# From Color Image Difference Models to Image Quality Metrics

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## Abstract

Color difference research has recently culminated in the creation of the CIEDE2000 color difference equation. This equation has been shown to accurately predict perceived differences between simple stimuli on a solid background. A similar metric is desired to predict differences of complex stimuli, such as color images. Such a metric would be useful for predicting both threshold and supra-threshold differences. Threshold prediction is valuable for determining if two images are perceptually different, such as an original and a compressed image. Supra-threshold prediction can determine the magnitude of differences between two images, a precursor to perceived image quality. There are several existing spatial-contrast threshold models, though these models tend to ignore color and magnitude information. This presentation details a modular framework for a color image difference metric, based upon CIE color difference formulas. Some of the modules described include spatial filtering (similar to S-CIELAB), spatial frequency adaptation, local attention filtering, local and global contrast compensation, and visual masking. The ability to predict both threshold and magnitude errors can be combined with traditional psychophysical image scaling experiments to create a metric of perceived image quality.

## Introduction

In order for an observer to determine whether one image is of higher quality than another, they must first be able to perceive a difference between the two images. Current color difference equations excel at predicting magnitude differences of simple stimuli, but they have been shown to be inadequate for predicting the differences for complex image stimuli. Similarly, spatial-vision models have traditionally been used to detect threshold differences of monochromatic stimuli. A color image difference model must combine the strengths of traditional color difference equations with those of the spatial-vision community.

Towards this goal, the authors have created a modular framework for the creation of a color image difference metric.[1,2] This model is easily extensible, and has shown success at predicting psychophysical results. Figure 1 shows the workflow of the model, with modules for spatial filtering, spatial frequency adaptation, local attention, and local contrast detection.

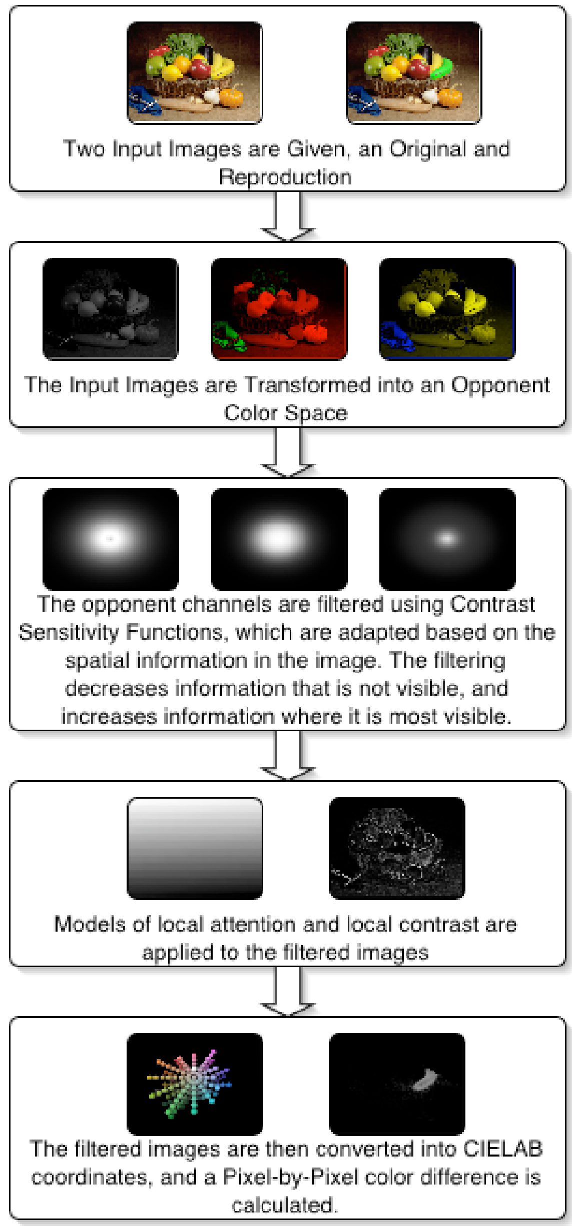


*Figure 1. Workflow of Modular Color Image Difference Metric*

The proposed model is similar in nature to the S-CIELAB spatial extension described by Zhang and Wandell.[3] The S-CIELAB model extends traditional colorimetry and color difference with a pre-processing spatial filtering. This pre-processing can be considered a single module in the image difference framework. Several other modules have already been described, as shown in Figure 1. These modules are briefly described below.

*Spatial Filtering and Spatial Adaptation*

The first step in the model is the conversion to device independent coordinates such as CIE XYZ tristimulus values. These coordinates are then transformed into an opponent color space, where the spatial filtering is applied. In the S-CIELAB model , this filtering involves a series of separable convolution kernels that approximate the human contrast sensitivity functions (CSF). It has been shown that more accurate approximations can be utilized when the filtering is performed in the frequency domain, rather than the spatial domain.[1] Several frequency based CSFs have also been analyzed in greater detail.[2,4,5] These filters serve to both modulate details in images that are imperceptible, as well as enhance details where they are most perceptible. The CSFs can also be modified based on the frequency information contained in the images themselves. This is known as spatial frequency adaptation. Several models of adaptation have been previously described.[2]

*Local Attention and Contrast*

In addition to frequency filtering based on the human CSF, several models of localized attention and contrast have been described.[1] The local attention metrics serve to enhance image information based upon where the observer is most interested. This might include edge information, or areas of large differences.

The contrast metrics serve to detect differences in contrast, both global and local, between two images. Local contrast is generally described as contrast of a small area judged in relation to the average value of a localized region.

*Color Difference Calculations*

The final step in the image difference model is to convert the filtered images back into CIE XYZ tristimulus values. These values are then converted to CIELAB values, and a pixel-by-pixel color difference is calculated. This results in an error image, where each pixel represents the perceived magnitude of error. This image can be further distilled, if desired, to create a lower dimensional representation. Often image statistics such as mean, standard deviation, maximum, minimum and median are enough to describe the overall perceived image difference. Many times, however, these statistics mask error information. Much more research needs to be focused on the process of data reduction.

## Experimental Verification

For an image difference metric to be useful, it is necessary to compare predictions with psychophysical experimentation. Both threshold detection, and magnitude scaling experiments are important. One such magnitude experiment was designed to specifically test the ability to predict sharpness differences.[4] Other experiments are underway to scale additional dimensions important to image difference, such as contrast and local attention.

## Linking Difference to Quality

Whereas the ability to determine if two images are perceptually different is a useful tool in itself, it is also thought to be a crucial step in the formulation of a computational model of perceived image quality. In order to do this, it is necessary to first link scales of difference with experimentally determined scales of quality. It is doubtful that a single difference magnitude will scale directly with image quality scales, as they are known to be multi-dimensional. This is where the modular nature of the image difference framework can be leveraged, as it is possible to get difference scales at each stage or module. For example, if it is determined that contrast is very important in predicting image quality then the local contrast module can be weighted appropriately.

In order to link the uni-dimensional scales such as contrast, color balance, resolution and sharpness to a multi-dimensional image quality scale, more experimental verification is necessary. An example of this type of experiment would be the simultaneous scaling of both sharpness and quality.

## Conclusions

Like any construction project, building a comprehensive model of image quality requires a strong foundation. This foundation is based upon a color image difference equation. Using such an equation, it should be possible to link perceived differences between images with perceived quality of those images.

We have presented a framework for the creation of an image difference metric. Using the framework, we have also designed and implemented several psychophysical experiments to bridge the gap between image difference and image quality.

## References


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