Color Correction In Video: Determining the Best Combination of Equipment and Settings to Capture Brand Color

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Abstract

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Abstract

Accurately displaying the brand target color of a sports team's uniforms on screen has been a challenge. The color of the orange uniforms worn by the Clemson Tigers football team is often distorted when displayed on LCD screens. Previous research tried to calibrate the LCD adjustments while the live matches were playing using an artificial intelligence solution called ColorNet (Walker et al., 2020). This research determines the most optimal camera location and configuration to obtain the closest RGB values compared to the original RGB measurements of the team's uniform. Each camera produced a separate dataset of variables, including lens, position, picture profile, location, and lighting conditions. We performed a norm analysis to determine the closest La*b* values to the target ones. The results indicate the most appropriate camera-based variables to satisfy our goal.

Introduction

Color is an essential tool that provides a brand with more substantial persuasive power than shape alone, and it appeals to emotions rather than rationality. Color is also closely related to consumer behavior. As a result, color plays an influential communication role in situations where direct and specific verbal expression is complex. Moreover, color serves as a visual language that provides information to the sensory mode – sight – with the highest information capacity of the five human senses (Rubio, 2015).

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In live sports broadcasting, the team color can look different from the intended color when displayed on screen. Accurately recreating the team brand color is very important. Companies spend a lot of money on developing and protecting their brand color palette. They choose specific colors for their brand to identify between crowded marketplaces and they want to see accurate brand colors portrayed on screen at live events. Sports team fans recognize their team color and expect to see the consistent color reproduction (Mayes, et al., 2021). Displaying the wrong color on screens may confuse fans.

Multiple variables play a role in capturing and displaying colors such as camera body, lenses, camera settings, ambient light, and camera position to the field and lights. Current systems of ensuring the accuracy of the brand color of sports teams on screen require manual adjustments of the camera footage in real-time or in post-production. To reduce this manual effort, we need to understand the variables that impact color capture and display.

In this study, we test the camera-level capture of a specific target brand color, Clemson orange (R:218 G:73 B:43). We have examined the following variables in this experiment: five camera models, six lenses, five camera positions to the jersey and helmet, two in-camera Picture Profile settings, and two types of lighting (inside lighting using LED lights and outside lighting with ambient light). Our investigation resulted in 600 unique samples from the collected video clips. These cameras, settings, and lens combinations were chosen to mimic the on-field situations encountered by content creators for Clemson Athletics (Walker, et al., 2020).

We shot 4-second video clips of a still life that included a helmet, a jersey, a Pantone book open to uncoated Pantone 152 U and coated Pantone 1595 C, and an X-Rite Color Checker for reference with the different combinations of camera bodies, lenses, positions, and lighting. Using a program written in Python and leveraging the strengths of Artificial Intelligence and previous work in this area on ColorNet (Walker, et al., 2020), we sampled frames from the footage to create the data set for this study. In the next step, we measure specific pixels from each frame. To increase the pixel sampling randomness, we extract multiple pixels in different areas displaying Clemson Orange including shadow, mid-tone, and highlight areas of the frame. Then we calculated the RGB values for each pixel and averaged the selected RGBs values for each clip.

Then we compared the produced RGB values with the target Clemson brand RGB values in the different permutations to better understand the variables that impact brand color capture on video and determine the ideal settings and situations to reproduce this specific brand color accurately at the camera level. We used the T-test to compare produced RGB values with Clemson brand RGB values and determined the difference between the two values expressed as a Delta E (ΔE) calculation.

Literature Review

An object's overall appearance is impacted by its interaction with the light shining on it. Color is defined by spectral absorption and diffuse reflection of light by pigments or other colorants. The surface of most objects reflects some light, which we perceive as gloss or haze. The quantity of light scattering determines transmission as it passes through various portions of an object. Moreover, texture refers to spatial imperfections on or near a surface. The appearance of a color is also affected by other colors close to it. This is termed simultaneous contrast (or chromatic induction) (Hunt & Pointer, 2011).

A camera's light metering system is designed to see an approximate middle 18 percent gray reflectance which means the meter reading tells a photographer how to set the camera for an average exposure that assumes an 18 percent reflectance (Hirsch, 2015). Each camera manufacturer and updated model handles color and exposure interpretation differently and therefore they capture videos with different colors.

