Color Me Good: Branding in the Coloring Style of Movie Posters

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Abstract

Brand logos are often rendered in a different style based on a context such as an event promotion. For example, Warner Bros. uses a different variety of their brand logo for different movies for promotion and aesthetic appeal. In this paper, we propose an automated method to render brand logos in the coloring style of branding material such as movie posters. For this, we adopt a photo-realistic neural style transfer method using movie posters as the style source. We propose a color-based image segmentation and matching method to assign style segments to logo segments. Using these, we render the well-known Warner Bros. logo in the coloring style of 141 movie posters. We also present survey results where 287 participants rate the machine-stylized logos for their representativeness and visual appeal.

(a) *Original* (b) *Troy*

(c) *Rendered* (d) *Poster*

Figure 1: Stylized version (b) of WB logo (a) used in the movie *Troy* and our stylized render (c) based on poster (d).

1. Introduction

Companies often render their brand logos in a different visual style for a given context, such as the promotion of an event. For example, the well-known Warner Bros. (WB) logo is often rendered to suit the style of a movie it features in for aesthetic and promotional purposes. This is accomplished often by changing the color or texture to suit the colors or textures found in the movie. For example, Figure 1b shows the stylized rendering of the WB logo in 1a using prominent colors from the movie *Troy*, glittering gold and bronze. Such renderings are created by skilled graphic designers and animators based on the original logo. Typically, the logo creation process consumes time and effort. Our motivation is to render such derived artwork (in this case, a brand logo as seen in Figure 1c) automatically or semi-automatically to aid graphic designers. If the machine-rendered logos can be considered visually appealing by a general audience, it can save time and effort for the designers, and can expedite the branding process.

For stylizing logos using color, a representative of movie color style is needed. One can choose dominant colors in a movie from a palette generated by color analysis of the movie. But this takes computational effort in terms of processing the movie frame by frame, or identifying keyframes and performing color analysis. Movie posters, being a marketing tool, represent the content and style of movies to convey what is important about the movie. In this paper, we use movie posters such as Figure 1d to stylize the WB logo.

Photo-realistic style transfer proposed by Luan et al. [5] employs neural networks to transfer a color palette of a style image onto a target image. In doing so, objects with similar visual properties are segmented together and their colors are transfered to a corresponding segment in the target image. We adopt this method for style transfer, but propose a color-based method of segmenting the posters and mapping poster segments onto logo segments.

Our contribution in this paper is: 1. We present a method for rendering stylized derived artwork (i.e. WB logos) from style content (i.e. posters of movies) using photo-realistic neural style transfer. 2. We present an image segmentation and matching method to match poster color styles to logo segments. 3. We present survey results from 287 participants on representativeness and visual appeal of machine-rendered logos.

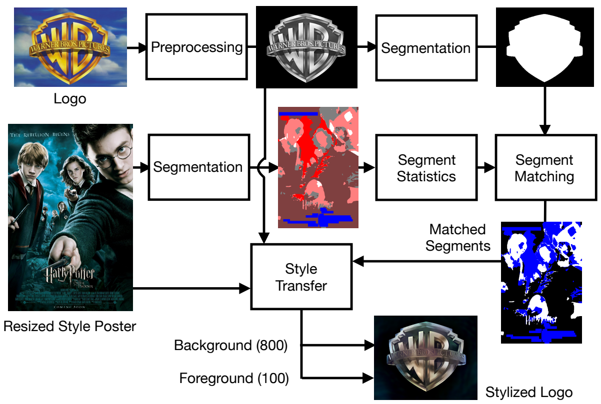


Figure 2: Schematic of the proposed method.

2. Related Work

Neural Style Transfer (NST) proposed by Gatys et al. [3] is popularly used to transfer various dimensions of style from one image (called the *style*) to another (called the *content*). However, using such a network on realistic photographic images such as posters creates wiggly edges out of straight ones, and does not retain the realism of the original images. Luan et al. [5] addressed this limitation by constraining the stylizing transformation to be locally affine in the color space. This eliminated stylistic distortions while preserving style in color space. They also employed a Matting Laplacian [4] to reinforce original content on the stylized output. Further, they segmented the image using DeepLab [2] to obtain semantic segments while grouping together similar objects such as clouds and sky. They then transfered the style of these segments to the most appropriate segments in the image to be stylized (e.g. sky to sky, buildings to buildings). We found that this type of segmentation did not do well on content such as movie posters with unrealistic objects and gradients. In this paper, we use the photo-realistic style transfer proposed by Luan et al. [5] for stylizing the WB logo with a color-based segmentation approach proposed by us.

