Abstract

This paper considers the intra-image color-space of an object or a scene when these are subject to a dominant single-source of variation. The source of variation can be intrinsic or extrinsic (i.e., imaging conditions) to the object. We observe that the quantized colors for such objects typically lie on a planar subspace of RGB, and in some cases linear or polynomial curves on this plane are effective in capturing these color variations. We also observe that the inter-image color sub-spaces are robust as long as drastic illumination change is not involved.

We illustrate the use of this analysis for: discriminating between shading-change and reflectance-change for patches, and object detection, segmentation and recognition based on a single exemplar. We focus on images of food items to illustrate the effectiveness of the proposed approach.

1. Background

This paper studies the intra-image color appearance of objects that are subject to a single process that alters their color properties. Specifically, we consider the existence and nature of the subspace of the color appearance of an object for which an unknown but a single intrinsic or extrinsic attribute varies across its surface. Intrinsic attributes include changes that cause variations in the spectrum of light wavelengths absorbed/ reflected under typical illumination. For example, baking changes the reflected wavelengths with respect to the uniform reflectance of dough. Extrinsic attributes are related to image formation including surface normal change, light absorption coincident with translucent objects, etc. Although these properties apply primarily to intra-image appearance we demonstrate some generalization to inter-image within-class objects as long as illumination does not significantly alter the color space.

We assume that object appearance takes on gradual change in reflectance properties when exposed to a single unknown process that is possibly challenging to quantify (e.g., baking dough). We focus on qualitative and empirical attributes.

Figure 1 shows exemplar images in which a single attribute varies in the object or its image formation leading to variations in reflectance. The hanging cloth simply reflects smooth-surface shading variations (i.e., surface normal variations), the sweater conveys surface-roughness variations (i.e., normal variations), the roast beef reflects different levels of cooking, the bok choy reflects different levels of Chlorophyll at the leaves and stems, the toasted bread conveys different levels of browning, the leaves show different levels of Chlorophyll withdrawals, the wood conveys different micro-structure variations due to growth patterns, the vase reflects different light transmission through glass, the foam reflects different coffee presence in a cappuccino drink, the sunset conveys variations in light transfer through clouds, the banana shows different levels of oxidation, and the bread rolls show different levels of browning in the baking process.

While the images in Figure 1 are visually diverse and each appears internally quite variable, the observation that there is a single dominant process that caused this variability led us to hypothesize that there is a compact subspace that reflects this single-cause variation in the image color patterns.

The contribution of the paper is in identifying a class of seemingly complex objects and scenes that can be represented economically using simple parametric models. Specifically, we show that a linear model is sufficient for representing color variations due to smooth and rough surface shading, and that cubic polynomials are sufficient for representing the colors of objects that have undergone physical or imaging change by a single process.

Although there are alternative methods for representing color variations of the images in Figure 1, (e.g., histograms), parametric models are more economic, well-constrained and readily support interpolation and extrapolation allowing generalization from exemplars. In contrast,
histograms have no interpolation or extrapolation power.

It is critical to note that we are considering single-process objects and images, and in many real-life images it is likely that multiple processes operate at once. For example, we will show that while the toasted bread in Figure 1 can be parameterized as a cubic polynomial in RGB space, if drastically different illumination is imposed, a different cubic polynomial may be needed to represent the colors of the same bread. We show, however, that for generic appearances of toasted bread (and baked goods in general) the model is reasonably robust. It remains open for research to convey, perhaps parametrically, how the parametric model of toasted bread changes under significantly variable imaging conditions in conjunction with normal variations in browning. At a minimum, it is possible to represent the diverse appearances of toasted bread under different illumination conditions as a set of polynomials which is more economic and effective than alternative representations.

2. Approach

All the images used in this paper were downloaded from the web and thus imaging conditions and camera parameters are unknown. We chose source images larger than 2MP, without blur and little JPEG compression degradation.

Let’s assume that an exemplar image, $I$, is of an object that has an unknown but uniform base material that was subjected to a single unknown process, $P$, that caused changes in its light reflectance properties. As Figure 1 shows there is a wide latitude in defining $P$. In some cases it is an absorption/scattering phenomenon (e.g., the vase and sunset), surface geometry (e.g., hanging cloth, sweater) while in others it is actual micro-structure material variations (e.g., the cooked and baked objects, bok choy, leaves, bananas).

