

Shading and Highlight Invariant Color Image Segmentation

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ABSTRACT

A new color image segmentation algorithm is presented in this paper. This algorithm is invariant to highlights and shading. This is accomplished in two steps. First, the average pixel intensity is removed from each RGB coordinate. This transformation mitigates the effects of highlights. Next, the Mixture of Principal Components algorithm is used to perform the segmentation. The MPC is implicitly invariant to shading due to the inner vector product or vector angle being used as similarity measure. Since the new coordinate system contains negative numbers, it is necessary to modify the MPC algorithm since in its original form it does not distinguish between positive and negative color space coordinates. Results on artificial and real images illustrate the effectiveness of the method. Finally, the use of the total within-cluster variance is investigated as possible criterion for selecting the number of clusters for the new algorithm.

Note: This report is an overview of the work published in [16] which was carried out while I was a Foreign Researcher in [Prof. Tominaga's lab](#) at the Osaka Electro-Communications University on an IEEE NNC scholarship.

PROBLEM STATEMENT

In recent years, color constancy - the perception of objects in the real world without illumination effects - has been a major concern in the research community of image science and technology. Humans perceive object surfaces in a scene in spite of shading and highlight effects. Can machines do a similar feat?

METHOD

Introduction

This project resulted in devising an algorithm for color image segmentation which is invariant to shading and highlight effects. The Dichromatic Reflection Model [11] is a useful tool for modeling light reflection, which causes essential illumination effects. It is used in this paper as the theoretical foundation.

In this project, the Mixture of Principal Components (MPC) algorithm was further examined. This method has already been analyzed previously within an unsupervised color image segmentation task [14]. The MPC is similar in nature to the k-means algorithm [7] except that the Euclidean distance measure has been replaced by the vector angle (or inner vector product) and the cluster prototype previously represented by the vector mean of all cluster points becomes the principal eigenvector corresponding to the largest eigenvalue of the covariance matrix of those cluster points. It has been shown that the use of the vector angle within the MPC makes this method implicitly shading invariant [15]. In this paper, we introduce a transformation to extend the result of MPC clustering to highlight invariance based on the Dichromatic Reflection Model.

Dichromatic Reflection Model

The Dichromatic Reflection Model (DRM) was introduced by Shafer [8,13]. The basic premise behind this model is that light is reflected in two distinct components: specular reflection and diffuse reflection. This model has since been expanded for a variety of materials [11]. In this paper, the focus will be on inhomogenous dielectric materials such as plastics. The presentation of the DRM follows closely that given in [12].

Light reflected from an object surface (called the color signal) is described as a function of pixel location x and wavelength λ :

$$C^o(\lambda, x) = \text{body reflection} + \text{interface reflection} \quad (1)$$

$$C^o(\lambda, x) = \alpha(x)S^o(\lambda)E(\lambda) + \beta(x)E(\lambda)$$

where $E(\lambda)$ is the spectral power distribution of a light source, $S^o(\lambda)$ is the spectral-surface reflectance of an object o , $\alpha(x)$ is the shading factor and $\beta(x)$ is a scalar factor for the specular reflection term. The sensor responses R , G , and B for a camera can then be represented using the following set of equations

$$\begin{bmatrix} R \\ G \\ B \end{bmatrix} = \int C^o(\lambda, x) \begin{bmatrix} R_R(\lambda) \\ R_G(\lambda) \\ R_B(\lambda) \end{bmatrix} d\lambda \quad (2)$$

where $R_i(\lambda)$ ($i=R,G,B$) are the spectral sensitivity functions of the camera in the visible spectrum. Substituting (1) into (2), we have

$$\begin{bmatrix} R \\ G \\ B \end{bmatrix} = \alpha(x) \int S^o(\lambda)E(\lambda) \begin{bmatrix} R_R(\lambda) \\ R_G(\lambda) \\ R_B(\lambda) \end{bmatrix} d\lambda + \beta(x) \int E(\lambda) \begin{bmatrix} R_R(\lambda) \\ R_G(\lambda) \\ R_B(\lambda) \end{bmatrix} d\lambda = \alpha(x)\bar{c}_b + \beta(x)\bar{c}_i \quad (3)$$

where \vec{c}_b is the body color vector and \vec{c}_i is the illumination color vector. These color vectors are normalized into a unit vector length. If the sensor outputs R, G, and B are balanced for a white surface, then we have

$$\int E(\lambda)R_R(\lambda)d\lambda = \int E(\lambda)R_G(\lambda)d\lambda = \int E(\lambda)R_B(\lambda)d\lambda \quad (4)$$

