ChromaCorrect: Prescription Correction in Virtual Reality Headsets through Perceptual Guidance

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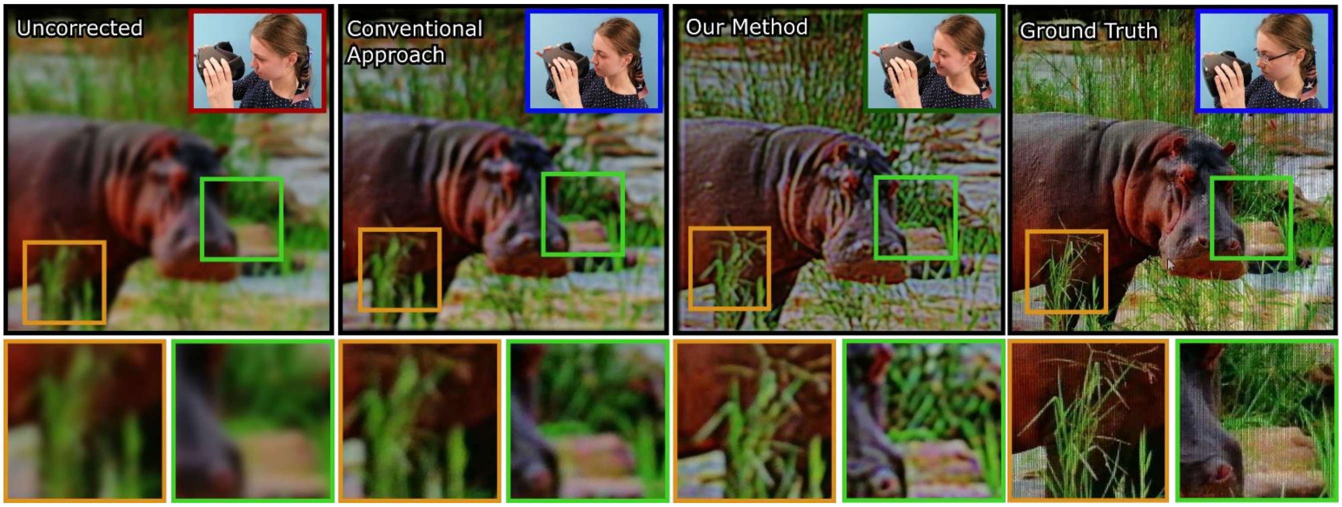

Figure 1. Perceptual Guidance in Prescription Correction. Intentionally defocused images on a prototype Virtual Reality headset are captured by a camera and simulate common refractive errors on a human eye. An uncorrected eye would see images in a blurry way as demonstrated (column 1). We capture the performance of the conventional algorithmic approach to solve prescription correction (1) in column 2. Our proposed computational approach to algorithmic prescription compensation improves the perceived images, both in color and contrast, as can be seen in the third column. The source image is from Rich Franzen (2). A ground-truth photograph focused at the display plane is provided for reference (column 4). It illustrates what the user would see while wearing prescription lenses incorporated into the virtual reality headset.

Abstract

The enthusiasm for Virtual Reality (VR) brings forward the question of accessibility. Current hardware is not suitable for usage with prescription correction glasses despite the prevalence of refractive eye problems, and algorithmic solutions are not optimal. We tackle this issue by proposing a differentiable visual perception model that derives key insights from the human visual system, the target display, and the target user's eye refractive errors. Using our algorithmic approach, we optimize the rendered images using stochastic gradient-descent solvers to provide contrast enhanced images at interactive rates for a visually impaired user.

Author Keywords

Prescription Correction, Image Processing, Neural Image Processing, Computational Displays, Perceptual Graphics and Color

1. Introduction

As the consumers' interest for Virtual Reality (VR) grows increasingly, enabling fully immersive remote experiences has become a new objective in research (3). However, potential VR users may suffer from common refractive vision problems such as myopia, hyperopia, or astigmatism. These conditions are especially prevalent after 40 years old, and represent 23.9%, 8.4% and 33% of the population respectively (4), which highlights the need for more accessibility in near-eye display technologies (5). Although research in the ergonomics of VR technology aims to reduce headsets to eyeglasses form-factor (6,7), it is incompatible with the feelings of discomfort that arise when wearing prescription glasses under a VR headset, hence reducing the feeling of immersion.

