Deformation-Aware Luminance Compensation using Gaussian-Weighted Kernels for Stretchable Displays

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Abstract
Advancements in display technology enable stretchable displays, but luminance degradation from empty pixels remains a challenge. We propose a Gaussian-Weighted Kernel-based method to address this for linear, non-linear, unidirectional, and bidirectional stretching. By assigning higher weights near empty pixels, it compensates luminance loss while minimizing color distortion. The proposed simulator shows superior visual outcomes and improved distortion metrics, advancing the feasibility of stretchable displays.

Author Keywords
Stretchable Display; Luminance Compensation; Gaussian-Weighted Kernel; Color Distortion.

1. Introduction
Advancements in display technologies have made flexible and thin displays possible, broadening their range of applications [1]. In particular, stretchable displays offer innovative possibilities in wearable devices, smart clothing, and interactive devices. However, a major challenge for stretchable displays arises from luminance degradation caused by empty pixels, which occurs as the display stretches over curved or elastic structures [2]. This issue becomes more pronounced with higher stretching ratios and in irregular deformations with non-uniform strain, ultimately leading to a decline in display quality. Hardware-based research efforts have addressed the issue of luminance degradation in stretchable displays using various approaches [3, 4]. In contrast, software-based post-processing compensation, which manipulates pixel values on the display, has been limited to basic image processing techniques such as gamma operation and mean scaling. These simple methods fail to effectively address issues like color distortion, luminance imbalance, and the more severe luminance degradation that occurs with higher stretching ratios.

In response, this study proposes a novel approach to compensate for the luminance loss caused by stretching in stretchable displays using a Gaussian-Weighted Kernel that applies weights based on a normal distribution. The proposed method can be effectively applied to various types of stretching (linear and non-linear) and different stretching ratios. Furthermore, the proposed simulator is designed to easily adjust parameters such as stretching type and ratio, helping to identify optimal design conditions, and enabling both qualitative and quantitative performance evaluations of the proposed method compared to existing techniques under different stretching conditions. This paper introduces a robust luminance compensation method against color distortion and provides a comparative analysis of its performance against existing methods through quantitative and qualitative evaluations. The proposed method demonstrates superior performance in key visual quality metrics.

2. Background
Flexible and Stretchable Displays: Flexible and stretchable display technologies have made significant advancements in recent years, largely due to developments in display technologies such as OLED and MicroLED. OLED, with its ability to be implemented on flexible substrates, has established itself early on as a key technology for flexible displays. On the other hand, MicroLED, known for its high brightness and durability, has contributed to the evolution of stretchable displays [1, 5]. These technologies enable the realization of thinner and more flexible displays, greatly expanding potential applications in areas such as wearable devices, smart clothing, and adaptable screens [5, 6]. However, despite these advancements in stretchable displays, the issue of luminance loss that occurs when the display is deformed remains a significant technical challenge [2].

Luminance Compensation Techniques: Geometric compensation techniques for addressing luminance degradation typically involve hardware-based approaches aimed at correcting the physical deformation of the display. Zou et al. [7] developed a method to enhance the flexibility of displays by utilizing shape-deformable Micro-LEDs. Their approach focused on maintaining display performance during deformation, making the technology suitable for advanced applications such as healthcare. Furthermore, Min et al. [8] introduced a strain sensor-integrated pixel compensation method to address resolution degradation in stretchable displays. This approach uses integrated strain sensors to monitor deformation in real time, allowing for immediate compensation and ensuring the stability of the display quality.

In contrast, optical compensation techniques are software-based post-processing methods that aim to adjust pixel values in response to display deformation to compensate for luminance loss. These methods, such as gamma operation and mean scaling, are simpler but often result in color distortion and luminance imbalance, particularly as the stretching ratio increases. Consequently, these software-based methods struggle to address the physical deformation of the display effectively. Overall, while hardware-based geometric approaches to solving luminance degradation issues in stretchable displays have been actively pursued, the development of software-based compensation techniques has remained limited.