As long as the illuminant $E(\lambda)$ is white with a constant over the visible wavelengths and the spectral sensitivity functions $R_i(\lambda)$ ($i=R,G,B$) have the same area, the above condition obviously holds. However, if the illuminant is not white, a color balancing step is needed where the three sensor outputs are adjusted to be equal to each other. This is explained in [16].

Highlight Invariance

The image data including such illumination effects as shades, shadows, and specular highlight are transformed into the following coordinates:

$$R' = R - \text{AVG}$$

$$G' = G - \text{AVG}$$

$$B' = B - \text{AVG}$$

where the (R, G, B) values are the sensor outputs with white balancing and AVG represents the average over the spectrum of R, G, and B at a particular pixel location. A similar transformation is presented in [12]; however, the normalization step is not needed here due to it being implicitly part of the MPC algorithm. The above transformation decreases the effect of the interface reflection term. The transformed R'G'B' histogram then consists of a single linear cluster for the same object surface.

By averaging RGB pixel values over three channels and subtracting this value from each component, the interface reflection term will be eliminated since the condition of equation 3 holds as

$$\begin{bmatrix} R' \\ G' \\ B' \end{bmatrix} = \alpha(x) \int S^o(\lambda)E(\lambda) \begin{bmatrix} R_R(\lambda) \\ R_G(\lambda) \\ R_B(\lambda) \end{bmatrix} d\lambda - \frac{1}{3} \alpha(x) \int S^o(\lambda)E(\lambda) \begin{bmatrix} R_R(\lambda) + R_G(\lambda) + R_B(\lambda) \\ R_R(\lambda) + R_G(\lambda) + R_B(\lambda) \\ R_R(\lambda) + R_G(\lambda) + R_B(\lambda) \end{bmatrix} d\lambda$$

$$\begin{aligned}
\begin{bmatrix} R' \\ G' \\ B' \end{bmatrix} &= \alpha(x) \int S^o(\lambda) E(\lambda) \begin{bmatrix} (2R_R(\lambda) - R_G(\lambda) - R_B(\lambda))/3 \\ (-R_R(\lambda) + 2R_G(\lambda) - R_B(\lambda))/3 \\ (-R_R(\lambda) - R_G(\lambda) + 2R_B(\lambda))/3 \end{bmatrix} d\lambda \\
&= \alpha(x) \int S^o(\lambda) E(\lambda) \begin{bmatrix} R'_R(\lambda) \\ R'_G(\lambda) \\ R'_B(\lambda) \end{bmatrix} d\lambda
\end{aligned} \tag{5}$$

The scale factor $\beta(x)$ for the interface reflection term has been eliminated. Moreover, the above color coordinate transformation leads to a linear transformation of the spectral sensitivity functions of the camera. Thus, the new representation will be highlight-invariant.

The Mixture of Principal Components Algorithm

For completeness, the Mixture of Principal Components (MPC) algorithm is presented here [1]. It has been presented earlier for the purpose of color image segmentation in [14,15]. This algorithm was adapted for color image segmentation since for color clustering the vector angle cannot be substituted directly for the Euclidean distance in the k-means algorithm [15].

Figure 2 illustrates the modular architecture of an MPC network for a single basis vector per class. Each module consists of a basis vector and represents a class of the input data. If a single color vector is used for clustering within each module, it will be made up usually of three values. For multispectral images, there will be a corresponding increase in size of the basis vector.