Hardware-driven approaches to prescription correction (8–10) may result in bulkier and less affordable VR headsets. Additionally, it would require upgrading components with newer devices. On the other hand, algorithmic approaches tackle the prescription issue without the need for specialized components and with the benefit of more accessible software updates (1).

Our work presents a novel algorithmic approach to prescription correction and eliminates the need for corrective lenses with a perceptually guided and prescription aware technique. To this end, we first study the low-level workings of color perception in the Human Visual System (HVS), i.e., how the different types of cone cells respond to various wavelengths of light. We then model the target display's specific light spectrum, i.e., subpixels emitting various wavelengths, and the associated response of cone cells on the retina. Hence, we build an end-to-end differentiable color perception model that simulates how a user with a given Point-Spread Function (PSF) model using Zernike polynomials (11) perceives images on a specific display. Finally, our framework enables the optimization of the display rendering to produce an in-focus image for a user with vision impairments and without glasses. Specifically, our work makes the following contributions:

- **Perceptually guided Prescription Correction**. Our novel differentiable model incorporates display-specific color perception and a user's PSF to enhance the contrast and color characteristics distinctly in visual perception.

- **Learned Prescription Correction.** Correcting prescription at interactive rate is possible with a Convolutional Neural Network (CNN), trained to estimate optimal corrected imagery.
- **Evaluation on Actual Displays**. We analyze our approach on VR headsets and conventional displays and demonstrate real-life use cases, beyond simulations.

2. Related work

Previous research proposes various approaches to solve the quality of prescription glasses-free experiences. Relevant papers are shown in in Table 1. However, many solutions compromise one aspect for another by trading the image quality or requiring bulkier hardware which may cause discomfort.

Table 1. Comparison of prescription correction techniques. SW refers to Software while HW refers to Hardware.

Name	Method	Perceptual Guidance	Real-time	Image Quality	Display Type
Multi-domain (12)	SW	Preliminary	No	Poor	Desktop
Constrained Total Variation* (1)	SW	Preliminary	No	Poor	Desktop
Tone Mapping (13)	SW	Preliminary	No	Poor	Desktop
Network (14)	SW	No	No	Poor	Desktop
Vision Enhancement (15)	SW	No	No	Poor	AR
SharpView (16)	SW	No	No	Poor	AR
FocusAR (8)	HW	No	Yes	Good	AR
Autofocals (17)	HW	No	Yes	Good	AR
Phase Modulated (18)	HW	No	Yes	Good	AR
RectifEye (19)	HW	No	Yes	Good	VR
Alvarez Lenses (20)	HW	No	Yes	Good	VR
Software (21)	SW	No	Yes	Poor	VR
Ours	SW	Yes	Yes	Fair	VR

*Referred to as the conventional method throughout the paper.

3. Modeling Display-specific Visual Perception:

We put forward an enhanced algorithmic solution that combines a perceptual model of the human visual system and prescription correction for real-time image generation of improved quality. Imagery on the target display appear as perceived by the HSV.

Characterizing the target display. A given display has three types of emission spectra for red, green, and blue channel pixels, noted λ_R, λ_G, λ_B respectively. With a spectrometer, we measure the spectral bands of our target display at multiple pixel levels to calibrate the display. The display color primaries are then defined from the spectral measurements by fitting a proxy function such as a Gaussian mixture model with weighted sum of Gaussians. We instead use a multi-layer perceptron (MLP) network to act as a general function approximator and the color perception responses from the HVS can then be investigated.