The image of an object reflects a combination of the impact of the process $P$ and the imaging process. Unfortunately, these processes may be poorly understood or quantitatively challenging to model. However, qualitative descriptions derived from exemplar images may still be useful. It is critical to note that while some processes create simple sub-spaces of appearance, others do not and in this paper we show conforming processes only. We assume single-process variations under illumination that does not significantly alter the intra-object or inter-image appearance of an object. If multiple processes are involved the color appearance space remains open for research.

We treat RGB values as representatives of distinct spectral wavelength (i.e., red, green and blue), although cameras, in fact, normally output multi-spectral responses. The color sub-spaces within RGB may be as simple as a single point, line or curve or as complex as disjoint point clouds that require rich representations. We focus on line and curve subspaces and show that they capture the appearance space of certain classes of objects.

2.1. Preprocessing exemplar images

Determining the dimensionality of the RGB data (represented as a vector of 3D points) is done through eigenspace analysis to uncover if the data is one or two dimensional within the RGB space (i.e., a line or a plane, respectively). If the largest eigenvalue captures a very high percentage of the variation in the data then the data is considered to fit a straight line defined by the respective eigenvector in RGB space. Similarly, if the largest two eigenvalues capture most of the variations then the data lies on a 2D plane that is defined by the respective eigenvector directions in the RGB space. Let a Planarity Measure (PM) $= [v_1, v_2]$ express the amount of variation captured by the two largest eigenvalues, respectively. A value near 100% for $v_2$ indicates perfectly planar data.

An image typically consists of hundreds of thousands of distinct colors that create a point cloud in RGB space that in a raw form is not revealing. Instead, a reduction of the colors to a small representative sample improves our ability to assess the color variations of objects and scenes. There are numerous approaches to color reduction via quantization. We perform color quantization of the exemplar image into 256 colors using four approaches for evaluation purposes: Minimum Variance Quantization (part of Matlab), Octree Quantization, Median Cut, and K-Means. We found no visual differences in the quantization results. The computed 256 colors in each quantization were assessed for planarity and fitted as a cubic polynomial. Figure 2 shows the PMs and the fitted polynomials for the four approaches applied to the toasted bread image. Note that the octree curve is completely covered by the others. The planarity measure is very similar for all quantization methods, the data points are clearly planar since the largest two eigenvalues capture upwards of 99% of the variation. Therefore, we established that the planarity of the quantization is an attribute of the data and not a side effect of the quantization algorithms. In the rest of the paper the Minimum Variance Quantization
where the dot product and $R(x, y)$ is the reflectance of the surface (i.e., albedo in each color channel). This equation can be rewritten as:

$$I(x, y) = L(x, y) \times R(x, y) \quad (2)$$

where $L(x, y)$ is the incident illumination also known as shading. Equation 2 can be rewritten using the 3 RGB wavelengths as,

$$RED(x, y) = L(x, y) \cdot F_{red}(x, y)$$
$$GREEN(x, y) = L(x, y) \cdot F_{green}(x, y)$$
$$BLUE(x, y) = L(x, y) \cdot F_{blue}(x, y) \quad (3)$$

where $RED(x, y)$, $GREEN(x, y)$ and $BLUE(x, y)$ are the R, G, and B wavelength images and $F_{red}(x, y)$, $F_{green}(x, y)$ and $F_{blue}(x, y)$ are the spectral reflectance of pixels for each channel. The shading image is the same in the three equations since shading is independent of reflected wavelengths (i.e., scene material reflects all wavelengths in the same direction). As a result we have three equations with four unknown images.

If we assume an image of a uniform material in terms of reflectance (e.g., the hanging cloth, but not the toasted bread), the reflectance functions reduce to unknown albedo scalars $\alpha_{red}$, $\alpha_{green}$ and $\alpha_{blue}$ that can be determined up-to a scale parameter. It is clear from Equation 3 that it should pass through the origin (0, 0, 0) regardless of albedo values, therefore, equation 3 reduces to an equation of a line in 3D that passes through the origin:

$$\frac{RED(x, y) - 0}{\alpha_{red}} = \frac{GREEN(x, y) - 0}{\alpha_{green}} = \frac{BLUE(x, y) - 0}{\alpha_{blue}}. \quad (4)$$

This can be observed in Figure 4 (left) for the hanging cloth. Similar analysis can be applied to objects that have shading variations due to surface roughness (Figure 4 (right)), since they involve a different pattern of change in the surface normal (i.e., non smooth change over local spatial areas). The curves in Figure 4 are fit as cubic polynomial curves and not lines and therefore bending is visible. For the hanging cloth $PM=[97.47,99.42]$ and the sweater $PM=[99.01,99.74]$ suggesting a single vector is sufficient for describing the data.

