Colorimetric Compensation in Video Mapping for Luggage Inspection

Maëlan Poyer[1,2] and Christophe Hurter[1]
[1]Ecole Nationale de l'Aviation Civile, Toulouse, France
[2]Thales AVS, Vélizy-Villacoublay, France

Keywords: Video Mapping, Colorimetric Compensation, Luggage Inspection, Interpolation.

Abstract: Airport luggage inspection agents work under time pressure to identify and localize dangerous items using three-dimensional scans. Video mapping can significantly enhance speed and efficiency by projecting real-time information helping to localize threats to be removed. However, maintaining color fidelity is crucial, as accurate color representation provides key information for decision-making. Previous research has explored color correction techniques for complex surfaces, but these often require extensive calibration, limiting their real-time applicability. Our approach addresses this limitation by using a pre-recorded database to maintain color compensation without the need for frequent recalibration. We built this colorimetric database that records how surfaces with similar textures reflect colors. Using Shepard's interpolation, our algorithm generalizes the color correction to new surfaces with similar textures, allowing for real-time adjustments without interrupting workflow. This paper aims to lay the foundation for large-scale studies. The results show good performance for hues such as orange but the method's effectiveness varies across the color spectrum, with limited improvements on blue hues due to predictable losses in luminance and saturation. This highlights the need for new techniques to overcome the physical limitations of projectors.

1 INTRODUCTION

Luggage inspection is a safety-critical environment, meaning that operations are carried out under significant pressure to achieve specific tasks within strict time limits. These settings often involve high-stakes decision-making. Delays or inefficiencies in such contexts can have serious consequences, including threats to security, safety, or operational efficiency. Security checkpoint operators use three-dimensional scans of luggage to identify and localize threats or dangerous items. This highlights the need to clearly differentiate the virtual representation of luggage, derived from scans, from the physical luggage being inspected. The transfer function renders the virtual volume of the luggage based on its X-ray absorbance (Drebin et al., 1988; Metz and Doi, 1979; Kindlmann, 2002). Therefore, colors provide key information about the materials constituting the objects, aiding in their recognition—Orange for organics, green for inorganics and blue for metals (Figure 1). Under these high-pressure conditions, the preattentive processing (Treisman and Gelade, 1980) allows operators to instantly differentiate metal, which is often the material constituting dangerous items, from other materials. This ties into Bertin's principles of semiology of graphics (Bertin, 1983), where visual variables like color are essential for effective communication and interpretation of information in complex visual environments. Furthermore, this also corresponds to Gibson's concept of ecological design (Gibson and Pick, 2000), which emphasizes that visual cues should be clearly perceptible and aligned with the task at hand to facilitate intuitive decision-making. If the displayed colors are inaccurate, it can lead to misinterpretation and slow the decision-making process. Thus, maintaining precise color accuracy in critical applications is essential for ensuring effective and reliable outcomes in these high-stakes environments.

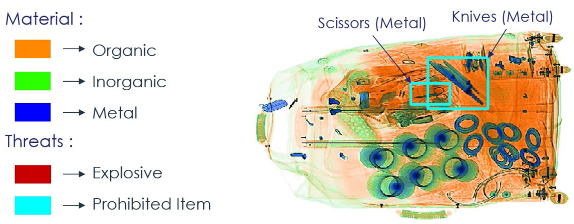

Figure 1: Baggage Scanner Output with Color Mapping. Colors represent different materials based on their density and composition.

Poyer, M. and Hurter, C.
Colorimetric Compensation in Video Mapping for Luggage Inspection.
DOI: 10.5220/0013312200003912

In *Proceedings of the 20th International Joint Conference on Computer Vision, Imaging and Computer Graphics Theory and Applications (VISIGRAPP 2025) - Volume 1: GRAPP, HUCAPP and IVAPP*, pages 947-954
ISBN: 978-989-758-728-3; ISSN: 2184-4321

