju, Z. Liang, Underwater image enhancement via standard deviation reconstruction, dynamic sigmoid mapping and gradient-aware enhancement, Optics and Lasers in Engineering, 195 (2025). doi:10.1016/j.optlaseng.2025.109339.

[14] X. Wan, Y. Liu, Q. Zhang, S. Chen, Underwater image enhancement based on dynamic sigmoid mapping and gradient-guided detail preservation, Signal Processing 221 (2025) 109492. doi:10.1016/j.sigpro.2024.109492.

[15] X. Gao, Y. Wang, Y. Chen, J. Wang, Low-light image enhancement via zero-reference Bezier curve estimation, Sensors, 23 (2023) ,9593. doi:10.3390/s23239593.

[16] C. Guo, C. Li, J. Guo, C. C. Loy, J. Hou, S. Kwong, R. Cong, Zero-reference deep curve estimation for low-light image enhancement, in: Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, 2020, pp. 1780–1789.
[17] D. Serrano-Lozano, L. Herranz, M. S. Brown, J. Vazquez-Corral, NamedCurves: Learned image enhancement via color naming, in: Computer Vision – ECCV 2024, Lecture Notes in Computer Science, volume 15129, Springer, Cham, 2024, pp. 92-108. doi:10.1007/978-3-031-73209-6_6.
[18] J. Wang, X. Ye, Y. Liu, et al., Learning mapping by curve iteration estimation for real-time underwater image enhancement, Optics Express 32 (2024), 9931-9948.
[19] M. Maksymiv, T. Rak, Adaptive video enhancement based on blind degradation estimation, Computer Systems and Information Technologies, 2 (2025), 181-189. doi:10.31891/csit-2025-2-21.
[20] N. Alasmari, et al., Perceptually optimal tone mapping of HDR images via two-stage Bayesian optimization, Electronics, 14 (2025), 4080. doi:10.3390/electronics14204080.