Challenges in Stretchable Displays: Stretchable displays hold great potential as a display technology for curved and various deformation environments. However, significant challenges, such as luminance loss due to stretching ratios and physical deformation, remain obstacles to their widespread adoption. When the display undergoes deformation, changes in pixel spacing lead to luminance degradation, which is particularly pronounced in cases of non-uniform stretching. Although some studies [7, 9] have focused on addressing these issues, most have primarily targeted linear deformation, leaving the more complex luminance loss problems resulting from non-linear deformation inadequately addressed.

3. Proposed Method
The proposed luminance compensation method is based on the Gaussian-weighted kernel and focuses on effectively compensating for luminance loss caused by empty pixels in both linear and non-linear stretching environments. The kernel is flexibly generated based on the stretching type using the Gaussian-weighted kernel to maximize computational efficiency.

Figure.1. Visual comparison of the proposed method with existing methods on the proposed simulator.

Operations According to Stretching Types: We have taken into account both linear and non-linear stretching environments to enable effective luminance compensation in various deformation scenarios that were not fully addressed in previous studies. Linear stretching occurs when the display stretches uniformly, resulting in evenly spaced pixels. In contrast, non-linear stretching involves areas that undergo more or less deformation, causing a sharp increase in empty pixels around highly deformed areas. Based on the stretching type and ratio, we analyzed the points where empty pixels should be placed and the cells surrounded by empty pixels on the display. In linear stretching, empty pixels are positioned at uniform intervals, while in non-linear stretching, the empty pixels are positioned based on the percent-point function (PPF) of the normal distribution. The PPF is the inverse of the cumulative distribution function (CDF), mapping probabilities to corresponding quantiles within the distribution. During this process, the location where the force is applied on the display and the intensity of the force are also considered. The formula for calculating the coordinates of the empty pixels in non-linear stretching is as follows:

$$y_i = \mu + \sigma \cdot \Phi^{-1}(p_i),\ p_i \in (0,1), \qquad (1)$$

where y_i represents the calculated stretching point, indicating the new position of a specific pixel after stretching. μ denotes the center of the normal distribution, which corresponds to the location where the stretching force is primarily applied. σ denotes the standard deviation, representing the scale of the stretching effect, describing how broadly or narrowly the impact of stretching is distributed across the display. Φ^{-1} is the inverse of the cumulative distribution function (CDF) of the standard normal distribution, providing the corresponding percentile value. The value p_i is uniformly distributed between 0 and 1, representing the desired probability level used to determine the corresponding y_i.

Gaussian-Weighted Kernel Generation for Luminance Compensation: The core technique for compensating luminance loss is the Gaussian-weighted kernel. In this study, we propose a method using a Gaussian distribution-based kernel to effectively compensate for the overall luminance loss caused by empty pixels during stretching. The Gaussian-weighted kernel is applied to cells surrounded by empty pixels, compensating for their luminance based on a normal distribution shape. The weights are set higher in areas with a concentration of empty pixels to minimize luminance loss. The process of generating the Gaussian-weighted kernel is as follows, where the brightness increase ratio (BIR) is predefined to be greater than 1.

$$d_i = \sqrt{(x_i - center_{x_i})^2 + (y_i - center_{y_i})^2},\ \bar{d} = \frac{1}{N}\sum_{i=1}^{N} d_i, \qquad (2)$$

where the Euclidean distance d_i between a point (x_i, y_i) and a set of center point $(center_{x_i}, center_{y_i})$ is calculated, and the average distance $\bar{d}$ is calculated, where N is the total number of the points.

$$K(x,y) = 1 + \frac{1}{2\pi\sigma^2}\exp\left(-\frac{\bar{d}^2}{2\sigma^2}\right). \qquad (3)$$

Based on the $\bar{d}$, a weight kernel $K(x,y)$ in the form of a Gaussian distribution is calculated. The farther away from the center, the lower the value.

$$K_{norm}(x,y) = 1 + \frac{K(x,y) - \min(K)}{\max(K) - \min(K)}, \qquad (4)$$

where $K(x,y)$ is normalized between 1 and 2, becoming K_{norm}, where the center point becomes 2 and the point furthest from the center becomes 1.

$$K_{rev}(x,y) = 2 - K_{norm}(x,y), \qquad (5)$$

$$K_{final}(x,y) = 1 + (BIR - 1) \times \frac{K_{rev} - \min(K_{rev})}{\max(K_{rev}) - \min(K_{rev})}, \qquad (6)$$

where K_{final} is obtained by reversing the trend of K_{norm}, and normalizing it so that its center point becomes 1 and the point farthest from the center becomes BIR.