Experimental procedure

Various parameters affect how colors are captured and rendered in-camera. For this research, we want to determine the best possible scenario to capture Clemson orange accurately. In this research, we used 5 different variable combinations: camera body, lens, picture profile, position, and location/lighting. Our primary purpose was to determine which variation provided the closest RGB values to the Clemson Tigers football team's original target brand color.

Five different camera bodies were used: Sony A7III, Sony A7SII, Sony A7SIII, Canon 5D Mark IV and Sony FX3. 24-70 mm, 70-200 mm, and 100-400 mm lenses were used on each of the Sony cameras and 24-70 mm and 100-200 mm on the Canon camera.

We used picture profile S Log2 on and off. Picture Profile is a menu for adjusting and changing parameters in DSLR cameras that determine an image's characteristics. There are many parameters that can be adjusted to get the desired color and lighting. We used picture profile 4 (S log2) for this research because it is used by the athletic content creation team to capture close color accuracy.

We shot the still life from five different positions: back, front, corner, left, and right. Each 4 second video clip included a jersey, a helmet, the Clemson orange Pantone uncoated and coated cards, and a X-Rite ColorChecker digital SG, Figure 1-2.

We recorded the inside footage in a studio under controlled lighting with four 95W LED artificial lights which illuminated the model from four directions. Stadium lights are mounted at tall heights with small beam angles, usually ranging between 12-60 degrees (Rowe, 2020). This kind of artificial light is the closest lighting to the LED stadium lights we could reproduce in a controlled studio space. Outside videos were recorded with natural light on a grass field on a sunny day during the early afternoon.

Python programming was used to convert the footage format from MOV to MP4, extract the 40th frame, label the images in LabelBox, export Jason file, measure x and y coordinate from the center of each label, convert each coordinate to RGB value, and output a spreadsheet with the RGB values for each variation. The 40th frame was chosen to avoid human errors like quick shakes of the hand that might have occured at the very beginning or end of each clip. Each resulting frame needed to be renamed according to the variables used for that clip. We used the following naming convention to rename each image "CAMERA_LENSE_POSITION_ PICTURE PROFILE_LOCATION.jpg." For example, the name of the frame displayed in Figure 1 is **"SonyFX3_2470_R_On_Inside.jpg."** The reason for renaming frames was to capture and annotate the output data with clear labels for each variation.

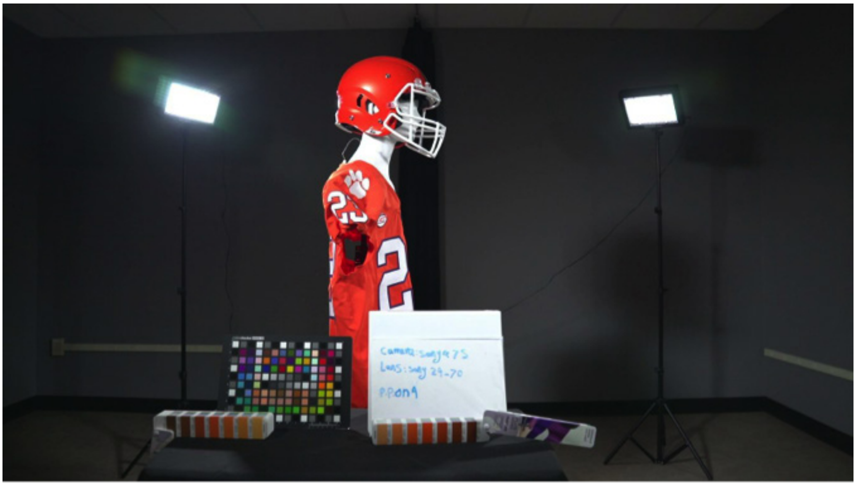


Figure 1: *Helmet and jersey of the Clemson Tigers football team; inside.*

Figure 2: *Helmet and jersey of the Clemson Tigers football team; outside.*

Next, we used the LabelBox website (https://labelbox.com/) to determine the coordinates associated with the orange color in the helmet and jersey in each image. For each of the obtained frames, we chose nine coordinates by the x and y position to represent three mid-tone orange colors, three bright orange (highlight areas of the image illuminated by light) colors, and three dark orange areas (parts of the jersey or helmet found in a shadowed area).

From the LabelBox website, we exported the data extracted from the labeled areas of the images in JSON file format. Using a Python script, we read the data from the JSON file and calculate the output RGB values.

