The Quality of Appearance

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ABSTRACT

With CIECAM02, a new level of accuracy was added to color appearance models capability predicting the appearance of simple color stimuli. Recently a new type of image appearance model, called iCAM, has been introduced to model the perception of complex image stimuli. This image appearance model is capable of predicting many spatial phenomena such as simultaneous contrast, crispening, and spreading. The models image appearance framework can be extended to predict image differences and image quality, through the addition of spatial filtering. The application of iCAM as an image difference metric, as well as an image quality metric is discussed. This paper also addresses the application of linear filters in a variety of color spaces and their impact on image quality prediction.

1. INTRODUCTION

Color appearance models, in essence, are tools that translate numbers into words. The inputs to these models are numerical measurements such as luminance and the tristimulus values of a stimulus and viewing conditions. The output are words describing what the stimulus looks like. These words are the color appearance attributes, such as brightness, lightness, colorfulness, chroma, and saturation. We often use numerical modifiers with these words to describe the amount of each attribute but their main purpose is to describe how a stimulus actually appears.

CIECAM02 represents the state-of-the-art in color appearance models and has been shown to accurately predict the appearance of simple stimuli across a variety of lighting and viewing conditions.[1] CIECAM02 is capable of predicting many well-known appearance phenomena, such as the Hunt and Stevens effects in which viewing conditions such as the background and surround greatly influence the appearance of a stimulus. These viewing conditions are well specified and understood when dealing with patches on a uniform background, but are less understood for dealing with spatially complex stimuli such as images. A different type of color appearance model, termed an image appearance model, has been suggested to handle spatially complex stimuli. These types of models can be considered a hybrid between models of temporal and spatial human vision and traditional color appearance.

An image appearance model extends color appearance to include additional attributes relating to images. These attributes, described by Engeldrum[2] as the "nesses," include such perceptions as contrast, graininess, and sharpness. To understand how an image looks, it is necessary to quantify these perceptions. A framework for describing image appearance, called iCAM, has been introduced.[3,4] By accurately describing the appearance of an image it is possible to extend the use of this type of model to describe image quality. This is typically achieved by predicting the quality "difference" between two images through the addition of spatial filtering as a pre-processing step. Image appearance attributes and the use of an image appearance model for predicting image quality are discussed in more detail below.

2. IMAGE APPEARANCE ATTRIBUTES

Color appearance research has identified and specifically defined several attributes that adequately describe the perceptual response to a stimulus. These are, lightness, chroma and hue for relative appearance matching, and brightness and colorfulness for absolute appearance matching. A sixth attribute of saturation has also been defined. With these terms it is possible to describe what a color looks like. Traditional image quality research has also focused on describing several attributes that affect the appearance and thus the quality of a given image.

These image quality approaches have traditionally been split into two distinct groups: an imaging systems approach, and a human visual system approach.[2,5,6] The imaging systems approach typically measures physical parameters such as resolution, MTF, grain, and gamut volume. THen through a weighted metric, it forms a model of how these parameters influence image quality. The human visual system approach typically uses metrics that approximate the behavior of the human visual system, such as the contrast sensitivity function that describes the threshold sensitivity to spatial frequencies.

One potential issue with either of these approaches when dealing with image quality and appearance that is routinely, and perhaps dangerously, ignored is that of image dependence. What may be detrimental to quality for one image may actually be good for another. This can be especially problematic if image quality/appearance "attributes" are measured completely independent of an image. An example of this may be the appearance attribute of graininess or its system correlate of grain, a low-frequency noise pattern. This attribute is typically measured using a CSF weighted metric measured off a uniform patch. This may not always correlate with the actual perception of graininess. in an image. An example of this is shown in Figure 1, where the same grain pattern is added to two images and is perceptible in one, but not the other. This is an example of visual masking, and some models of the human visual system take this into account.[7,8]