Converting color primaries to perceived colors. The human retina is populated by broadly classified rod and cone cells. Cone cells are primarily responsible for color perception and reduce wavelengths of incoming light into trichromat values by integrating them over their response functions (22). While red, green, and blue wavelengths are measured separately on a sensor of a general camera or for display responses, human color perception can instead be represented with cone cell activation values I_L, I_M, I_S for Long (L), Medium (M) and Short (S) cones. Each subtype of cone cell differs in its sensitivity to wavelengths of light. The conversion steps from an input color image on the target display to the corresponding cone response are shown below:

$$\begin{bmatrix} I_L \\ I_M \\ I_S \end{bmatrix} = \begin{bmatrix} L_R & L_G & L_B \\ M_R & M_G & M_B \\ S_R & S_G & S_B \end{bmatrix} \begin{bmatrix} I_R \\ I_G \\ I_B \end{bmatrix}, \tag{1}$$

where I_R, I_G, I_B represents the red, green and blue intensity values for all pixels on the image. Eq. (2) shows a sample conversion for L_R, which represents the L cone output for a displayed red pixel:

$$\sum_{\lambda_R} \lambda_L \lambda_R = L_R, \tag{2}$$

where λ_L is the L cone sensitivity function and λ_R is the red pixel emission spectrum function for a given display. By substituting the right values, we can compute the L, M and S cone sensitivity functions in a similar way for all three red, green, and blue subpixel emissions. Once the cone response is obtained, the complete perception model can finally be represented with the conversion of the color opponency model proposed by Schmidt et al. (23),

$$\begin{bmatrix} I_{(M+S)-L} \\ I_{(L+S)-M} \\ I_{\overline{(L+M+S)}} \end{bmatrix} = \begin{bmatrix} (I_M + I_S) - I_L \\ (I_L + I_S) - I_M \\ \overline{(I_S, I_M, I_L)} \end{bmatrix}, \tag{3}$$

where $I_{(M+S)-L}$, $I_{(L+S)-M}$, $I_{\overline{(L,M,S)}}$, represents the three channels of the image sensed in the color-opponency space.

4. Computing Point Spread Functions from Color Primaries

We define the point spread function with visual aberrations for the HSV over several wavelengths of light. The combined PSF for each color primary is shown in Eq. (4). It can be obtained by sampling a set of wavelengths from each color primary, calculating the single PSFs for each and combine them in a weighted sum of the PSFs.

$$PSF(x,y,c) = \sum_{\lambda_c} w_{\lambda_{c_i}} PSF(x,y,\lambda_{c_i}) \tag{4}$$

For a given color primary c, $PSF(x,y,c)$ is the point spread function. The PSF for a sampled wavelength λ_{c_i} in the color primary c is $PSF(x,y,\lambda_{c_i})$, with $w_{\lambda c_i}$ as the weight for that sampled wavelength. The above PSF kernel can be utilized in RGB or color opponency spaces, based on designers' choices. In our method, we introduce color opponency based PSF formulation (perceptually guided) to improve the perceptual characteristics (contrast, quality) of the retinal image. Eq. (4) is extended to formulate LMS based kernel,

$$PSF_{lms}(x,y,\lambda_{c_i}) = A * PSF(x,y,\lambda_{c_i}) \tag{5}$$

$$PSF_{lms}(x,y,c) = \sum_{\lambda_c} w_{\lambda_{c_i}} PSF_{lms}(x,y,\lambda_{c_i}) \tag{6}$$

where A is the conversion matrix defined in Eq. (1), $PSF_{lms(x,y,c)}$ is the PSF for a particular color primary with LMS components. Similarly, we modelled the digital camera color primary decoding using measurements from the display and captured images from the digital camera. In the Eq. (5) and Eq. (6), PSF_{lms} is represented for both the HVS and digital camera RGB decoding. We can now compute the retinal image $r(x,y,c)$ in the LMS space, by convolving PSF_{lms} with the input image $s(x,y,c)$,

$$r(x,y,c) = PSF_{lms}(x,y,c) * s(x,y,c) \tag{7}$$

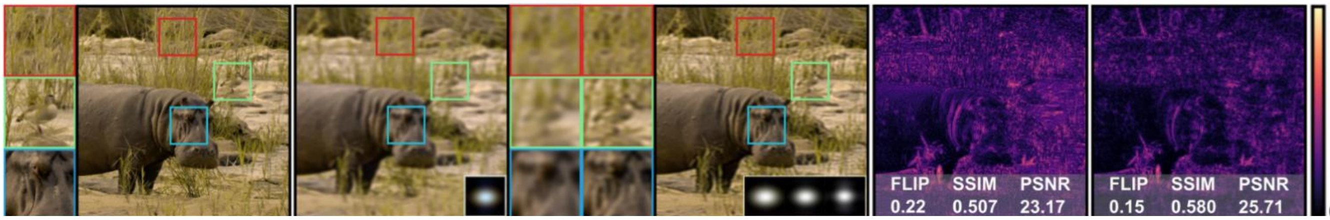

Figure 2. Outputs for a specific refractive vision problem example (hyperopic astigmatism). We provide the simulated LMS space representation of the target image, the conventional method output, and our method. FLIP (24) per-pixel difference along with its mean value (lower is better), SSIM and PSNR are provided to compare performance of methods. Our method shows better loss numbers in simulated LMS space. The contrast improvement can also be observed perceptually.