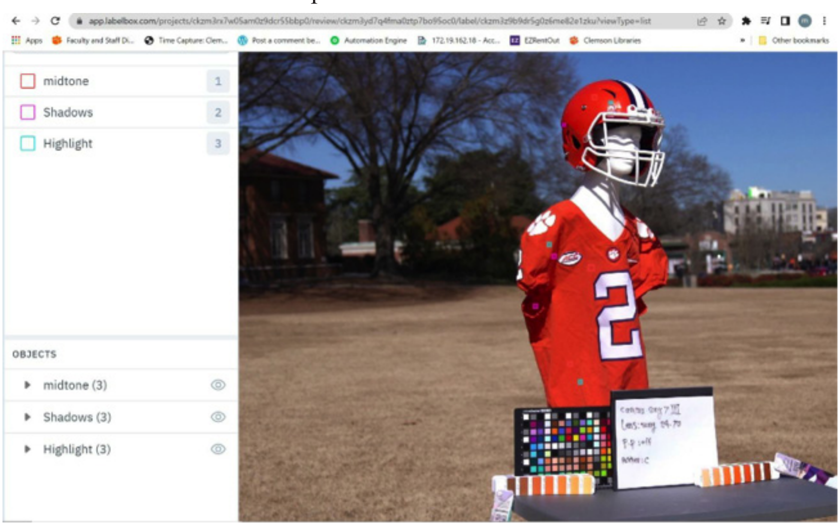


Figure 3: *Example of LabelBox bundle boxes for the obtained frames. The orange box stands for mid-tone orange color, shadows are selected in pink, and highlights are in green boxes.*

The LabelBox tool generates coordinates from the top-left side of our determined bundles but we needed the value from the center coordinate of each box. To resolve this issue, we wrote a Python script that could generate the center coordinate of those bundles then calculated the RGB values of corresponding x-y coordinates.

Then Python was used to export the output in .xlsx format. These files contained the parameters including camera type, lens, position, picture profile, location, and RGB values for each specified pixel. We assigned codes to these parameters. For example, each capitalized English character stands for a camera position in the "position" column. "L" stands for left, "R" for right, "B" for back, "F" for front, and "C" for corner, Table 1.

Camera	*Lens*	*Position*	*Picture Profile*	Location	R	G	B
Canon 5D markIV	2470	B	Off	outside	229	186	195
Canon 5D markIV	70200	B	Off	outside	224	182	183
Canon 5D markIV	2470	B	Off	inside	243	161	165
Canon 5D markIV	2470	B	On	outside	176	154	157
Canon 5D markIV	70200	B	On	outside	190	149	145
Canon 5D markIV	70200	L	Off	outside	235	188	144
Canon 5D markIV	70200	B	On	outside	152	121	129
Canon 5D markIV	2470	C	Off	inside	232	99	104
Canon 5D markIV	2470	R	Off	outside	221	72	92
Canon 5D markIV	2470	B	Off	outside	196	60	80

Table 1: *A sample of the .xlsx file for the Canon camera.*

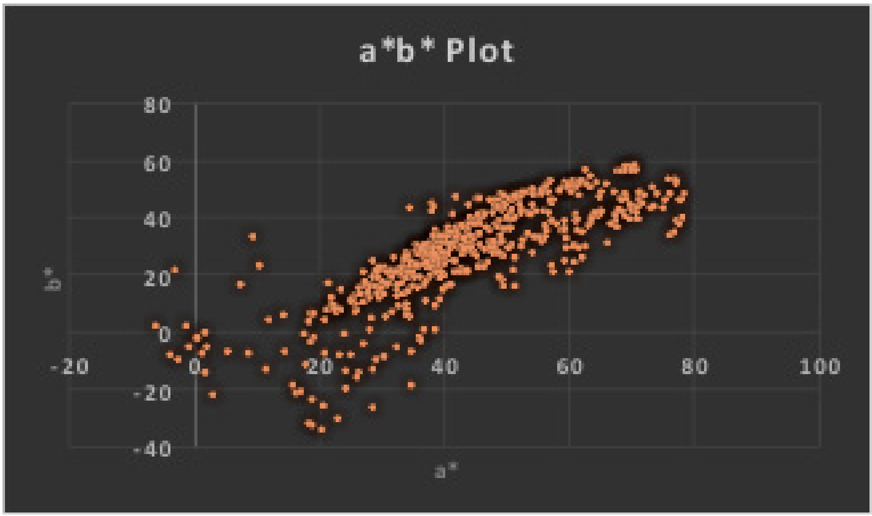


Figure 4: *ab diagram corresponding to the SonyFX3 camera.*
The L value was removed to allow for a 2D plot.