This kernel generation method can be flexibly applied to various kernel sizes. In other words, for each type of stretching and stretching ratio, kernels of the same size as the generated cells are created, and weights are calculated based on the kernel. We have preloaded the algorithm with weighted kernels for several

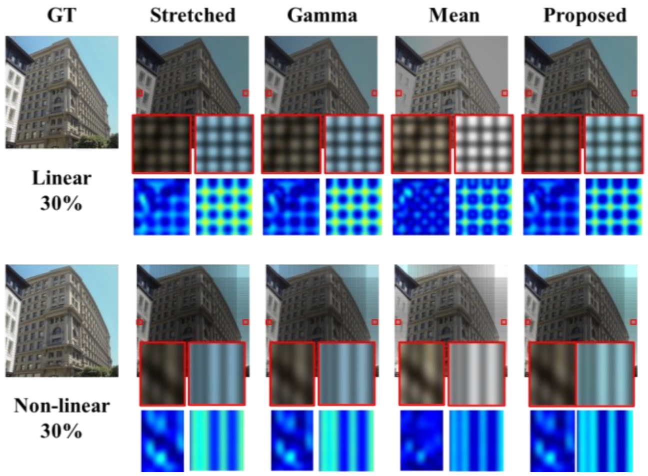

Figure 2. Visual comparison of various luminance compensation methods for linear and non-linear types, with a stretch ratio of 30% and a relative distance of 2.

representative kernel sizes, thereby minimizing the computational process of generating kernels based on the Gaussian distribution and maximizing computational efficiency. This enhanced efficiency increases the practical applicability of the technique.

Point Spread Function: The Point Spread Function (PSF) [10] represents how a point light source spreads in an image. By using PSF, the pattern of luminance loss can be mathematically modeled, enabling precise calculation of the spread of luminance loss around empty pixels. This process plays a crucial role in reducing the visual imbalance caused by empty pixels. PSF compensates for the luminance loss caused by empty pixels from the surrounding pixels, contributing to maintaining a more natural and consistent overall luminance distribution [11]. Specifically, PSF aims to improve visual quality by using a blurring effect to make empty pixels less noticeable. Instead of causing a sharp change in luminance, PSF distributes the luminance around the empty pixels smoothly, resulting in a more balanced and softer appearance. Additionally, as the distance between the image and the viewer increases, the image becomes more blurred due to the PSF. This effect is similar to how objects appear blurry to the human eye when they are out of focus or viewed from a distance. Therefore, PSF reflects this visual characteristic, providing a blurring effect that makes the area around the empty pixels appear more natural even when viewed from a distance.

$$I_{psf}(x,y) = G(i,j;\sigma) * I(x,y), \tag{7}$$

$$\sigma = 1.5 \times \left|1.0001 - \frac{1}{relative\ distance}\right|, \tag{8}$$

where the PSF image $I_{psf}(x,y)$ is defined as the convolution ($*$) of the original image $I(x,y)$ and the Gaussian kernel $G(i,j;\sigma)$.

4. Experiment and Analysis

Dataset: We used the Urban100 dataset [12] to evaluate the performance of the proposed method. This dataset consists of high-resolution images primarily taken in urban environments and includes 100 images captured under various lighting conditions and with complex color combinations. These images depict diverse urban scenes such as buildings, roads, bridges, trains, and street views, characterized by intricate structures and patterns. The high level of detail and complexity in these images makes it easy to detect even small changes in luminance or color distortion, making it an ideal dataset for evaluating the quality of stretchable displays. Additionally, since the images are taken in real urban environments, the dataset reflects real-world usage scenarios. This contributes to deriving realistic and practical results in display quality evaluation.

Table 1. Performance comparison of various luminance compensation methods for linear and non-linear types, with varying stretch ratios (R) and relative distances (D).

