Enhancing Image Classification through Exploitation of Hue Cyclicity in Convolutional Neural Networks

Jiatao Kuang[a], **Teryn Cha**[b], **Sung-Hyuk Cha**[a]
[a] Computer Science Department, Pace University, New York, NY, USA
[b] Computer Science, Essex County College, Newark, NJ, USA

Abstract

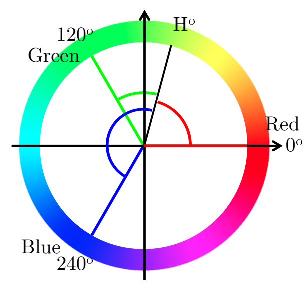
This study introduces innovative methodologies for image classification employing Convolutional Neural Networks (CNNs) by leveraging the cyclical attributes of hue within the HSV color space. Two distinct kernels are explored to linearize the circular values of hue. The first kernel converts the angular values to three modulo distance values corresponding to three color hue points. The second kernel utilizes trigonometry to convert angles into sine and cosine linear values. Experimental evaluations demonstrate that linearizing hue values leads to a notable enhancement in classification accuracy. This research provides insights into optimizing CNN-based image classification by integrating hue cyclicity, thereby advancing the capabilities of computer vision systems.

Introduction

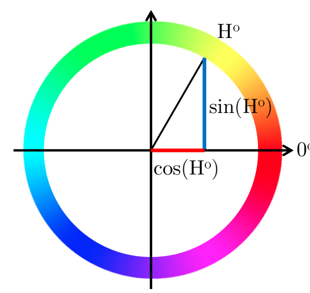
In recent years, Convolutional Neural Networks (CNNs) have emerged as a cornerstone technology in the realm of computer vision, revolutionizing image classification practices (Krizhevsky, Sutskever, and Hinton 2012). Renowned for their capacity to discern hierarchical representations of visual data, CNNs have propelled advancements across diverse domains including object detection, image segmentation, and facial recognition (He et al. 2016).

Central to the efficacy of CNN-based classification systems is the selection of an appropriate color space. Although the RGB (Red, Green, Blue) color model is prevalent in image processing, its alignment with human perception of color remains imperfect. In contrast, the HSV (Hue, Saturation, Value) color space disentangles luminance from color data, potentially affording more intuitive manipulation of color properties and bolstering classification accuracy amidst fluctuating lighting conditions (Gevers and Smeulders 1999).

This paper delves into innovative strategies within CNN frameworks, leveraging the cyclical nature of hue within the HSV color space to augment image classification performance.



(a) 3 color distance kernel



(b) Trigometric kernel

Figure 1: Kernels that linearizing angular values

HSV Color Representation

In the HSV color space, colors are represented in terms of Hue (H), Saturation (S), and Value (V). This representation differs from the more common RGB color space, which, while intuitive for digital displays, does not always align seamlessly with human perception of color. In the HSV model, the range of Hue (H) spans from 0 to 360 degrees, denoting the angle of color within a circular representation. Saturation (S) and Value (V) lie within the range of 0 to 1, representing the intensity and brightness of the color, respectively.

As depicted in Figure 1, in the HSV model, the hue component forms a circle, with red situated at 0 degrees, green at 120, and blue at 240. This circular arrangement enables the representation of hue's cyclic nature, where numerically distant values may correspond to visually similar colors. For instance, red, positioned at 0 degrees, and magenta at 300 degrees, exhibit a considerable numerical gap. However, in terms of clockwise distance, they are only 60 degrees apart, while counterclockwise, the gap extends to 300 degrees. This illustrates the cyclic continuity inherent in color perception facilitated by hue's circular metric.

Classification in HSV Color Space

Understanding hue distance is imperative in image classification tasks utilizing Convolutional Neural Networks (CNNs), as the cyclic nature of hue can significantly influence feature extraction and classification accuracy. Within the context of a hue circle spanning 0-360 degrees, each point can be uniquely identified by its distances to the primary colors: red, green, and blue.

Formally defining hue distance, we consider the circular arrangement of hues, where the distance between any two hues, H_x and H_y, is the length of the shorter arc on the hue circle connecting them:

$$d(H_x, H_y) = \begin{cases} \|H_x - H_y\| & \text{if } \|H_x - H_y\| \leq \pi \\ 2\pi - \|H_x - H_y\| & \text{if } \|H_x - H_y\| > \pi \end{cases} \tag{1}$$

This definition ensures a distance measure that respects the cyclic property of the hue space. In order to linearize the angular values, the first set of three kernels utilize the angular distance to three point hue values: red $0°$, green $120°$, and blue $240°$.

$$Rd(h°) = d(h°, 0°) \tag{2}$$
$$Gd(h°) = d(h°, 120°) \tag{3}$$
$$Bd(h°) = d(h°, 240°) \tag{4}$$

This conversion method is depicted in Figure 1 (a).