The linear nature of shading colors suggests that it can be used to classify image patches into shading-change versus reflectance-change induced images [2]. Figure 5 shows planarity measures and the outlier pixels (marked in red) for different objects and imaging conditions. The top row shows color variations due to shading-change. From left to right it shows:

![Figure 2. PMs and fitted cubic polynomials for quantizations of the toasted bread image using Minimum Variance Quantization (red), Median Cut (green), octree (blue) and K-means (magenta).](image2)

![Figure 4. The quantized RGB values of the hanging cloth (left) and sweater (right) that reflect single variables, smooth surface shading (i.e., surface normal) and roughness shading which lie on a curve that can be approximated as a line.](image4)
Figure 3. Minimum Variance Quantization error for a set of images. The percentage of points at each Euclidean error distance between the original and approximated images are shown in a form of histograms.

Figure 5. PMs and outlier pixels for images that are shading-change or reflectance-change. Top row, shading-change examples for a clay cylinder, metal cylinder, cardboard, eggshell and human face. Middle row, fire, cake, grilled hot dogs and green/red pepper. Bottom row, palm leaf, yellow/white squash, sorbet ice cream and conic coral.

right, a gray clay cylinder, orange painted metallic cylinder, dented cardboard, egg-shell and part of a face (the last two are under strong illumination). The egg-shell matte surface leads to near perfect linearity with the largest eigen-vector capturing 99.54% of the variation in the data. The other objects also show similar behavior despite some interference of specular reflections (orange-painted metal object) and skin markings (for the face). The middle row shows examples where reflectance-change is the dominant factor. From left to right, images of fire, cake, grilled hot-dogs and green-red pepper. The PMs suggest that the colors are not linear since the top eigenvector captures less than 90% of the variations. The bottom row shows examples in which the data is more ambiguous. The left-most image shows part of a palm-leaf, and although the yellow-lines are presumed to result from different reflectance, the data is strongly linear and the colors appear to lie on the shading-change line as well. The yellow/white squash shows reflectance change, however it exhibits some linearity since the white pixels can also be interpreted as shading change of the yellow surface. The mango sorbet is expected to show just shading-change but due to specular reflections of the ice the first eigenvector captures only 91.28% of the variations. Finally, the conic coral surface is genuinely ambiguous, on one hand the shading change is evident in the first eigenvector capturing 96.74% of the variations, but the coral could also have experienced reflectance change (we could not determine the correct interpretation from the source image).

The examples in Figure 5 illustrate that diversity of visual interpretations may occur when context and auxiliary information (e.g., light direction) are absent. Nevertheless, it is clear that the likelihood of correct interpretation of shading versus reflectance changes is high and therefore it can be used as a basis for bottom-up image interpretation.

2.3. Browned and cooked foods

Browned foods are materials that were exposed to heat that altered their reflectance properties from initial uniform color to multiple shades of brown. Figure 6 shows several examples of browned foods: baked foods (baguette, toasted bread, baked soda bread, baked breaded eggplants), grilled meats (roasted beef, grilled pork meat and grilled tuna steak), and food exposed to hot oil (fried onion rings, seared chicken, scallops and fish cake). Clearly, a diverse appearance can result from this food processing. Humans easily recover important attributes of the scene such as the: initial material, process of cooking involved, quality of the food, freshness, etc. Some of these attributes are derived from prior experiences and therefore they are subjective. However, we conjecture that there are unique patterns to the appearance of such objects.