Results and discussion

We converted each RGB value to the corresponding La*b* values used this formula: lab = rgb2lab(RGB). We plotted Figure 4 for other camera datasets from the xlsx files. We used these values to determine the best possible scenario that yields the closest La*b* (and subsequently RGB) values compared to the original values. We performed a ΔE formula (second-order norm) (Sogge, 1988) analysis to determine this optimal set of RGB values in the datasets, Table 2.

Camera	*Lens*	*Position*	*Picture Profile*	Location	R	G	B
Sony A7III	2470	C	Off	outside	220	62	37
Sony A7SII	2470	B	Off	inside	217	69	39
Sony A7SIII	100400	C	Off	outside	238	79	49
Canon 5D MarkIV	2470	R	Off	outside	231	78	46
Sony FX3	100400	L	Off	outside	228	68	44

Table 2: *The most accurate color results obtained from each camera. The optimal point among all datasets is highlighted in green.*

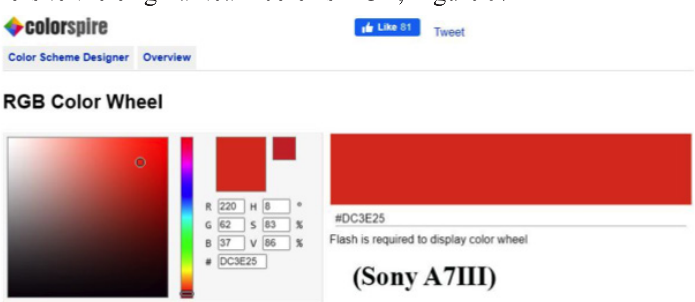
This parameter gives us a quantitative characteristic of the distance intensity between each La*b*'s components from their original value. In other words, we can determine the overall distance of each La*b* value from the original to determine the closest possible point to the original color's quantitative parameters. The mathematical equation of the second-order norm can be written as:

$$|x| = \sqrt{\sum_{k=1}^{n} |x_k|^2}$$

To satisfy our purpose, it becomes as:

$$\Delta E = \sqrt{(l_i - l^*)^2 + (a_i - a^*)^2 + (b_i - b^*)^2}$$

Using the https://www.colorspire.com/rgb-color-wheel/ website, we tested the RGB values of the best-obtained scenarios in each dataset. Then we compared these colors to the original team color's RGB, Figure 5.



(Sony A7III)