In such environments, real-time processing, rapid adaptability, and high accuracy are essential, as even minor errors or small loss of concentration can have cascading effects, potentially compromising the mission's objectives or endangering lives (Ensley, 1995). However, studies on luggage screening (Rieger et al., 2021) highlight how factors like time pressure, automation aids, and target expectancy influence visual search behavior and performance in security contexts. For that reason, new visualization techniques (Klein, 2008; Hurter et al., 2014; Traoré et al., 2018) need to be find in order to improve efficiency and safety of luggage inspection. According to Milgram, direct viewing the virtual data allows the user to better understand the link with the real world (Milgram and Kishino, 1994). Therefore, in these types of environments, video mapping technology has the potential to significantly accelerate decision-making processes by enhancing situational awareness and providing real-time visual augmentations (Berard and Louis, 2017; Wang et al., 2020; Sutherland et al., 2019; Douglas et al., 2016). By projecting images or information directly onto complex surfaces, video mapping allows for quick and precise visualization of critical data in a way that is easily interpretable. For instance, Panasonic's Medical Imaging Projection System (Nishino et al., 2018) enables surgeons to perform precise interventions without needing to switch focus between monitors and the patient, significantly improving surgical efficiency and decision-making speed during complex procedures. This approach can be extended to other high-stakes environments, such as airport security, where the ability to quickly and accurately visualize objects can streamline inspections and reduce decision-making times. Nonetheless, as shown on Figure 2, projection mapping can distort colors due to the interaction between the projected light and the surface properties, such as texture, color, and reflective characteristics. These interactions cause color shifts or accuracy loss in the projection. In critical environments, this distortion can lead to misleading information. Indeed, the operator can misinterpret the material information provided by the color and take the wrong decisions.

This paper aims to be a fundation for larger-scale studies on color correction algorithm for luggage inspection videomapping.

2 RELATED WORK

The issue of radiometric compensation in video mapping has been explored through various methods. A notable contribution comes from Yoshida et al.

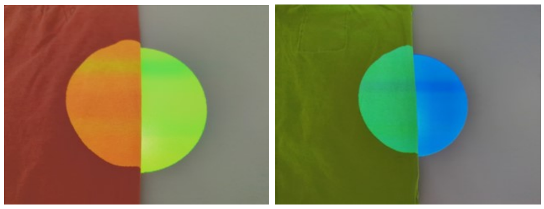

Figure 2: Projection on colored surfaces. Green reflected on a red surface becomes orange and blue reflected on a green surface becomes green. In luggage search, this means that, on the left, a medium-density material (green), like plastic explosives, would appear the same as a piece of clothe (orange). On the right, a metal (blue), would appear the same as medium-density materials (green).

(Yoshida et al., 2003), who proposed an approach based on solving optical equations. Their method provides precise control of color fidelity across different surfaces by compensating for variations in the surface's reflection and absorption properties. The approach works by projecting four reference colors onto the scene and calculating a transformation matrix for real-time adjustments. Following the approach by Yoshida et al., Matthew Post et al. (Post et al., 2018) and Anselm Grundhöfer & Daisuke Iwai (Grundhöfer and Iwai, 2015) developed two significant techniques aimed at applying colorimetric compensation without the need for prior radiometric calibration of the video projector. This advancement reduced the setup time traditionally required in video mapping applications, making these techniques more practical in scenarios where quick adaptations are needed.

However, while these methods are effective in static environments, they proves less efficient in dynamic contexts where surfaces move or change shape, as the calibration requires projecting these reference colors whenever the scene changes, limiting its applicability in scenarios with frequent or rapid change. In critical and time-sensitive contexts, such as airport luggage inspections or medical surgeries, delays or interruptions in the workflow can occur. These interruptions happen because the projection system must readjust for each new item or surface condition. Thus, while these methods significantly advanced the field, they still do not fully address the challenge of maintaining continuous, real-time color accuracy without interruptions (Post et al., 2018; Grundhöfer and Iwai, 2015). Nevertheless, Anselm Grundhöfer and Oliver Bimber advanced colorimetric correction by developing a technique that adapts to real-time variations in the scene (Grundhöfer and Bimber, 2006). Their method allows the system to continuously adjust the projection as the surface properties, such as texture and lighting, change. This real-time adaptability made their approach highly effective for dynamic environments, ensuring the overall consistency of the projected image. However, their technique requires certain compromises regarding the brightness and contrast of the image. These concessions arise because their primary objective is to maintain the global integrity of the image rather than ensuring perfect color fidelity. As a result, while the projection remains stable and adaptable, the precise accuracy of colors is sometimes sacrificed in favor of a broader focus on maintaining image stability under variable conditions.