3. Proposed Method

3.1. Dataset

The website by graphic designer Christian Annyas [1] lists more than 150 WB logo variations seen in movies produced after 1998. We downloaded high-resolution posters for 141 movies listed on this website as style sources for the experiments listed in this paper. For the target logo, we used a standard high-resolution WB logo with a shield and a plaque bearing the letters *Warner Bros. Pictures*.

3.2. Stylization Process

Figure 2 shows a schematic diagram of the proposed method for stylization, which has the following steps:

Logo Processing. We created a binary mask for the WB logo with the shield as a foreground and applied the mask to the logo to get its foreground. We converted the foreground to gray-scale. We enhanced the logo by applying the Contrast Limited Adaptive Histogram Equalization (CLAHE) algorithm [6]. We enhanced the edges using an unsharp mask and removed artifacts in the image using Gaussian filtering. We then applied anti-aliasing and sharpening to the image to get the final logo image to be stylized. We formed two main segments in the logo, the enhanced shield foreground (represented by a white mask) and the background (represented by a black mask).

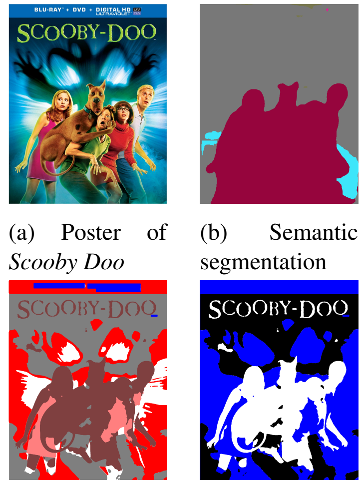
Poster Processing. Unlike Luan et al. [5] who employed semantic segmentation over the style image, we segmented the poster image for similar color styles. For this, we flattened the image using mean-shift filtering to remove variation in the color due to lighting and other effects. We then converted the image from RGB (Red-Green-Blue) to HSV (Hue-Saturation-Value) space. We clustered the image in 5 segments using k-means clustering with HSV value of pixels, to get a relatively uniform color content in each segment. While clustering, we applied weights of 0.66, 0.17 and 0.17 to H, S and V channels respectively, to increase the importance of color. We chose these weights by trial and error to give the best visual reconstruction of sample poster images when segmented. We color coded the segments for future use, blue representing the part of the image we discarded. We also used a pre-trained CNN for detecting credits text in the poster and added it to the blue segment [7], while kept the title as it could have a color style.

Segment Matching. We then selected the best segments from the aforementioned 5 segments of the poster to map to the foreground and background segments on the logo. We observed that the majority of WB logos used in movies showed a dark background. So we decided to assign the poster segment with the least luminance to the background segment of the logo. We also observed that WB logos with more contrast in foreground were more visually appealing. Therefore, from the remaining segments, we found the top two segments with the highest value of contrast, and chose the one with more luminance to map to the foreground. We merged the remaining segments in the blue segment which was discarded. Figure 3 shows the comparison of our segmentation with the semantic segmentation adopted by Luan et al. [5]. The semantic segmentation approach shown in Figure 3b segments the characters together, thus creating one foreground segment out of a variety of hues (e.g. skin tone, dog color, red dress, green dress). Its background segment clubs together of the shadow and the halo. Our proposed color-based segmentation shown in Figure 3c separates these hues and also separates the lighter shaded halo and the darker background. Using the segment matching strategy described above, we assigned the darker background segment (denoted by black in Figure 3d) to the logo background and the closer character hues to the logo foreground (denoted by white in Figure 3d).

Style Transfer. We used the photo-realistic style transfer network as prescribed by Luan et al. [5] for transferring the poster color style to the logo. Luan et al. [5] formulated L, the style transfer loss function (to be minimized) as:

$$L = \Gamma_c \sum_{i=1}^{N} \alpha_i {L^i}_c + \Gamma_s \sum_{i=1}^{N} \beta_i {L^i}_s + \lambda L_m \quad (1)$$

where N is the total number of layers in the convolutional neural network and i denotes the i^{th} convolutional layer. Γ_c and Γ_s are weights controlling content and style loss respectively, α_i and β_i are weights of i^{th} layer and λ is a weight for photorealism regularization. L_c and L_s are content and style losses, respectively, while L_m is the photorealism regularization introduced by Luan et al. [5]. As prescribed by Luan et al. [5], we provided the content and style images to one network that performed a segment-by-segment artistic style transfer. Since we used more uniform color-based segments, it reduced bleeding of style across segments. We ran this network for 1500 epochs to generate an intermediate artistic style-transferred image. We provided this image to a second network, which enforced photo-realism on the image, allowing only locally affine transformation in color space. In every epoch, it minimized the photorealism regularization term, L_m. We ran the network for 800 iterations for each poster-logo pair. We later combined a sharp shield from 100^{th} iteration with a smoothened background from 800^{th} using the logo masks. We found the content weight (Γ_c) and the style weight (Γ_s) to be 150 and 20 respectively by trial and error, so as to give the best visual quality across machine-rendered logos.