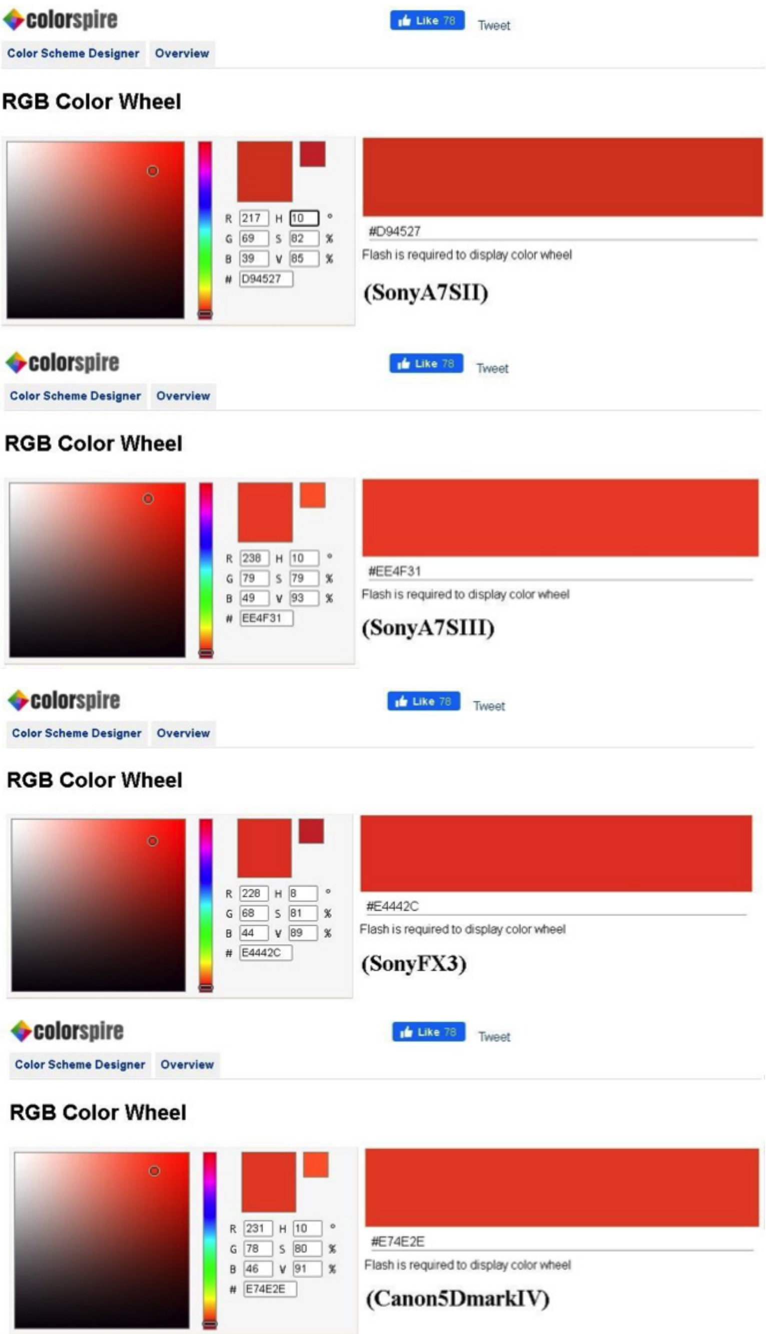
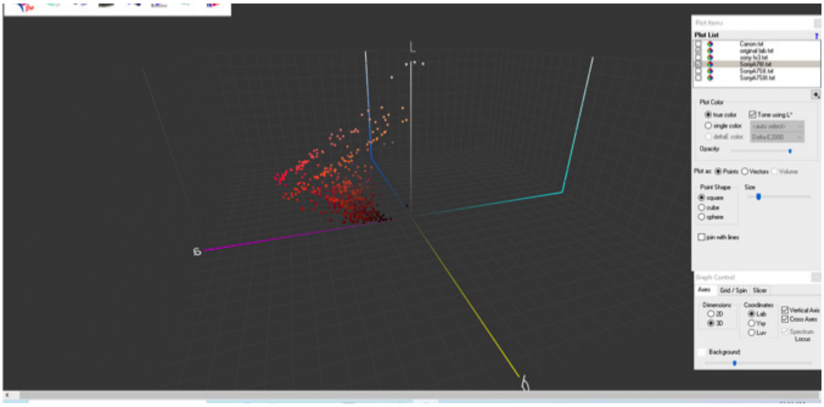


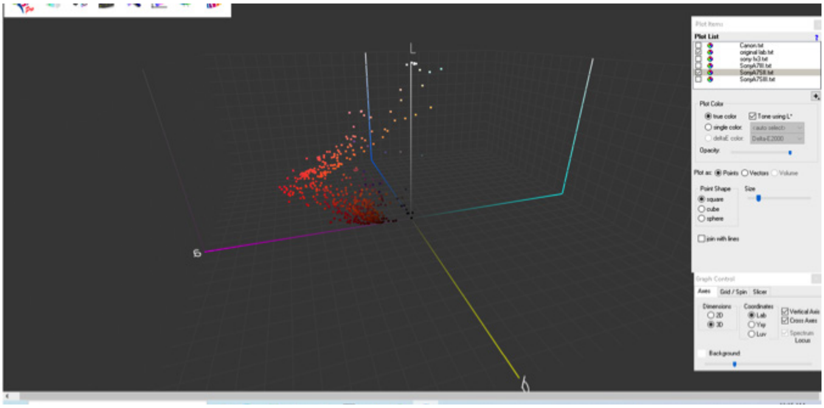
Figure 5: *Comparing the original RGB to the best scenarios from each dataset.*

Furthermore, the 3D plots of La*b* values for each dataset are observable in the following figures.