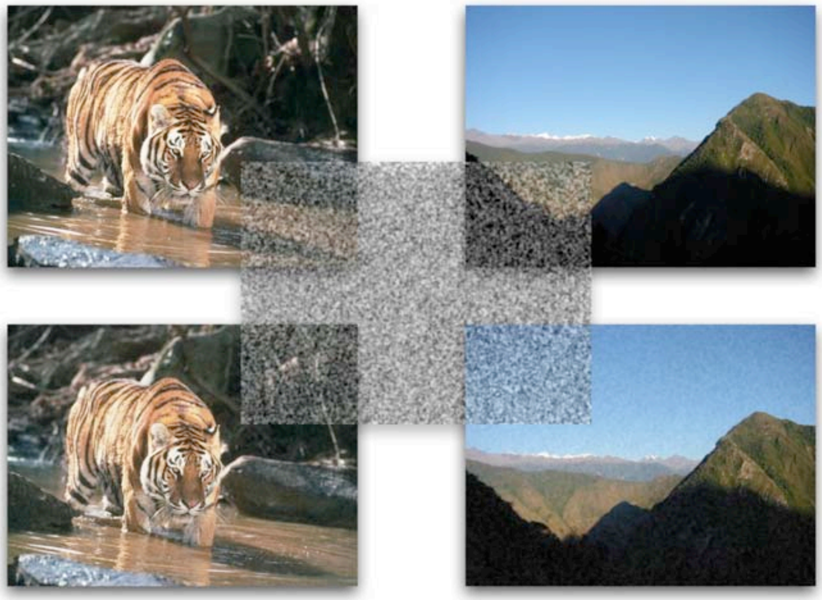

Figure 1. Graininess perception in two images. Original images (top) have the same grain pattern added to them (center) though it is not perceptible in the tiger image (bottom left).

Care must be taken when measuring other image appearance attributes, just as when quantifying color appearance attributes. An example of this is contrast, which is often described as the relationship between the darkest and brightest element in an image (also called Michelson contrast). The Stevens effect and Bartleson-Breneman equations suggests that the perception of contrast changes as a function of both overall luminance and the luminance of the surround. Simultaneous contrast also indicates that the color of the background also influences the perception of contrast. This is illustrated in Figure 2. What this suggests is that contrast cannot be described as simply the relationship between the darkest and brightest pixels in an image. Traditional color appearance models are able to account for changes in surround and overall luminance, but they fall short in accounting for local and simultaneous contrast. This is partly because the "background" is ill-defined for complex stimuli, is it the average of all pixels, 20% gray, or a localized average?.

Another interesting image perception is that of sharpness. This is often taken to be the integrated weight of MTF of an imaging system, or other similar metrics. Sharpness, like contrast and graininess, should not be measured independent of an image, as it is an attribute of the image itself.

This is evident in Figure 3, which shows that sharpness is both a function of image content and viewing conditions (such as viewing distance.)

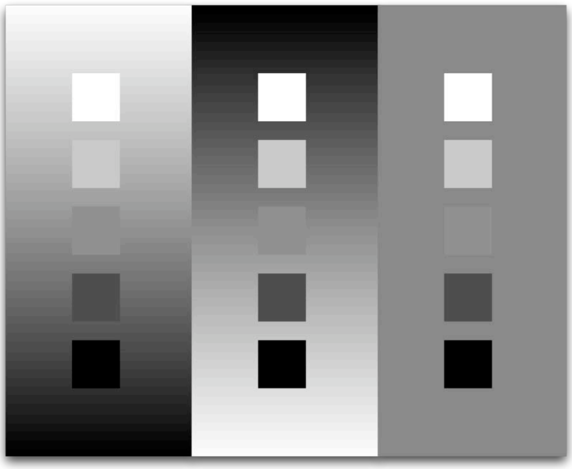

Figure 2. Contrast as a function of local background. The integrated background for all three sections is identical as well as the relationship between the minimum and maximum pixel values, though the perceived contrast of each scale appears different.

Figure 3. Image appearance attribute of sharpness as a function of viewing distance and image content. The top row images have been filtered identically. At a far viewing distance all the images look sharper but when viewed close up the portrait images are generally considered unnatural while the mountain still looks sharper.

Another interesting concept when dealing with image appearance is the idea of adaptation. Chromatic adaptation has been well studied in the color appearance world, and chromatic adaptation transforms are the fundamental basis for color appearance models.[9] Chromatic adaptation plays an important role in image appearance, though it is less well understood than for simple color stimuli. Afterall, what is considered the adapting stimulus when examining a complex image? Other forms of adaptation are important for quantifying image appearance. These includes luminance and local contrast adaptation, as well as spatial frequency adaptation. Spatial frequency adaptation is where the spatial frequency sensitivity of the human visual system is altered as a function of frequencies present in the scene. In essence, this suggests that the appearance of an image can be affected by the content of the image itself as we have seen in Figure 3. More details about spatial frequency, light, and contrast adaptation and their effects on image quality and appearance can be found in Webster[10] and Johnson.[11]

3. IMAGE APPEARANCE MODELING AND IMAGE QUALITY

A framework for an image appearance model called iCAM has been formulated and can be used to predict image quality.[4] Specifically this framework is designed to predict quality differences against a reference or ideal image. The general flowchart for the iCAM model as used to predict image quality is shown in Figure 4.