Recent advances (Park et al., 2022; Bokaris et al., 2015) have explored the use of optimization techniques and artificial intelligence (AI) for surface recognition and projection adjustments. These methods leverage machine learning algorithms to dynamically detect surface properties and adapt the projected content accordingly, enhancing the system's ability to deal with complex and varied surfaces. While these approaches are promising in terms of increasing adaptability and reducing the need for manual intervention, they come with significant drawbacks. The most notable issues are visual artifacts and loss of detail, particularly when fine-grained accuracy is required. These artifacts can be highly problematic in contexts where precise inspection of objects is crucial, such as in security screening or medical surgeries, where even minor inaccuracies can lead to significant errors or oversights. Nonetheless, their work also highlighted the limitations of Digital Light Processing projectors (DLP), which decompose colors at high speeds, making it difficult to achieve flexible and precise colorimetric correction in rapidly changing environments.

These existing techniques highlight both the progress and limitations in the field of color correction for video mapping. While substantial improvements have been made, existing methods often struggle with accurate color reproduction when projecting onto surfaces with varying textures, materials, and lighting conditions, which is crucial when colors carry specific meanings, such as indicating threats in luggage inspections or guiding surgical interventions.

Our contribution is a novel approach for improving color fidelity in video mapping, particularly in critical environments such as airport security and medical settings. To address these challenges, our approach capitalizes on the specific contextual consistency of the materials used in projection environments, such as fabric in luggage inspections. Although the colors of these surfaces may vary—depending on the objects within a bag—the underlying material properties remain relatively constant. This consistency allows us to develop a color correction algorithm based on a pre-constructed database. This avoids the need for recalibration for every new surface or lighting change, making our method usable in critical time-constrained environments. This method can easily be adapted to other materials or use cases by simply expanding the database.

3 MATERIALS AND METHODS

In this paper, we focus on the luggage inspection scenario, where the goal is to identify and differentiate between materials based on their projected colors. In such environments, the surfaces being inspected are typically colored fabrics found in luggage—representing various items of clothing, textiles, and other objects. The challenge is to maintain accurate color representation across these diverse surfaces to properly identify the types of materials present. To aid in this identification process, we project three distinct colors onto the fabric surfaces, each representing a different type of material: orange for organics (e.g., food or leather), green for inorganics (e.g., plastics), and blue for metals. Therefore, these are the colors and material categories that will form the basis of our investigation. Our goal is to ensure that, regardless of the color or texture of the fabric surfaces being projected onto, the system can accurately represent these materials using the assigned colors. Any deviation in color fidelity could result in misidentifying the nature of the objects in the luggage, affecting both security and efficiency.

This section is organized into three parts. The first part details the construction of a colorimetric database, which serves as the foundation for our algorithm. The subsequent parts describe the algorithm itself and the two user experiments conducted to validate our hypotheses.

3.1 Construction of the Colorimetric Database

With this context in mind, we proceed to build a colorimetric database to support dynamic color correction during real-time baggage inspections. This database included three key elements: ID, which uniquely identifies each surface tested, Projected Color (the color projected onto the surface), and Perceived Color (the color as it is reflected and perceived). We sampled RGB (Red, Green, Blue) values ranging from 0 to 255, in increments of 5, generating a total of 52^3 elements for each of the three pieces of fabric. An example is represented on Table 1. To achieve this, as shown on Figure 3 we project the complete range of colors that the projector can reproduce (known as the gamut) onto materials that share similar textures and properties but differ in color.

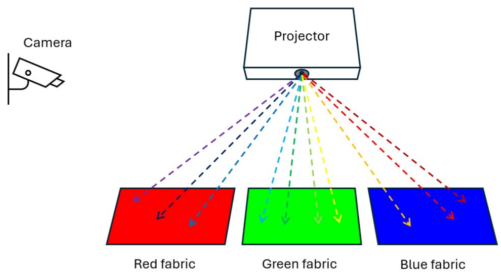

Figure 3: Building of the colorimetric database. To build it, the complete gamut of the projector has been projected onto three pieces of fabrics.