A basis vector corresponds to the principal eigenvector of the covariance matrix of a given class. The input vector, $\vec{x} \in \mathfrak{R}^N$, is linearly transformed by each of the K modules resulting in K coefficients, y_1, y_2, \dots, y_K . A one-dimensional linear subspace is defined by each single basis vector, \vec{w}_i , contained in the corresponding module. So, if \vec{w}_i is of dimension N , the coefficient y_i is calculated as

$$y_i = \vec{w}_i^T \vec{x} \tag{6}$$

The raw inner vector product is used instead of the vector angle form to compute the distance between the cluster centers and the data because the normalization of the result is done implicitly by the classifier. That is, since $\|\vec{w}_i\|=1$ and $\|\vec{x}\|$ is constant across all i , the vector angle formula reduces to equation 6. The classifier chooses the output of the winning module based on the subspace classifier

$$\arg\{\max_i(y_i)\} \tag{7}$$

The difference with [1] and [14] is that the norm of y_i is not calculated since we are now interested in differences in the sign of the coefficient. This unfortunately limits the use of the

MPC to only finding the first principal component under the current framework. For a network with unit norm basis vectors, this classifier is equivalent to minimizing the vector angle between \vec{w}_i and \vec{x} . The color spaces (either RGB or R'G'B') are considered to have their origin fixed at (0,0,0). The learning algorithm finds the principal eigenvector for each class with respect to the origin [1,2].

To compute the principal components while refining the class definitions, an iterative algorithm is employed:

1. Choose the number of classes, K .
2. Initialize the K principal components, $\vec{w}_1, \vec{w}_2, \dots, \vec{w}_K$, to some appropriate set of values.
3. Classify a data point using the subspace classifier (minimum vector angle) using equations 6 and 7
4. Modify the basis vector, \vec{w}_i , of the winning class using a Hebbian neural network algorithm which extracts the class principal component [2] according to the following equation

$$\vec{w}_{i,j+1} = \vec{w}_{i,j} + m \cdot y_{i,j} \cdot (\vec{x}_j - y_{i,j} \cdot \vec{w}_{i,j}) \quad (8)$$

where m is a learning parameter and \vec{x}_j is a training vector at iteration j (the basis vectors \vec{w}_i and the coefficient y_i are also iteration dependent).

5. If no convergence, go to 3, else stop

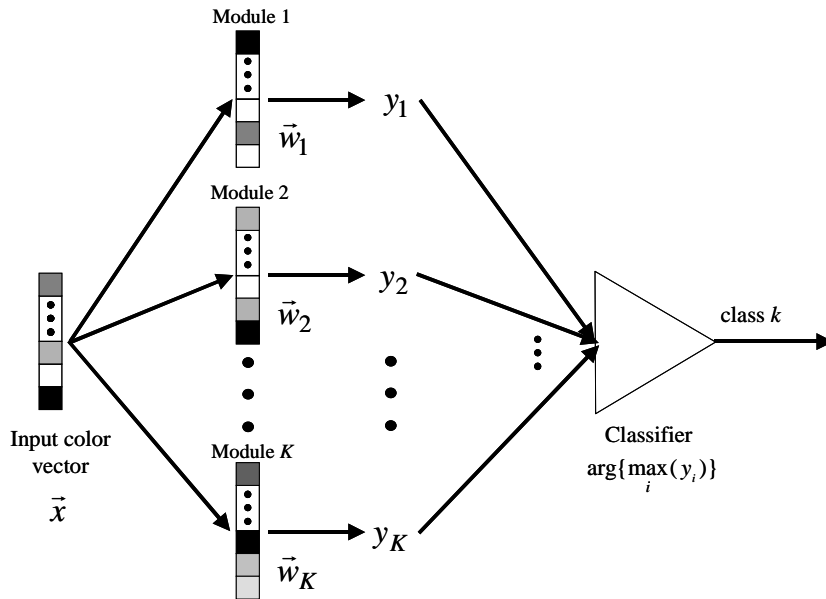


Figure 2: MPC network with K classes

This algorithm could also be represented in a batch form just like the k-means algorithms. However, instead of computing the class means the algorithm would compute the covariance matrix of the cluster and then obtain the principal eigenvectors of each of the covariance matrices.

In [16], the process of when to stop the clustering using The Within Cluster Variation (TWCV) is explained in detail.