(a) Poster of *Scooby Doo*

(b) Semantic segmentation

(c) Color-based segmentation

(d) Final mask for stylization

Figure 3: Comparison of segmentation approaches. (b) shows the mask created by semantic segmentation [2] used by Luan et al. [5]. (c) shows the 5 segments generated by our color-based approach. (d) shows the final mask to be used for stylization.

4. Results and Discussion

We used the above method to render stylized logos for 141 WB movie posters. We then conducted a survey to examine the perceived representativeness and aesthetic appeal of the machine-rendered logos. For this purpose, we chose 112 logos at random from the stylized logos. To capture the visual variety in posters, we measured three visual attributes, viz. luminance, contrast and hue count, of each poster to characterize it. We then divided the poster population based in eight groups with two levels of each parameter (low - below the median, and high - above the median). In each survey, we included one example from each group as 8 random poster and logo pairs. We asked participants' opinion about two statements for each poster and logo pair: 1) *The logo represents the poster well* (related to representativeness), and 2) *The logo looks visually appealing* (related to visual appeal). The participants rated these statements on a Likert scale of 1 (*Strongly Disagree*) to 5 (*Strongly Agree*).

We received 287 responses to the survey (63% male, 35% female, 2% not given; 1% below 18 years of age, 42% between 18-25, 40% between 25-35, 11% between 35-45 and 6% above 45). We received an average of 20.5 responses per poster-logo pair. We calculated average representativeness and appeal ratings per pair and per group. We observed that the representativeness was well correlated with the appeal (coefficient of determination $(R^2) = 0.64$). So, a logo considered to be a good representation of the poster was also likely to be visually appealing to the participants. Figure 4 shows the best and the worst rated posters using a combined rank for representativeness and appeal.

We found that group 3 (low luminance, high contrast, high hue count) had the highest mean ratings, while group 6 (high luminance, high contrast, low hue count) had the lowest ratings. We conducted a one-way ANOVA test and found that rating differed significantly among the groups ($F = 2.67, p < 0.05$ for representativeness, $F = 2.49, p < 0.05$ for visual appeal). We believe that group 3 received the highest ratings, since these were darker posters with good contrast and high colorfulness (Figure 5a). This combination allowed segmentation with some color variation, mostly a dark background to the logo background, and good contrast on the shield. This combination helped increase the visual appeal of the stylized logo. Group 6 received the

(a) $R = 3.80, A = 4.10$

(b) $R = 3.95, A = 3.90$

(c) $R = 3.78, A = 4.00$

(d) $R = 2.45, A = 2.30$

(e) $R = 2.30, A = 2.4$

(f) $R = 2.55, A = 2.38$

Figure 4: Best and worst rated machine-stylized logos with corresponding posters. Top row has the best-rated logos by combining ranks of representativeness (R) and visual appeal (A), while bottom row the worst rated. The best logos (a-c) have high contrast over the shield, reflect important colors in the poster. In the worst logos, (d) is smudged, does not reflect poster colors and background well; (e) appears too bright and smudged; (f) is too dark though reflecting the poster colors.

(a) $R = 3.63, A = 3.81$

(b) $R = 2.75, A = 2.60$

Figure 5: Examples from groups 3 and 6. These groups showed the highest and the lowest ratings, respectively.

lowest ratings, since these were brighter posters with high contrast but with less colors (Figure 5b). Low hue count caused less color variety in segmentation, so while the darkest segments went to the background, bright segments with less color variation often went to the shield. This caused a glowing effect often not representative of the poster.

5. Conclusion

In this paper, we demonstrated a method to render the WB logo in the style of movie posters. We proposed a color-based approach to segment posters rather than the semantic one used by Luan et al. [5]. We found that the best of the logos created were representative of the posters as well as appealing to a general audience. We also found that posters with low brightness, high contrast and high variety in color were more amenable to stylization using our method. We believe since acceptable stylization was possible with our automated method, a semi-automated method of allowing graphic designers to choose color segments, and then using our method stylization would increase the output quality and reduce the designer's effort. Though this method has been demonstrated on only the WB logo, we believe it to be applicable to equivalent artwork for creating branding material, though parameters such as content/style and HSV weights may need tuning. In future, we would like to conduct a survey with graphic designers using the best rated logos in this survey to establish the utility of this method.

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