By projecting the full spectrum of colors, we ensure that our database captures the entire set of possible interactions between the projected light and the surface, providing a comprehensive reference for real-time color correction. A lamp-based projector was used to avoid DLP color deconstruction. The materials chosen for this experiment consist of three pieces of clothing in the colors red, green, and blue. We chose them to cover a maximum range of the color wheel with a minimum of colors. Each garment is made from the same type of fabric to ensure that only the color—not the texture or material properties—varies across the projection surfaces. This allows us to isolate the effect of color on the projection, ensuring that the colorimetric data recorded reflects the response to different hues rather than surface variations. We measure the reflected color using a camera with manual exposure and white balance settings. Calibration of the projector and camera is not necessary in this context, as the primary objective is to test the method itself rather than to fully optimize the system for practical applications like baggage inspection. This approach allows us to focus on the method's effectiveness without being constrained by hardware-specific adjustments. (Figure 3)

3.2 First Experiment: Testing Color Corrections for Surfaces in the Database

The next step in our process is to determine the optimal color correction for each surface in the colorimetric database. Since we have recorded a sample the gamut of perceptible colors for the three selected surfaces, our task now is to select the best matching color for each surface in real-time projections.

To ensure optimal color fidelity, we tested two different selections for minimizing the difference between the expected color (the color intended for projection) and the reflected color (the color perceived after projection on the surface). The industry standard for measuring color differences is the DeltaE 2000 (CIEDE2000)(Sharma et al., 2005) in CIELab colors space. We used it for our first correction method. We called this method DeltaE Correction. However, the presented scenario do not requires color accuracy in the traditional sense but rather when the color results in a misclassification. Therefore, for our second correction method, we used the HSL color space and we selected the closest color from the colorimetric database with a maximum deviation of 5 degrees in the hue angle. This method ensures that the projected color maintains a perceptually close hue to the intended color, while also ensuring that the saturation and brightness remain within acceptable thresholds to ensure the recognition of the hue. We called this method Hue Correction.

To evaluate the performance of the proposed corrections, we conducted an experiment designed to test the system's ability to maintain color fidelity across various projection surfaces. The experiment involved projecting different colors onto a range of materials and asking participants to rank the accuracy of the color reproduction against a reference color. The experiment involved 17 participants (4 females and 13 males), aged between 25 and 38, all without color blindness and from diverse research labs. Three types of fabric were selected as projection surfaces, representing red, green, and blue base materials. For the projections, three target colors—orange, green, and blue—were chosen, along with their respective corrections, as these correspond to key material categories in baggage inspection: organic, inorganic, and metallic. During each trial, participants were shown three variations of the projected colors on the same surface: one without any color correction, one with Hue Correction applied, and one with DeltaE Correction.

As shown on Figure 4, the participants were tasked with ranking the three projected colors from closest to farthest in relation to a reference color displayed alongside them. This ranking system allowed us to gather data on which method produced the most perceptually accurate colors on the different fabrics. Each participant completed four trials for each color-surface combination to account for variability in perception and ensure the robustness of the results. This means that in total, each of the participants completed 36 rankings (four trials for each of the three colors projected on the three pieces of fabric). On aver-

Table 1: An example of the colorimetric database, showing each surface's ID, the projected color, and the perceived reflected color. The data provided a reference for the system to apply color correction.

ID	Projected Color (R,G,B)	Reflected Color (R,G,B)
2	250,100,25	52,97,87
2	255,100,25	52,97,87
2	0,105,25	0,102,91

age, participants completed the task in fifteen minutes. Colors and pieces of fabric were presented in a randomized order.

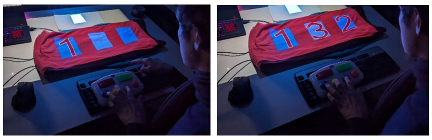

Figure 4: During the first experiment, participants were asked to rank colors from the closer to the farthest to the reference color projected above.