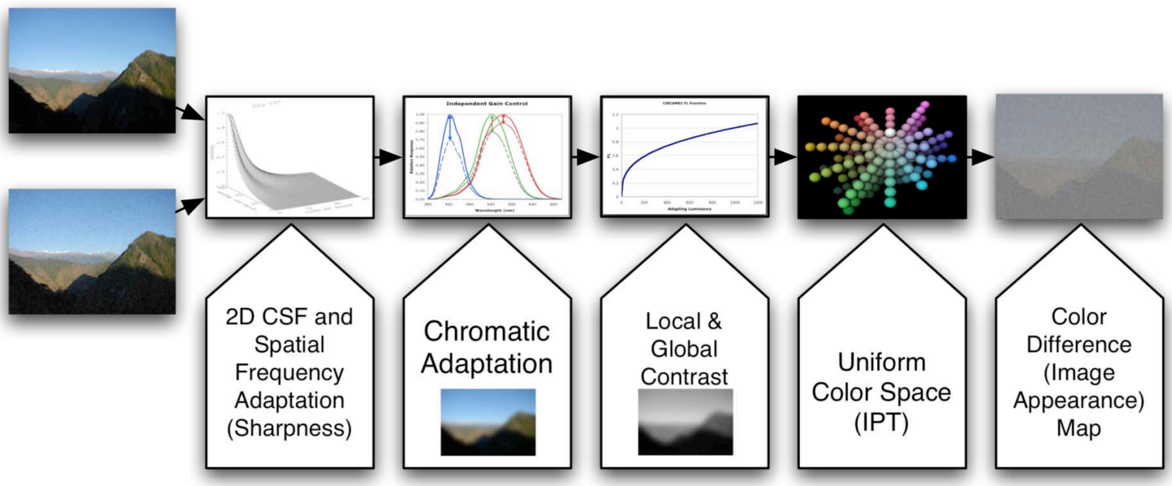

Figure 4. Flowchart for using iCAM as an Image Quality Metric.

To begin, two images are passed into the iCAM model. These images are first spatially-filtered using a two-dimensional contrast sensitivity function in an opponent (luminance, red-green, yellow-blue) color space. This approach is based on the S-CIELAB spatial pre-processing model.[12] The spatial filters serve to remove information where it is not visible and normalize all spatial frequencies so that the perceived color differences are equal. In essence, this means that it will take more of a color difference at higher spatial frequencies to match a color difference at a lower frequency. The general behavior of the spatial filters is low-pass for the chromatic channels and band-pass for the luminance channels. The choice of opponent color space is crucial for this step as it is necessary that the luminance and chromatic channels be mathematically orthogonal. Problems can arise when this is not the case, as shown in Figure 5. If the chromatic channels contain luminance information there can be chromatic or achromatic leakage when different spatial filters are applied. This is shown by the color fringing evident in Figure 5. The iCAM framework performs spatial filtering in a orthogonal color space called $Y'C_1C_2$. More details on this space can be found in Johnson.[13] The contrast sensitivity functions are also subjected to a spatial frequency adaptation based upon the frequency content of the image and local background.[11] This allows the framework to predict image dependent sharpness differences as described above and tends to shift the peak sensitivity of the luminance CSF to higher frequencies.

The next stage in the iCAM framework is a local von Kries type chromatic adaptation. This is similar in nature to that used in CIECAM02, though it is performed using a low-passed version of the image itself. This facilitates the prediction of overall color balance shifts, as well as local color changes. A local contrast predictor, again based upon a low-passed version of the image itself, follows the chromatic adaptation stage. The local contrast predictor allows the model to accommodate simultaneous contrast changes and can give an estimate of the overall contrast changes between the two images. The final step is a transform into a uniform color space for pixel-by-pixel color appearance calculations. The color appearance of any given pixel is now governed by the individual image content, as well as the overall viewing conditions. A pixel-by-pixel color difference can be taken to get an "appearance change" map between the two images.