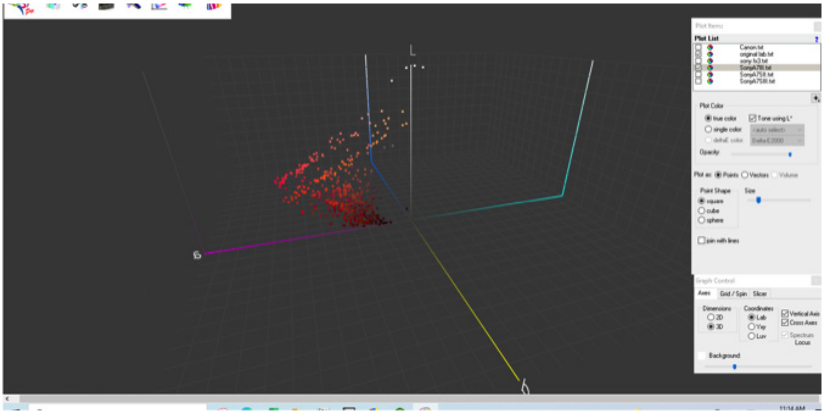
Sony A7SIII



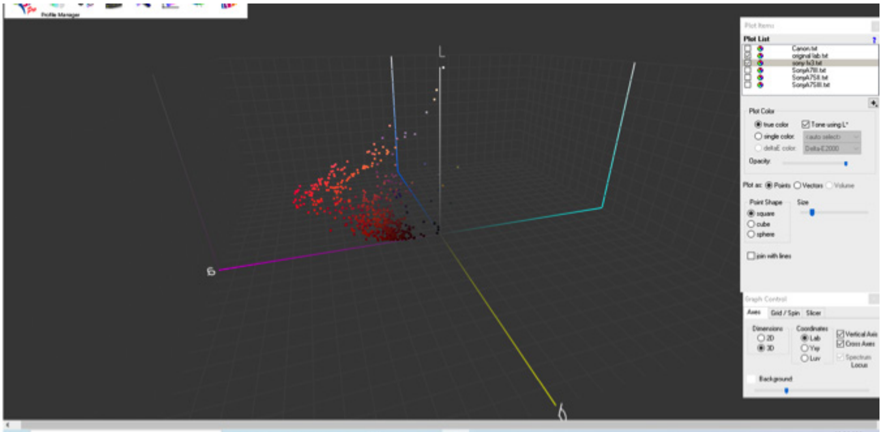
Sony A7SII



Sony A7III



Sony FX3



Canon 5D Mark IV

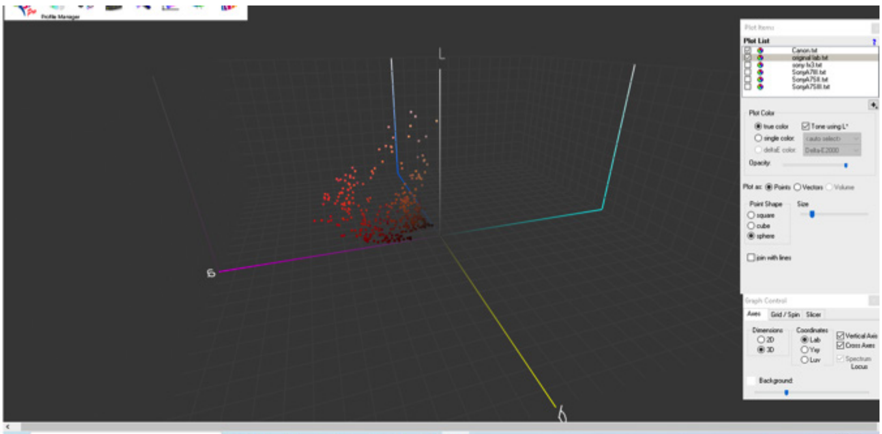


Figure 8: *3D plots of La*b* values for each dataset.*

The RGB obtained from each dataset has the closest color to the target RGB, although the other colors are also very close to the original color.

In the next step, we calculate the ΔE (Z-scores) (Curtis, 2016; Cheadle, 2003) of the corresponding La*b* values to determine the essence of the highest and lowest ΔE scores in our datasets. Figure 6 shows the bar diagram of the obtained ΔE scores for each dataset. After sorting the ΔE scores from the highest value to the lowest, we can plot them in a clearer format, Figure 7.