The results of this experiment are discussed in detail in the following sections, where we analyze the effectiveness of each correction method across different materials. The generalization of the color corrections to new surfaces has been tested throught a new experiment.

3.3 Second Experiment: Testing the Color Corrections on New Surfaces

Since it is impossible to have a database containing all the possible colors, the purpose of our second experiment is to test the generalization of our correction methods to new surfaces made of the same material but different colors. To generalize these two methods, we implemented an interpolation method, which allows the algorithm to estimate the appropriate color correction for surfaces that were not part of the initial database. As the colors have three components, we needed a three dimensional linear interpolation. Thus, we decided to use the generalization of Shepard's interpolation method(Shepard, 1968). This method allowed us to compute a weighted average of the known color values from the database. Shepard's method assigns greater weight to the colors that are closer to the current surface's properties, ensuring that the final interpolated color closely matches the surface's behavior. This minimized the color discrepancy between the targeted color and the reflected color (Figure 5).

To test the generalized corrections, we proceeded to repeat the previous experiment using new projection surfaces. Results are discussed in the next sections.

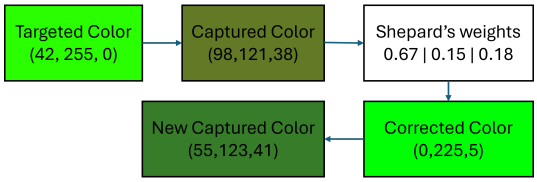

Figure 5: Pipeline of the color correction algorithm. The camera-captured color is compared to the database using Shepard's interpolation, and the resulting weights are used to compute the corrected color for projection.

4 RESULTS

This section presents the colorimetric database recorded to compute the color correction methods and the results of the two experiments which aimed at testing the methods and their generalization.

4.1 The Colorimetric Database

The first phase of the experiment focused on constructing the colorimetric database, which served as the foundation for the color correction process. In typical color science, a color gamut is often represented using a chromaticity diagram, such as the CIE 1931 chromaticity diagram, which maps out colors based on their hue and saturation. This 2D diagram provides a clear way to visualize the range of colors that can be produced by a device or material. However, while these diagrams are widely used, they have an important limitation: they do not account for luminance, which plays a crucial role in how colors are perceived.

When representing the gamut reflected on pieces of fabrics in the HSL color space (Hue, Saturation, Luminance), it becomes evident that although we can observe all hues, there is a loss of luminance in most parts of the spectrum (Figure 6). In this space, while hue and saturation are maintained, the luminance of colors can vary significantly across the same hue, leading to colors that appear darker or lighter depending on their positioning in the space. This loss of brightness can affect the perception of colors, especially in real-world applications such as video mapping, where color fidelity across varying surfaces and lighting conditions is critical.

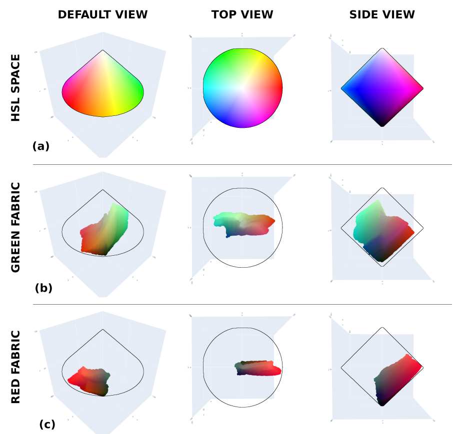

Figure 6: Representation of the projector's color gamut in the HSL space reflected on different surfaces. (a) The full HSL space. (b) The gamut reflected on a green fabric surface. (c) The gamut reflected on a red fabric surface.

4.2 The First Experiment

To compare the performance of the three color correction methods—without correction, Hue Correction, and DeltaE Correction—we applied the Friedman test (Sheldon et al., 1996), a non-parametric statistical test used to detect differences in participants' rankings across repeated measures.

In order to highlight any differences between how the corrections performed on various colors, we separated the tests for the orange, green, and blue projections (Figure 7). This allowed us to evaluate whether the performance of the color correction methods varied depending on the color projected onto the surfaces.