		SSIM ↑ / LPIPS ↓ / CIEDE2000 ↓		
R	D	Gamma	Mean	Proposed
		Linear Stretching		
15%	2	0.09/0.65/10.35	0.09/0.64/12.70	**0.11/0.59/9.90**
	3	0.12/0.60/9.37	0.11/0.59/11.28	**0.14/0.54/8.90**
	4	0.14/0.57/8.96	0.13/0.56/10.75	**0.16/0.51/8.54**
30%	2	0.10/0.55/13.27	0.07/0.59/16.25	**0.11/0.51/13.24**
	3	0.16/0.40/**12.19**	0.12/0.44/14.18	**0.17/0.36**/12.49
	4	0.20/0.32/**12.24**	0.16/0.37/13.64	**0.21/0.29**/12.64
		Non-linear Stretching		
15%	2	0.40/0.46/6.66	0.39/0.45/8.77	**0.43/0.42/6.36**
	3	0.46/0.40/5.86	0.46/0.39/7.48	**0.50/0.35/5.44**
	4	0.50/0.37/5.56	0.50/0.36/7.00	**0.53/0.32/5.04**
30%	2	0.39/0.44/9.53	0.36/0.47/12.69	**0.40/0.40/9.19**
	3	0.51/0.32/9.00	0.48/0.36/10.84	**0.52/0.29/8.66**
	4	0.57/0.28/8.90	0.54/0.32/10.56	**0.58/0.25/8.53**

Evaluation Metrics: We used three performance evaluation metrics—CIEDE2000 [13], Learned Perceptual Image Patch Similarity (LPIPS) [14], and Structural Similarity (SSIM) [15]—to assess luminance degradation and color distortion as the display stretches. CIEDE2000 [13] is a metric designed to measure color differences between two colors, developed to better reflect human visual perception. It calculates the difference in L^*, a^*, b^* values in the CIELAB color space. A lower CIEDE2000 value indicates that the two colors are more similar. LPIPS [14] uses a deep learning model to measure the perceptual similarity between two images. It compares the feature maps extracted from a pre-trained neural network and calculates the Euclidean distance between them, with a lower LPIPS score indicating higher similarity. SSIM [15] measures the structural similarity between two images based on luminance, contrast, and structure. SSIM values range from -1 to 1, where a value closer to 1 indicates that the two images are very similar.

Results: We evaluated the performance of three luminance compensation methods: gamma operation-based, mean scaling-based, and the proposed method with BIR 1.1. In the case of the gamma operation method, the γ parameter was set to 1.2, as this value has been experimentally proven to yield the highest performance. Figure 1 shows the stretching results of each method for both linear and non-linear types, with a stretch ratio of 30% and a relative distance of 2. In both stretching types, the simple stretched image without any luminance compensation showed significantly reduced luminance compared to the ground truth, and as can be seen from the color maps, there were large gap areas caused by the empty pixels. The mean scaling-based method excessively increased the overall luminance in proportion to the stretch ratio, resulting in severe color distortion.

The gamma operation-based method did not show significant luminance compensation compared to the simple stretched image, and there were no notable differences in the color maps. In contrast, the proposed method effectively reduced the gap areas caused by the empty pixels while maintaining the original color. Table 1 shows the CIEDE2000, LPIPS, and SSIM performance comparison of the three luminance compensation methods for various stretch ratios and relative distances in two stretching types. In all cases, the proposed method demonstrated superior numerical performance.

5. Conclusion

This paper proposed a deformation-aware luminance compensation method using a Gaussian-weighted kernel to address the luminance degradation issue in stretchable displays. The proposed method effectively compensated for significant luminance loss in the areas adjacent to the empty pixels that emerge as the display stretches by applying weights based on a Gaussian distribution centered on the kernel. This approach minimized color distortion while effectively compensating for luminance, which has been demonstrated through visual results and key color distortion evaluation metrics. Additionally, we developed a simulator that takes into account various stretching types and ratios, providing a tool to identify optimal design conditions and compare the performance of the proposed method against existing methods. This research further enhanced the potential for the commercialization of stretchable displays and is expected to drive innovation in display technology across various application fields in the future.

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