RESULTS

The feasibility of this approach is demonstrated two fold. An artificial computer graphics image made up of several object surfaces with highlight parts was constructed and analyzed with this transformation (this is presented in detail in [16]). A real scene image with fruits is demonstrated here. The color image segmentation results are evaluated quantitatively using the TWCV measure and qualitatively. The black background (i.e., achromatic) region in the real image is removed using an experimentally determined threshold for the purposes of chromatic clustering (a threshold of 5 for the image in R'G'B' and a threshold of 10 for the image in RGB). Given that white light was used in capturing the image, the white balancing transformation matrix \mathbf{T} was the identity matrix.

Figure 3 shows that for all practical purposes all traces of highlights are subsumed into the corresponding color regions. The histograms for the image in the RGB and the R'G'B' spaces confirm the qualitative results since as can be seen the clusters are nearly linear in the R'G'B' space while this is not the case for the same clusters represented in the RGB space (see Figures 4 & 5). Therefore, it could be said that the R'G'B' space provides an appropriate tool for modeling highlights in color images for the purpose of image segmentation with color constancy.

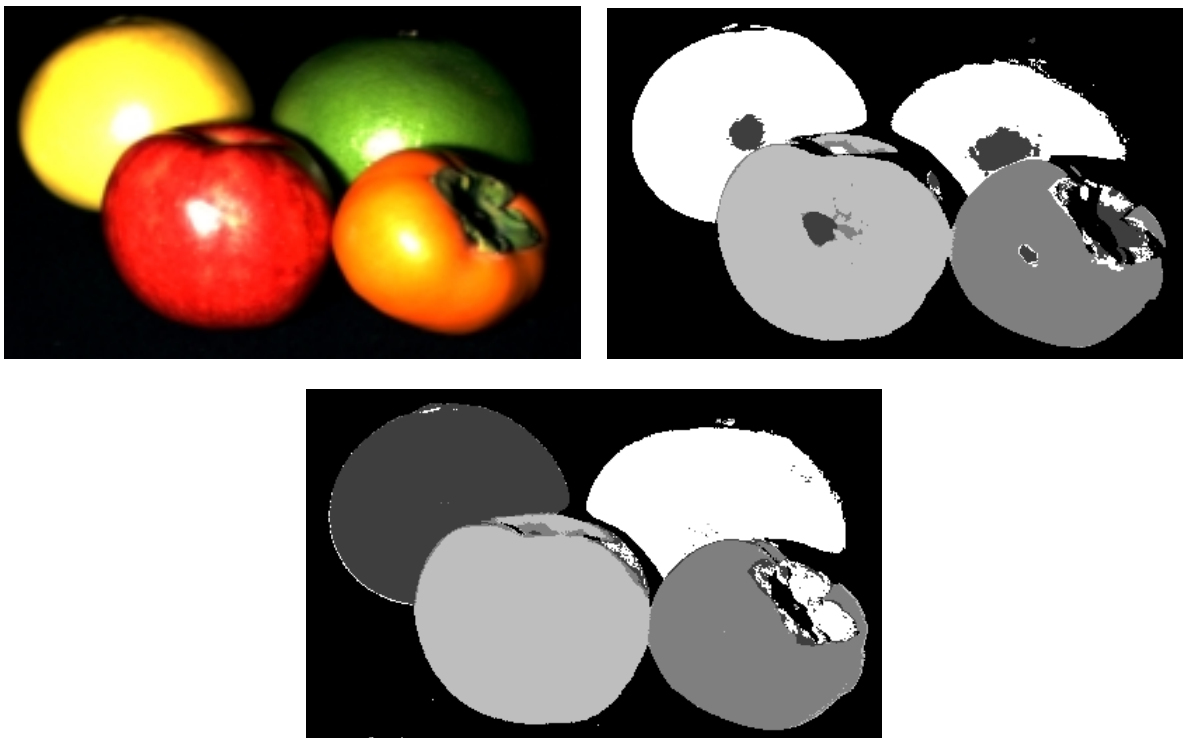


Figure 3: Color image segmentation of fruit image (original, RGB using MPC, R'G'B' using MPC)