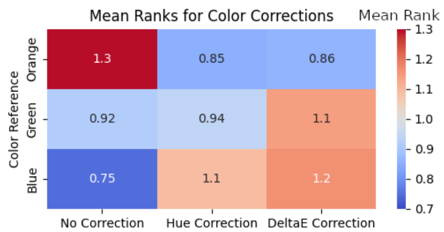

Figure 7: Results of the first experiment. Both corrections seem to perform better than the original color for the orange, but not for the blue. For the green, the differences between the methods are not significant.

- **Orange:** the results of the Friedman test indicated a significant difference between the three color correction methods, with a p-value less than 0.01, demonstrating strong statistical evidence that the correction methods impacted participants' perception of color accuracy. The mean ranks of the three methods were as follows: 1.30 for no correction, 0.85 for the Hue Correction, and 0.86 for the DeltaE Correction. These values indicate that the corrected methods were ranked significantly higher in terms of color accuracy compared to the uncorrected condition.
- **Green:** the mean rankings were 0.92 for no correction, 0.94 for the Hue Correction, and 1.10 for the DeltaE Correction, with p-value less than 0.05, suggesting a moderate difference between the methods.
- **Blue:** the Friedman test resulted in a p-value less than 0.01, indicating a highly significant difference between the methods. The mean rankings were 0.75 for no correction, and 1.2 for both the Hue Correction and DeltaE Correction, with uncorrected condition significantly outperforming both methods.

The results show that the Hue Correction method performed significantly better than the uncorrected condition for the orange color, where it demonstrated superior color fidelity. However, this same method proved ineffective for the blue color. This suggests that while the Hue Correction excels in certain contexts, it struggles with colors like blue, where the reflected color loses too much saturation and luminance.

4.3 The Second Experiment

The second experiment was conducted with the same parameters as the first one, allowing us to use the same analytical tools to evaluate the results (Figure 8).

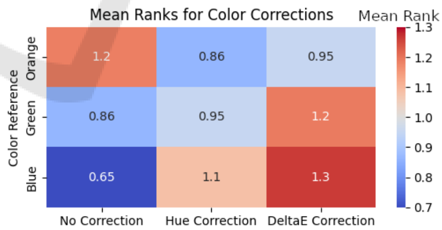

Figure 8: Results of the second experiment. They are similar to the previous result, which confirms the efficiency of Shepard's Distance to compare similar textures.

- **Orange:** the p-value less than 0.01 indicated a significant difference, with mean rankings of 1.20 for no correction, 0.86 for Hue Correction, and 0.95 for DeltaE, confirming the superiority of the Hue Correction for maintaining color fidelity.
- **Green:** the mean rankings were 0.86 for no correction, 0.95 for Hue Correction, and 1.20 for DeltaE, suggesting that the corrections were not able to do better than the original color.

- **Blue:** the p-value less than 0.01 indicates an extremely significant difference between the methods. The mean rankings were 0.65 for no correction, 1.10 for Hue Correction, and 1.30 for DeltaE, confirming that the corrections methods struggle to accurately reproduce blue hues.

The use of Shepard's interpolation to compare similar projection surfaces appears to be effective, as evidenced by the results of the second experiment, which closely align with the findings from the first. The consistency in performance across both experiments suggests that this approach successfully maintains color fidelity across different projection surfaces. The results were similar, confirming that the Hue Correction method worked well for orange, while the uncorrected provided better results for blue hue.

5 DISCUSSION

In this paper, we conducted a series of experiments to have a fundation for large-scale study on our color correction algorithm. Using a colorimetric database and Shepard's interpolation, we compensated color variations across different surfaces with similar textures in video mapping. The goal was to maintain color fidelity in real-time projections without frequent recalibration, ensuring smooth and accurate color reproduction across varied projection surfaces. The results demonstrate that our color correction method significantly outperforms the uncorrected condition for colors close to orange. Within this range, the hue of the light tends to shift slightly upon reflection, which is why the algorithm can effectively compensate for these deviations.