5. Optimizing Images for Prescription Correction

We optimize our retinal image for a user's eye to be as close as possible to the ground truth by solving Eq. (8) and obtaining *s'*:

$$s' \leftarrow \underset{s \notin \emptyset}{\operatorname{argmin}}\, \mathcal{L}(PSF * s, t) \tag{8}$$

where t is the ground truth image and PSF is the kernel defined in Eq. (4). We reformulate the above equation to incorporate color opponency space optimization, where PSF_{lms} is the kernel in Eq. (6) and t_{lms} is the ground truth image in LMS space in Eq. (9). To perform this optimization, we calculate the error between the ground truth image and the retinal image, $\mathcal{L}(r(x,y,c), t(x,y,c))$, using a loss function (e.g., least-squared error), where x and y are image coordinates and c the color channels (RGB or LMS space). Note that we have also built a learned equivalent of our approach.

$$s' \leftarrow \underset{s \notin \emptyset}{\operatorname{argmin}}\, \mathcal{L}(PSF_{lms} * s, t_{lms}) \tag{9}$$

5. Results

Our evaluation method is separated into two parts. Our source images were taking from the DIV2K dataset (25). We first evaluated our method for the defocus prescription using an Oculus Quest 1 VR headset and defocus lens. We captured images using a fixed pose and focus camera. We show improvements in contrast and color compared to the conventional method (Figure 1). In the second section, we modelled various refractive eye problems in simulated retinal image representation to evaluate our method on various prescriptions. The contrast of the retinal output image is improved with our color opponency based kernel modelling. From the per-pixel difference loss maps, we found that our method is better in low frequency features and provides slight improvements in high frequencies. Overall, our perceptually guided color-based kernel results in images with better contrast than with the conventional method (Figure 2).

6. Conclusion

We present a new rendering approach that aims to improve visual experiences and reduce discomfort in VR by enhancing contrast and color. Our technique uniquely merges key insights from the HSV and provides sharp images when viewed by users with vision impairments without prescription glasses.

7. References

1. Montalto C, Garcia-Dorado I, Aliaga D, Oliveira MM, Meng F. A Total Variation Approach for Customizing Imagery to Improve Visual Acuity. ACM Trans Graphics. 2015 May;34(3):1–16.

2. Franzen R. Kodak lossless true color image suite. source: http://r0k us/graphics/kodak. 1999;4(2).

3. Orlosky J, Sra M, Bektaıfmmode\mboxş\elseş\fi K, Peng H, Kim J, Kos'myna N, et al. Telelife: The Future of Remote Living. Front Virtual Real. 2021;0.

4. Ophthalmology AA of. Eye health statistics [Internet]. 2019. Available from: https://www.aao.org/newsroom/eye-health-statistics

5. Koulieris GA, Akşit K, Stengel M, Mantiuk RK, Mania K, Richardt C. Near-eye display and tracking technologies for virtual and augmented reality. In: Computer Graphics Forum. Wiley Online Library; 2019. p. 493–519.

6. Kim J, Gopakumar M, Choi S, Peng Y, Lopes W, Wetzstein G. Holographic glasses for virtual reality. In: ACM SIGGRAPH 2022 Conference Proceedings. 2022. p. 1–9.

7. Maimone A, Wang J. Holographic optics for thin and lightweight virtual reality. ACM Trans Graphics. 2020 Jul;39(4):1–67.

