Predicting Perceptual Attributes Using Neural Networks

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1 Introduction

Color appearance models (CAMs) aim to predict how colors appear to human observers under various viewing conditions, such as changes in illuminants, luminance levels, and surrounding backgrounds. Accurate prediction of color appearance is essential in various industries such as printing, textile, display technologies, and color management systems.

A method is proposed using a neural network approach, specifically a Multilayer Perceptron Regressor (MLPRegressor), to predict perceptual attributes such as lightness (J), chroma (C), hue angle (h), and saturation (s) based on the spectral reflectance data of color patches and viewing conditions. The methodology integrates the use of a known color appearance model (CIECAM02) and machine learning to enhance prediction accuracy.

2 Problem Statement

Color appearance models like CIECAM02 provide a mathematical framework to estimate how colors appear to human observers. However, there are challenges when these models are extended to a broader range of viewing conditions and color spaces. Traditional methods may fail to accurately predict appearance attributes when complex or non-standard viewing conditions are involved.

Objective: The aim of this work is to develop a machine learning-based method that improves the prediction accuracy of perceptual attributes (J, C, h, s, Q, M, H) under various viewing conditions, as computed by CIECAM02, and demonstrate how neural networks can enhance the model's performance.

3 Related Work

Traditional color appearance models (CAMs) like CIECAM02 are widely used for color management. While these models can be accurate under controlled conditions, they do not always generalize well to complex lighting environments and non-standard observers.

Machine learning approaches, specifically neural networks, have been proposed in recent years to improve predictions in scenarios where CAMs struggle. Techniques such as Multilayer Perceptron Regressor (MLPRegressor) are effective in capturing non-linear relationships between spectral reflectance data and perceptual attributes.

4 Methodology

The proposed method leverages a combination of spectral reflectance data, color appearance models, and machine learning to predict how colors appear under various viewing conditions. The method proceeds as follows:

4.1 Data Preparation

The spectral reflectance data along with their tristiumulus values for 1600 Munsell color patches [1], spanning wavelengths from 380 nm to 780 nm at 1 nm intervals. These data were combined with simulated viewing conditions, including three standard illuminants (D65, A, and FL1), luminance levels (31.83, 318.3, 3183 cd/m^2), and three background conditions (Gray, White, Black). For each combination, we computed the perceptual attributes using the CIECAM02 color appearance model.

4.2 Model

A Multilayer Perceptron Regressor (MLPRegressor) was trained to predict perceptual attributes (J, C, h, s, Q, M, H) from the given spectral reflectance data and viewing conditions. The neural network was set up with three hidden layers, utilizing ReLU activation functions and the Adam optimizer.

The input features include the spectral reflectance data and categorical variables representing the illuminant, luminance level, and background. The targets were the perceptual attributes calculated using CIECAM02.

4.3 Hyperparameter Tuning

To optimize the performance of the neural network, we applied grid search with cross-validation to find the best hyperparameters, including the number of neurons per layer, learning rate, and activation function. Grid search identified the optimal configuration as using hidden layers of sizes (256, 128, 64), a ReLU activation function, and a learning rate of 0.0001.

5 Results

The trained model was evaluated using the R-squared (R^2) score and mean squared error (MSE) on a test set, comprising 20% of the data. The overall results are summarized below:

- **Model $\mathbf{R^2}$ Score (overall):** 0.76
- **Model Mean Squared Error (overall):** 1110.93
- **Attribute: Lightness (J) - $\mathbf{R^2}$:** 0.9912, **MSE:** 0.4885
- **Attribute: Chroma (C) - $\mathbf{R^2}$:** 0.6766, **MSE:** 0.0306
- **Attribute: Hue Angle (h) - $\mathbf{R^2}$:** 0.5484, **MSE:** 3668.23
- **Attribute: Saturation (s) - $\mathbf{R^2}$:** 0.9349, **MSE:** 0.7269
- **Attribute: Brightness (Q) - $\mathbf{R^2}$:** 0.9986, **MSE:** 39.13
- **Attribute: Colorfulness (M) - $\mathbf{R^2}$:** 0.5149, **MSE:** 0.0280
- **Attribute: Hue Composition (H) - $\mathbf{R^2}$:** 0.6879, **MSE:** 4067.87

6 Discussion and Future Work

The results show that the neural network model performs moderately well for predicting lightness (J) and brightness (Q), with R-squared scores close to 1. However, the performance for hue angle (h) and colorfulness (M) can be improved.

6.1 Improving Model Accuracy

Several techniques can be employed to improve the current model's performance:

- **Feature Engineering:** Introducing interaction terms or additional polynomial features might help capture more complex relationships between the input features and target variables.
- **Regularization:** Adding regularization methods such as L2 (Ridge) regularization could prevent overfitting and improve the model's generalization.
- **Alternative Models:** Experimenting with other machine learning models, such as Random Forest or Gradient Boosting, might yield better performance for the perceptual attributes with lower R-squared scores.
- **Refinement of Viewing Conditions:** Incorporating more detailed or diverse viewing conditions could make the model more robust to a wider range of scenarios.

7 Conclusion

This work demonstrated the use of a machine learning approach to predict perceptual attributes under various viewing conditions using spectral reflectance data. The results show promising accuracy, particularly for lightness and brightness, but further work is needed to improve predictions for other perceptual attributes. With additional feature engineering and model tuning, this approach has the potential to enhance existing color appearance models.

8 References

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