However, both correction methods struggled with blue hues, as indicated by consistently poor results in both trials. This result could have been predicted from the database as the Figure 6 already showed that surfaces tend to do not reflect blue hues. This suggests that the reflected blue color experiences a significant loss in luminance and saturation, making it difficult for the human eye to correctly identify the hue. The loss of brightness causes the blue to appear too dark, while the reduction in saturation diminishes its vividness, leading to a misinterpretation of the color. This highlights a fundamental limitation of projectors, particularly when handling colors like blue. The projector's inability to maintain sufficient luminance and saturation in the reflected light significantly hampers the accurate reproduction of blue hues.

One potential solution to address the limitations of projector color accuracy, particularly for blue hues, could be to explore the concept of simultaneous contrast(Mittelstädt et al., 2014). This phenomenon occurs when the perception of a color is influenced by the surrounding colors, potentially enhancing the brightness and saturation of colors that might otherwise appear too dark or muted. By adjusting the contrast of the surrounding colors in the projected scene, it may be possible to counterbalance the loss of luminance and saturation in the blue hues, making them appear more vivid and recognizable. Integrating simultaneous contrast adjustments into the color correction algorithm could help overcome the projector's inherent limitations (Akiyama et al., 2018). However, this approach would require modifying the colors in the projected image. In critical environments, where the accurate representation of colors plays a crucial role in decision-making, altering the surrounding colors to improve the perception of blue could potentially compromise the clarity or meaning of the projected information. Therefore, while simultaneous contrast is a promising solution, further research is necessary to explore its applicability in contexts where color fidelity is essential and must remain consistent.

The algorithm could be easily adapted to other environments by adding additional projection surfaces to the colorimetric database. As more surfaces are incorporated, the system becomes capable of handling a wider range of materials and lighting conditions, further enhancing its versatility. This flexibility allows the algorithm to remain effective in environments beyond those initially tested. This makes the algorithm suitable for critical environments where hues within this spectrum are crucial for decision-making.

Being able to project any desired color not only enhances color fidelity of the interface, but it also allows for dynamic alterations in the appearance of physical objects (Amano et al., 2012; Iwai and Sato, 2011). This capability opens up the potential for new interactions by changing how objects are perceived. For instance, it would be possible to diminish reality (Mori et al., 2017) to help the user focusing on his task.

ACKNOWLEDGEMENTS

We acknowledge the use of GPT-4o to correct the grammar and syntax.

REFERENCES

Akiyama, R., Yamamoto, G., Amano, T., Taketomi, T., Plopski, A., Sandor, C., and Kato, H. (2018).

Light projection-induced illusion for controlling object color. In *2018 IEEE Conference on Virtual Reality and 3D User Interfaces (VR)*, pages 499–500. IEEE.

Amano, T., Komura, K., Sasabuchi, T., Nakano, S., and Yamashita, S. (2012). Appearance control for human material perception manipulation. In *Proceedings of the 21st international conference on pattern recognition (ICPR2012)*, pages 13–16. IEEE.

Berard, F. and Louis, T. (2017). The object inside: Assessing 3d examination with a spherical handheld perspective-corrected display. In *Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems*, pages 4396–4404.

Bertin, J. (1983). Semiology of graphics.

Bokaris, P.-A., Gouiffès, M., Jacquemin, C., Chomaz, J.-M., and Trémeau, A. (2015). One-frame delay for dynamic photometric compensation in a projector-camera system. In *2015 IEEE International Conference on Image Processing (ICIP)*, pages 2675–2679. IEEE.

Douglas, D. B., Petricoin, E. F., Liotta, L., and Wilson, E. (2016). D3d augmented reality imaging system: proof of concept in mammography. *Medical Devices: Evidence and Research*, pages 277–283.

Drebin, R. A., Carpenter, L., and Hanrahan, P. (1988). Volume rendering. *ACM Siggraph Computer Graphics*, 22(4):65–74.

Ensley, M. (1995). Toward a theory of situation awareness in dynamic systems. *Human factors*, 37:85–104.

Gibson, E. J. and Pick, A. D. (2000). *An ecological approach to perceptual learning and development*. Oxford University Press, USA.

Grundhöfer, A. and Bimber, O. (2006). Real-time adaptive radiometric compensation. In *ACM SIGGRAPH 2006 Research posters*, pages 56–es.

Grundhöfer, A. and Iwai, D. (2015). Robust, error-tolerant photometric projector compensation. *IEEE Transactions on Image Processing*, 24(12):5086–5099.