8. Chakravarthula P, Dunn D, Akşit K, Fuchs H. FocusAR: Auto-focus Augmented Reality Eyeglasses for both Real and Virtual. IEEE transactions on visualization and computer graphics. 2018;

9. Kim RA Jonghyun, Michael Stengel, Jui Yi Wu, Ben Boudaoud, Josef Spjut, Kaan Akşit et al. Matching prescription & visual acuity: Towards ar for humans. ACM SIGGRAPH 2019 Emerging Technologies. 2019;1–2.

10. Wu JY, Kim J. Prescription AR: a fully-customized prescription-embedded augmented reality display. Optics Express. 2020;28(5):6225–41.

11. Lakshminarayanan V, Fleck A. Zernike polynomials: a guide. Journal of Modern Optics. 2011;58(7):545–61.

12. Alonso M, Barreto A, Jacko JA, Adjouadi M. A multi-domain approach for enhancing text display for users with visual aberrations. In: Assets '06: Proceedings of the 8th international ACM SIGACCESS conference on Computers and accessibility. New York, NY, USA: Association for Computing Machinery; 2006. p. 34–9.

13. Ye J, Ji Y, Zhou M, Kang SB, Yu J. Content aware image pre-compensation. IEEE Transactions on Pattern Analysis and Machine Intelligence. 2018;41(7):1545–58.

14. Tanaka H, Kawano H. Image Correction for Improving Visual Acuity Using Zernike-Based Vision Simulation. In: 2021 20th International Symposium on Communications and Information Technologies (ISCIT). IEEE; 2021. p. 32–6.

15. Itoh Y, Klinker G. Vision enhancement: defocus correction via optical see-through head-mounted displays. In: AH ’15: Proceedings of the 6th Augmented Human International Conference. New York, NY, USA: Association for Computing Machinery; 2015. p. 1–8.

16. Oshima K, Moser KR, Rompapas DC, Swan JE, Ikeda S, Yamamoto G, et al. SharpView: Improved clarity of defocused content on optical see-through head-mounted displays. In: 2016 IEEE Symposium on 3D User Interfaces (3DUI). IEEE; 2016. p. 173–81.

17. Padmanaban N, Konrad R, Wetzstein G. Autofocals: Evaluating gaze-contingent eyeglasses for presbyopes. Science Advances. 2019 Jun;5:eaav6187.

18. Itoh Y, Langlotz T, Zollmann S, Iwai D, Kiyoshi K, Amano T. Computational Phase-Modulated Eyeglasses. IEEE Transactions on Visualization and Computer Graphics. 2021;27(3):1916–28.

19. Laffont PY, Martin T, Gross M, Tan WD, Lim C, Au A, et al. Rectifeye: A Vision-Correcting System for Virtual Reality. In: SIGGRAPH ASIA 2016 VR Showcase [Internet]. New York, NY, USA: Association for Computing Machinery; 2016. (SA ’16). Available from: https://doi.org/10.1145/2996376.2996382

20. Stevens RE, Rhodes DP, Hasnain A, Laffont PY. Varifocal technologies providing prescription and VAC mitigation in HMDs using Alvarez lenses. In: Kress BC, Osten W, Stolle H, editors. Digital Optics for Immersive Displays [Internet]. SPIE; 2018. p. 142–58. Available from: https://doi.org/10.1117/12.2318397

21. Xu F, Li D. Software based visual aberration correction for hmds. In: 2018 IEEE Conference on Virtual Reality and 3D User Interfaces (VR). IEEE; 2018. p. 246–50.

22. Wuerger S. Colour Perception. In: London Imaging Meeting. Society for Imaging Science and Technology; 2022. p. YZ-MK.

23. Schmidt BP, Neitz M, Neitz J. Neurobiological hypothesis of color appearance and hue perception. Journal of the Optical Society of America A, Optics, image science, and vision. 2014;31 4:A195-207.

24. Andersson P, Nilsson J, Akenine-Möller T, Oskarsson M, Åström K, Fairchild MD. FLIP: A Difference Evaluator for Alternating Images. Proc ACM Comput Graph Interact Tech [Internet]. 2020 Aug;3(2). Available from: https://doi.org/10.1145/3406183

25. Agustsson E, Timofte R. NTIRE 2017 Challenge on Single Image Super-Resolution: Dataset and Study. In: The IEEE Conference on Computer Vision and Pattern Recognition (CVPR) Workshops. 2017.