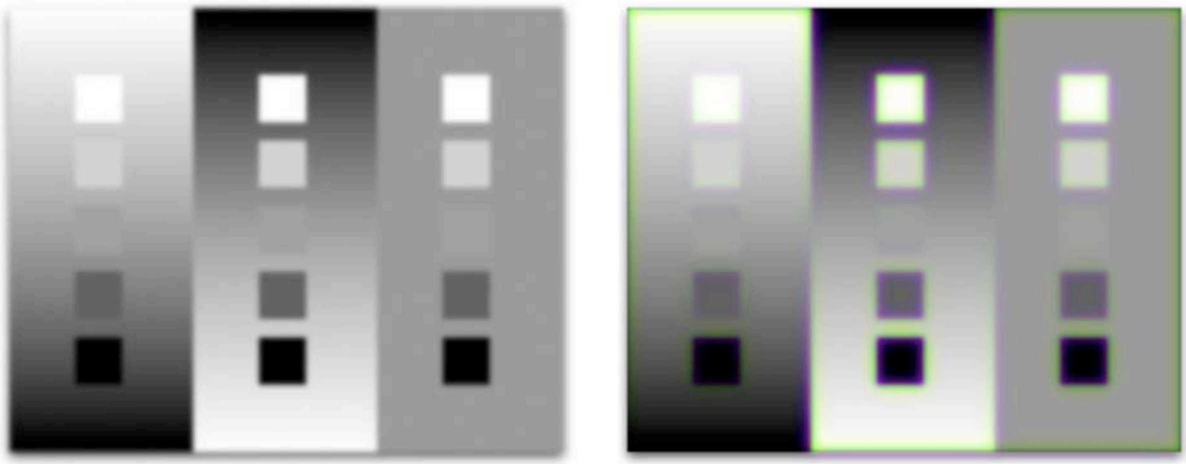

Figure 5. Dangers of spatial filtering in a non-orthogonal color space. The figure on the left has been filtered in an orthogonal space (luminance separate from chromatic) while the figure on the right was filtered in a non-orthogonal space. Chromatic fringing is evident in the right figure, because the luminance and chromatic filters are different sizes.

Image appearance attributes and their relationship to image quality can be evaluated at every stage of calculation. The overall difference between the two images may provide an indication of overall quality changes, but often will not provide enough information to determine whether those changes result in an increase or decrease in quality or what the overall quality differences are caused by. If a single dimension is being examined, for instance examining the relationship between dynamic range and quality, then it is quite possible that the overall image difference is adequate for determining quality. However, if multiple attributes are changing, then it may be necessary to examine the appearance at each stage in the difference calculations. An analogous situation is with traditional CIE color difference calculations. A color difference between two stimuli is calculated using one of the suggested formulas, such as ΔE_{94} or CIEDE2000, which provides an estimate for overall perceived differences between the stimuli. This does not provide an estimate as to what direction that change is. To see the direction of change it is necessary to examine the individual lightness, chroma and hue changes (ΔL, ΔC, Δh). The image appearance map provides insight into the overall magnitude of changes, but it does not show the directions causing the change. The individual image attributes must be examined to understand the root cause of the differences.

4. CONCLUSIONS

Image appearance extends the world of color appearance to account for complex spatial stimuli. Image quality can be thought of in terms of overall image appearance, whereas image quality is a function of several attributes such as color, sharpness, contrast, and graininess. As such, being able to accurately predict the appearance of an image should be useful as a method for also predicting overall image quality.

Several potential pitfalls in the prediction of image quality have been discussed. These are especially important to consider when using image independent metrics of quality, either based upon image systems parameters or models of the human visual system. The visual system constantly adapts to its environment and this includes the stimulus itself. It is crucial to consider this constant change in adaptation if we are ever to achieve the goal of an image quality metric that behaves as a human would. Example image appearance attributes such as graininess, contrast and sharpness, and how these attributes are influenced by the image content itself were given. These examples illustrate why it is important to consider image content when evaluating quality.

An image appearance framework, iCAM, and its use as a image quality metric was also discussed. Provisions for image dependent luminance, chromatic, and spatial frequency adaptation are included in this framework. The framework described was designed as an introduction to how an appearance model could be used to predict quality differences between two images. This method is also referred to as image quality modelling with a reference. Using image attributes such as perceived color appearance, contrast and sharpness as guidance, it may also be possible to use this type of model as a reference free quality metric. This would involve specific quantifications of all individual attributes, as well as an overall weighting of those attributes on image quality.

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