Figure 6 (bottom row) shows also plots of the quantized exemplars, their best-fit 3D plane and cubic polynomial curves fitting. It is apparent that materials that share a similar browning process tend to cluster in a relatively small
Plants are distinguished by their use of Chlorophyll to convert light to energy. The amount of Chlorophyll varies in different parts due to material properties, growth patterns and function for each part of the plant. The amount of Chlorophyll determines the reflected wavelengths, so that low concentrations lead to reflecting all light wavelengths, while high concentrations reflect mostly the wavelengths around green color. We observe that Chlorophyll acts as a single process that controls the reflectance of light, and therefore it is an example of a constrained color space. Figure 6 illustrates the planar and curve qualities for four sample images. Note that shadows, shading variations and specular reflections affect the analysis. The red pixels indicate points farther than $d_t$ from the polynomial fit. Nevertheless, the planarity of colors in each image is strong, and the joint planarity of all colors holds despite the diversity in the shades of green across the images.

### 2.5. Miscellaneous objects and scenes

Figure 7 illustrates a set of images that we presume that a single process is involved in creating the diversity of colors. The PMs suggest that the colors lie on a planar subspace. Polynomial fitting shows different degrees of adequacy. Images have few outlier pixels that are far from the curves so overall it appears that these curves provide a good abstraction to the color space in the images.

The sunset image is formed due to variable density of cloud cover and consequent absorption/scattering of light. The foreground regions (e.g., bird) are detected as outliers and the Sun is also an outlier since its distance is greater than $d_t$. The wood, cappuccino foam, and dyed hair show almost no outliers. The beer in the glass shows multiple processes at play. The primary process is the glass-thickness and beer volume that the light is passing through (observe light artifacts at the sides), other processes include the water condensation on the surface of the glass and the image formation causing specular reflections. The vase outliers primarily occur at specular reflections. The fire outliers appear at extreme brightness and are due to the inadequacy of cubic fit. The green/yellow banana outliers are due to secondary browning process and the wave outliers are due to poor cubic fit.

### 2.6. Outliers

Points that are farther from the curve than the threshold $d_t$ are considered outlier points and stem from:

- **Background.** Pixels that are clearly due to patches that do not belong to the object (e.g., center-top area of the baked eggplants in Figure 6 belongs to the plate).

- **Independent processes.** Interference of independent processes from the primary process. For example, specular reflections and poorly illuminated pixels tend to be classified as outliers since they involve a second independent process (e.g., image formation artifacts).

- **Boundary conditions.** The cubic polynomial fitting imposes boundary conditions that are not perfectly aligned with the object reflectance or image formation. This typically occurs at the locations where the polynomial exits the RGB space (e.g., sunset and fire images in Figure 7).

- **Compression.** Block Compression artifacts that accompany JPEG occasionally bias the pixel values and affect the...
Figure 6. Baguette, toast, bread, breaded eggplants, beef, pork and tuna, fried onion rings, tofu, seared chicken, seared scallops and fish cake followed by plants. Outliers shown in Red and Green as well as PMs, joint PMS, fitted planes and polynomials.

Figure 7. Sunset, wood, cappuccino, dyed hair, beer in a class, vase, fire, bananas (greenish and browning), and an ocean wave. The respective curve fit for colors in image image. In the bottom image the outlier points to the curve (measured by a fixed distance threshold equal for all images) are shown in green or red colors.

distribution of colors.

3. Detection and segmentation

The hypothesis that some objects and scene colors cluster in a highly reduced dimensionality is useful for image understanding. However, this compact representation is not invariant to significant illumination changes in which case polynomials change shape and location in RGB space, while maintaining their polynomial prototype. Nevertheless, an exemplar material can be used to search for similar materials in images as long as the color variations are within $d_t = 25$ with respect to the subspace represented by the polynomial fit to the quantized colors of the exemplar.

Let $POLY$ represent the exemplar polynomial, and $(R_x,y, G_x,y, B_x,y)$ be the color value at $(x,y)$ in the probe image. We employ two steps for detection of color distributions that conform to the exemplar:

**Step I**: A pixel in the probe image is conforming if:

$$D((R_x,y, G_x,y, B_x,y), POLY) < d_t$$  

where $D$ represents the closest Euclidean distance between
the point and the points of \( POLY \).

**Step II:** For a spatially-contiguous region \( M \) in the probe image, the set of corresponding closest points of \( POLY \) is computed and labeled as \( S \). We define \( M \) to conform to the exemplar if

\[
L(S) > l_t
\]

where \( L \) is the length of the segments of \( POLY \) that the points in \( S \) cover (a threshold \( l_t = 10 \) is used so that only points in \( S \) that have a greater number of votes than \( l_t \) are used). In the experiments below we use \( l_t = 150 \). Effectively, this means that only if a significant portion of the points of \( M \) are spread-out over \( POLY \) is \( M \) considered conforming to the exemplar. The correspondence between \( M \) and \( POLY \) is to any part of the space defined by \( POLY \) (subject to exceeding \( l_t \)).