Hurter, C., Taylor, R., Carpendale, S., and Telea, A. (2014). Color tunneling: Interactive exploration and selection in volumetric datasets. In *2014 IEEE Pacific Visualization Symposium*, pages 225–232. IEEE.

Iwai, D. and Sato, K. (2011). Document search support by making physical documents transparent in projection-based mixed reality. *Virtual reality*, 15:147–160.

Kindlmann, G. (2002). Transfer functions in direct volume rendering: Design, interface, interaction. *Course notes of ACM SIGGRAPH*, 3.

Klein, G. (2008). Naturalistic decision making. *Human factors*, 50(3):456–460.

Metz, C. E. and Doi, K. (1979). Transfer function analysis of radiographic imaging systems. *Physics in Medicine & Biology*, 24(6):1079.

Milgram, P. and Kishino, F. (1994). A taxonomy of mixed reality visual displays. *IEICE TRANSACTIONS on Information and Systems*, 77(12):1321–1329.

Mittelstädt, S., Stoffel, A., and Keim, D. A. (2014). Methods for compensating contrast effects in information visualization. In *Computer Graphics Forum*, volume 33, pages 231–240. Wiley Online Library.

Mori, S., Ikeda, S., and Saito, H. (2017). A survey of diminished reality: Techniques for visually concealing, eliminating, and seeing through real objects. *IPSJ Transactions on Computer Vision and Applications*, 9:1–14.

Nishino, H., Hatano, E., Seo, S., Nitta, T., Saito, T., Nakamura, M., Hattori, K., Takatani, M., Fuji, H., Taura, K., et al. (2018). Real-time navigation for liver surgery using projection mapping with indocyanine green fluorescence: development of the novel medical imaging projection system. *Annals of surgery*, 267(6):1134–1140.

Park, J., Jung, D., and Moon, B. (2022). Projector compensation framework using differentiable rendering. *IEEE Access*, 10:44461–44470.

Post, M., Fieguth, P., Naiel, M. A., Azimifar, Z., and Lamm, M. (2018). Fast radiometric compensation for nonlinear projectors. *Journal of Computational Vision and Imaging Systems*, 4(1):3–3.

Rieger, T., Heilmann, L., and Manzey, D. (2021). Visual search behavior and performance in luggage screening: effects of time pressure, automation aid, and target expectancy. *Cognitive Research: Principles and Implications*, 6:1–12.

Sharma, G., Wu, W., and Dalal, E. N. (2005). The ciede2000 color-difference formula: Implementation notes, supplementary test data, and mathematical observations. *Color Research & Application*, 30(1):21–30.

Sheldon, M. R., Fillyaw, M. J., and Thompson, W. D. (1996). The use and interpretation of the friedman test in the analysis of ordinal-scale data in repeated measures designs. *Physiotherapy Research International*, 1(4):221–228.

Shepard, D. (1968). A two-dimensional interpolation function for irregularly-spaced data. In *Proceedings of the 1968 23rd ACM national conference*, pages 517–524.

Sutherland, J., Belec, J., Sheikh, A., Chepelev, L., Althobaity, W., Chow, B. J., Mitsouras, D., Christensen, A., Rybicki, F. J., and La Russa, D. J. (2019). Applying modern virtual and augmented reality technologies to medical images and models. *Journal of digital imaging*, 32:38–53.

Traoré, M., Hurter, C., and Telea, A. (2018). Interactive obstruction-free lensing for volumetric data visualization. *IEEE transactions on visualization and computer graphics*, 25(1):1029–1039.

Treisman, A. M. and Gelade, G. (1980). A feature-integration theory of attention. *Cognitive psychology*, 12(1):97–136.

Wang, X., Besançon, L., Rousseau, D., Sereno, M., Ammi, M., and Isenberg, T. (2020). Towards an understanding of augmented reality extensions for existing 3d data analysis tools. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems*, pages 1–13.

Yoshida, T., Horii, C., and Sato, K. (2003). A virtual color reconstruction system for real heritage with light projection. In *Proceedings of VSMM*, volume 3, pages 1–7. Citeseer.