The second kernel utilizes trigonometry.

$$N(h°) = \frac{\sin(h°) + 1}{2} \tag{5}$$

$$C(h°) = \frac{\cos(h°) + 1}{2} \tag{6}$$

This conversion method is depicted in Figure 1 (b).

In our research, we employ Convolutional Neural Networks (CNNs) for image classification, utilizing two primary methods to effectively harness color information. Initially, we process images with a single CNN, employing diverse input channels derived from the HSV color model. We explore three distinct configurations: HSV-CNN, HSV-3CD CNN, and HSV-Trigonometric CNN.

The HSV-CNN model is the conventional three-channel HSV without any kernel. The HSV-3CD CNN model, illustrated in Figure 2 (a), utilizes the hue 3CD kernel, resulting in the expanded five-channel setup integrating mathematically defined hue distance along with saturation and value.

The HSV Trigonometric CNN model, illustrated in Figure 2 (b), utilizes the hue trigonometric kernel, resulting in the four-channel approach representing the hue component through its sine and cosine values along with saturation and value.

Experiments

In our experimental evaluation, detailed in Table 1, we tested the CNN methodologies against the Oxford102 and Food101 datasets. Both CNN models with kernels outperform the naïve HSV-CNN model on both datasets. Notably, the highest test accuracies were attained with the HSV-3CD CNN: 84.31% accuracy on Oxford102 and 80.85% on Food101.

Conclusion

We introduced several kernels capturing the cyclic nature of the hue component of color images. These configurations were devised to evaluate the impact of different color representations on the CNN's ability to classify images, providing insight into the format of color information that significantly enhances accuracy. Our experimental findings suggest that incorporating linearized hue values in CNNs facilitates better generalization, resulting in improved accuracy on test datasets. This underscores the efficacy of leveraging hue characteristics for enhancing the performance of color-sensitive image classification tasks.

Table 1: HSV Color Space Experimental Results

Methods	Training	Validation	Test
HSV-CNN	99.06%	84.98%	83.43%
HSV-3CD CNN	99.22%	86.17%	**84.31%**
HSV-Trigo-CNN	99.06%	85.90%	83.45%

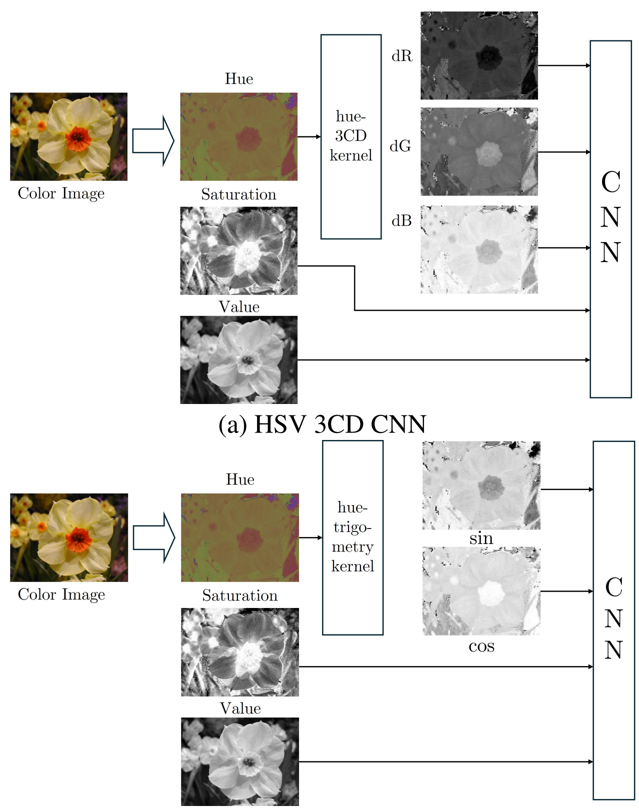
(a) Oxford102 Flower dataset

Methods	Training	Validation	Test
HSV-CNN	99.18%	78.62%	80.53%
HSV-3CD CNN	99.18%	79.06%	**80.85%**
HSV-Trigo-CNN	99.22%	78.48%	80.36%

(b) Food11 dataset

References

Gevers, T., and Smeulders, A. W. M. 1999. Color-based object recognition. *Pattern Recognition* 32(3):453–464.



(a) HSV 3CD CNN

(b) HSV Trigometric CNN

Figure 2: CNN models with different Hue kernels

He, K.; Zhang, X.; Ren, S.; and Sun, J. 2016. Deep residual learning for image recognition. In *2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 770–778.

Krizhevsky, A.; Sutskever, I.; and Hinton, G. E. 2012. Imagenet classification with deep convolutional neural networks. In Pereira, F.; Burges, C.; Bottou, L.; and Weinberger, K., eds., *Advances in Neural Information Processing Systems*, volume 25. Curran Associates, Inc.