Figure 8 shows a large set of example detections and segmentation of materials based on single exemplars shown at the left side of each row. The input image is shown above the detection image. The pixels in Red/Green depict outlier pixels to the exemplar model. In the first row the exemplar bok choy is used to detect a variety of vegetables that have different range of green colors. An example of cooked greens (broccoli) as well as ones covered by a salad dressing are shown in addition to raw vegetables. Similarly, examples for baked food are detected based on a toasted bread exemplar, fried foods are detected based on an exemplar of fried Tofu, grilled foods are detected based on a grilled pork exemplar, bananas are detected based on green/yellow exemplar and finally fires are detected based on an exemplar of flames. Note that in the presence of white plates, in grilled and fried food the white parts of the plate were detected since the color is close to the exit point of the polynomial. A similar event happens in very dark areas. Both can be reduced by either limiting the extrapolation of the representation or pre or post processing.

The examples in Figure 8 show that despite the use of a single exemplar the modeling approach is effective in capturing the essence of the variation in appearance. The combination of interpolation, extrapolation and enforcing a minimal length of the model to be matched enhances the detection and reduces outliers. The images are taken under diverse illumination, indoor and outdoor scenes. While the representation currently does not account for illumination change it is evident that a measure of robustness is already embedded in the representation.

4. Recognition

The color-subspace representation supports recognition and aesthetic evaluation of objects with respect to the exemplar. Given a probe image we calculate how well its raw colors project on the polynomial curve via a tighter measure than \( L(S) \) in Equation 6. Specifically, this measure uses an adaptive threshold \( l_s \) (taking into outlier ratio with respect to the length of \( POLY \)) instead of a fixed scalar. Figure 9 shows examples of baked goods (top row), fried foods (middle row) and green/yellow bananas. The baked and fried food images are matched against the exemplar of the toasted bread, while the banana images are matched against the exemplar of green/yellow bananas (see exemplars in Figure 8). Distinguishing between baked and fried food is a challenging objective that involves recovering subtle visual cues (e.g., specular reflections of leftover oil, pattern of browning that indicates frying on a flat surface or deep frying, etc.).

In Figure 9 most scores of baked foods are high with the highest values corresponding to objects that have wide distributions of colors that match strongly the color spectrum of the exemplar image. The saltines (right most image) is the exception since the colors are more clustered and cover only small part of the curve. The middle row shows results for fried and grilled food compared against the baking exemplar. Some objects easily pass for baked foods (the left most 7 objects). The fried bread (sixth image form the left) is similar to the exemplar and clearly subtle cues are needed to make the classification. The scores of the five objects at the right are low and they are not classified as baked. The bottom row shows the results of different yellow/green bananas. The highest scores are given to bananas that have similar color characteristics to the exemplar shown in Figure 8. The images on the right show different color patterns and receive low scores.

5. Summary

This paper proposed that a single process tends to create gradual changes in color appearance of objects and as a result a subspace of RGB can represent this information. The paper did not address the impact of illumination variations, but illustrated using web images that well-illuminated scenes of familiar objects tend to be close to subspace representations derived from exemplars.

The color representation via polynomials naturally interpolates and extrapolates from limited color samples. The parametric representation allows recognizing colors that do not occur in the exemplar colors of the object. Thus, providing a clear advantage with respect to other representations where unobserved data is not accounted for.

The representation enables determining whether a set of pixels matches a significant part of the exemplar polynomial. Therefore, the degree of correspondence between a set of spatially coherent pixels in the probe image and the exemplar polynomial determines if a region complies with exemplar characteristics. For example, different toasts of bread lead to different color distributions. However, as long as the distances between the probe pixels and the exemplar
Figure 8. Detections using one exemplar (shown at the left of each row). Plant colors, baked, fried and grilled food, yellowing bananas and fire.

Figure 9. Recognition and evaluation of appearance with respect to the toasted bread (top two rows) and bananas. The top row has baked food while the middle row has fried foods. Below each image we show the distance.
are small and sufficient segment of the closest points on the polynomial is found than it is likely that image is that of toasted bread.

References

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