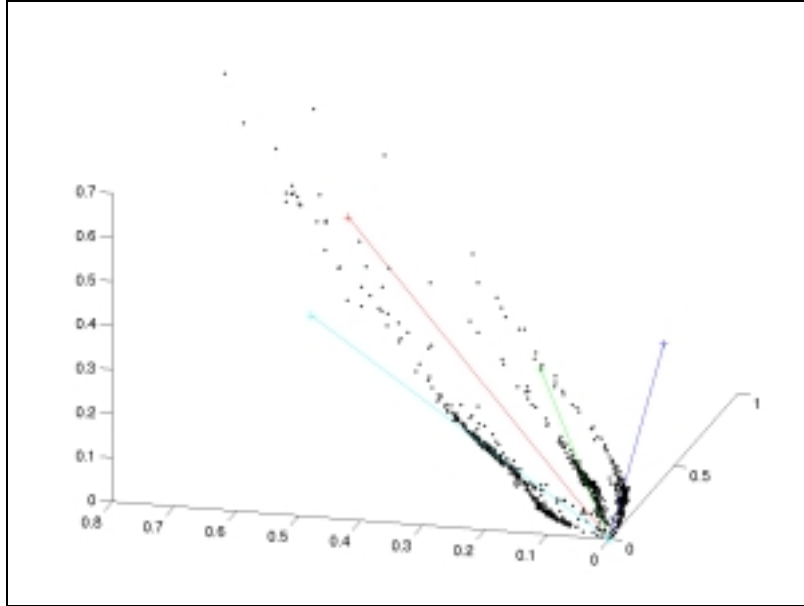


Figure 4: Color histogram of RGB image in Fig. 4 with vectors from MPC classification

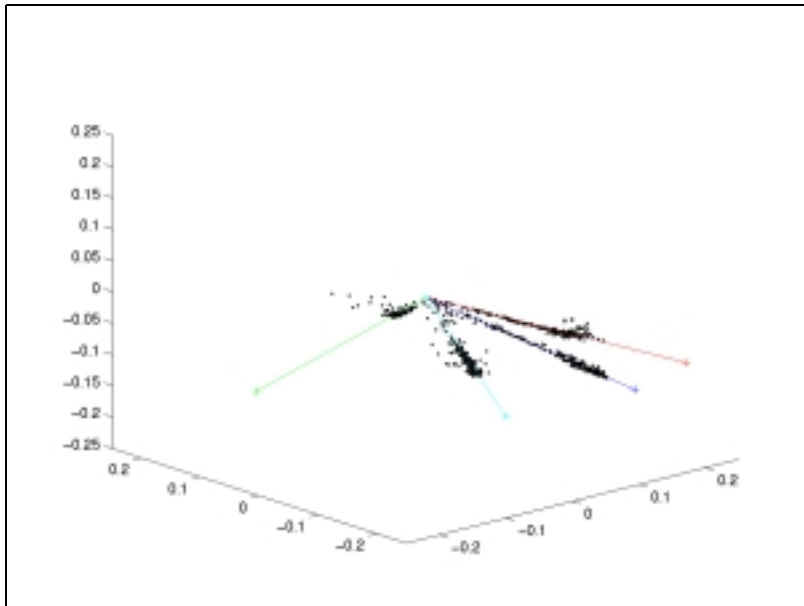


Figure 5: Color histogram in R'G'B' of image in Fig. 4 with vectors from MPC classification

CONCLUSIONS

A new highlight invariant transformation has been introduced. This transformation coupled with the Mixture of Principal Components algorithm is able to cluster colors irrespective of highlights and shading under the condition of white balancing. The results obtained with the new color space / MPC clustering algorithm were analyzed qualitatively and quantitatively. Further research in this area especially concerning the problems caused by small R'G'B' values, as well as illumination color changes is being carried out.

The main problem associated with this method is that a special algorithm will be needed to deal with achromatic image regions. Also, this algorithm does not work for images where highlight regions have been saturated and therefore appear as achromatic regions in the image. Both of these problems are currently being addressed.

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