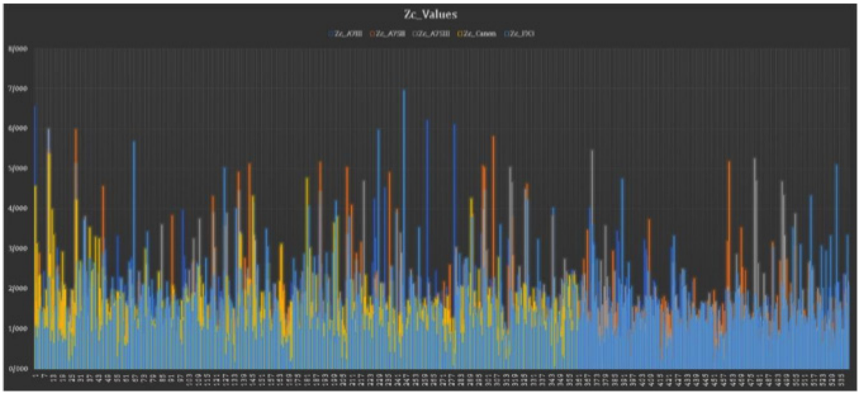


Figure 6: *Bar diagram of the obtained ΔE scores for each dataset.*

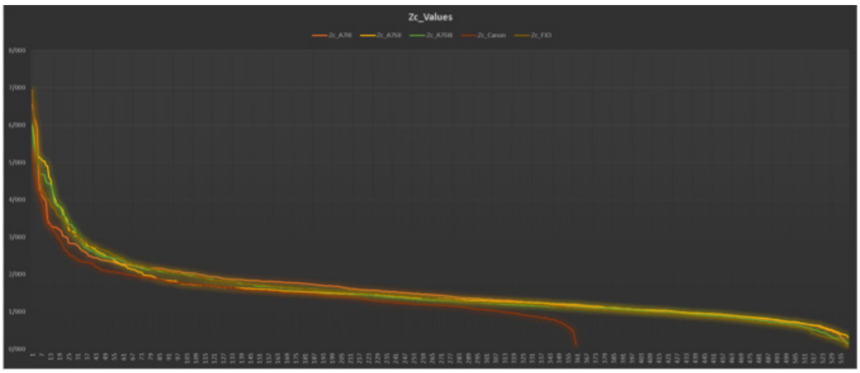


Figure 7: *Sorted z-score values of all datasets.*

Now we examine the extreme values of ΔE score and what inferences we can make about them. First, we need to determine the frequency of ΔE score for particular intervals in order to determine how many values are falling outside of the accepted norm for ΔE, Table 3.

Camera	**ΔE < 2**	**2 < ΔE < 5**	**ΔE > 5**
Sony A7III	79.406%	19.852%	0.742%
Sony A7SII	86.481%	11.852%	1.667%
Sony A7SIII	81.111%	17.963%	0.926%
Canon 5D markIV	82.5%	17.222%	0.278%
Sony FX3	81.481%	17.593%	0.926%

Table 3:*Frequency of ΔE score for intervals in each dataset.*

According to Table 3 and ΔE score analysis, we can state that extremely low ΔE scores represent dark (shadow) orange areas and extremely high ΔE scores represent highlighted areas. Since the material of the helmet is metallic, light reflection is seen in the brightness areas, and high ΔE scores are related to very bright spots on the helmet. In other words, the camera has a more difficult time capturing accurate brand orange in the extreme highlight areas of the frame.

Conclusion

Using the proper settings during camera capture for broadcast will help to reduce the timely post-production process and create accurate brand colors in camera. In this research, we set out to replicate the equipment and situations commonly experienced by the Clemson Athletic Media Team in order to determine the best possible situation to replicate the brand-specified orange of the Clemson Tigers. The data and resulting analysis shows that the optimal data point is from the SonyA7SII camera, 24-70 mm lens, back position, picture profile adjusted as off, and inside location (in the studio).

The ΔE scores between zero to two represent the most desirable values, closest to the target color value. The ΔE scores between two to five are considered acceptable in most cases and ΔE scores greater than five are not acceptable representations of brand color. Many of the outlier color readings were determined to be mostly irrelevant colors, for example highly overexposed or from very reflectant parts of the helmet. We should note that extremely low ΔE scores tend to represent shadow (dark) orange RGB values. However, we could not determine a consistent variable (like camera lens or profile picture setting) that caused extremely high or extremely low ΔE scores.

Videos in this study were taken in outside and inside locations on static objects. For future research, I suggest collecting and analyzing the samples from live events. Another research study might consider different lighting conditions for inside videography and different weather conditions or times of day for outside capture.

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