# DIFFERENCES OF EDGE PROPERTIES IN PHOTOGRAPHS AND PAINTINGS

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**ABSTRACT**

*We compare the properties of intensity and color edges in photographs of real scenes and paintings. We demonstrate that paintings contain significantly more color-only edges, whereas the amount of intensity-only edges does not differ significantly between the two classes. In addition, color edge strength is significantly higher for paintings. The differences between paintings and photographs are more accentuated when high-resolution, losslessly compressed images are used. These distinguishing features can be used for the automatic differentiation between the two classes of images.*

## 1. INTRODUCTION

The following question is addressed: are there any systematic differences in the properties of intensity and color edges between photographs of real scenes and paintings? Research on edge detection has focused primarily on intensity (gray-scale) images, and only secondarily on finding edges in color images. Even less studied is the relation between intensity and color edges in the same image; several older studies [1, 2] suggest that more than 90% of edges are the same in grayscale and color images. We will show that photographs and paintings differ in the relation between intensity and color edges, and that this difference is significant enough to permit automatic differentiation between these two image classes. In previous work [3] we addressed the problem of automatically differentiating photographs of real scenes from photographs of paintings. We found that photographs differ from paintings in their color, edge, and texture properties. Based on these features, we trained and tested a classifier on a database of $6,000$ paintings and $6,000$ photographs, achieving discrimination rates of over $90\%$. The present paper extends this study by analyzing in detail the edge properties of the two image classes.

## 2. MAIN HYPOTHESIS OF THE PAPER

Edges are essential image features, in that they convey a large amount of visual information. Edges in photographs are of many different types: occlusion edges, edges induced by surface property (texture or color) changes, cast shadow edges. In most cases, however, the surfaces meeting at the edge have different material or geometrical properties, resulting in a difference in the intensity (and possibly color) of the reflected light. One exception to this rule is represented by edges delimiting regions painted in different colors on a flat surface—as on billboards or in paintings on building walls for example; in effect, such cases are paintings within photographs of real world scenes. On the contrary, in paintings, adjacent regions tend to differ in their hue, change often not accompanied by an edge-like change in image intensity.

The above observations led to the following hypotheses:

(1) Perceptual edges in photographs are, largely, intensity edges. These intensity edges can be at the same time color edges and there are few color-only edges – color, not intensity edges.

(2) Many of the perceptual edges in paintings are color-only edges, as they result from color changes that are not accompanied by concomitant edge-like intensity changes.

These conjectures will be examined in the remainder of this paper.

## 3. METHOD

### 3.1. Test images

Two image databases were used. The first dataset contained over 12,000 JPEG images with various compression rates and average resolution of $500 \times 500$ pixels and no restrictions imposed on the content. Half of this image set were photographs and half were images of paintings from the Indiana University Digital Library collection. The second set contained over 100 high-resolution ($2500 \times 2500$ pixels) images taken with a high-end digital camera. Half were photographs of several real world scenes, including architecture, plants and landscapes. The other half were photographed oil paintings from Indiana University Art Museum's collection, ranging from impressionism to baroque. The images were compressed using the lossless PNG technique, thus being identical to the original uncompressed images. Non-lossy compression was used since we were interested in the characteristics of the fine color image details, namely, color edges. We found JPEG images to be inadequate for the purposes of our study due to the color information reduction that the JPEG algorithm causes. Most JPEG generators convert the color data from RGB to a system that identifies the brightness of each pixel [4]. One such system is known as HSL (Hue-Saturation-Luminance). Once the conversion is made, the first data reduction takes place in a process called subsampling. The brightness scale is left alone, while half of the other two scales are eliminated by replacing two neighboring pixels with a single value representing their average. The next step, performing a discrete cosine transform (DCT), works on 8 by 8 blocks and applies equally to all channels. Therefore JPEG compression reduces the hue and saturation information of a color image to a larger extent than it does the intensity information. As a result, the hue and saturation channel images acquire a blocky appearance that results in artifacts in the color edges. The intensity edges are affected to a lesser extent, and thus the relation between the color and intensity edges of the original image is altered.

### 3.2. Edge Extraction

Two types of edges were extracted and analyzed for both photographs and paintings: pure color edges and intensity edges. The scale of the edge filters was at a pixel level accuracy (for the high resolution paintings varying from $0.5$ to $1$ millimeters in the original painting).

#### 3.2.1. Pure color edges

To obtain the *pure color* edges (which means color-edges detected on the de-intensified color image) each RGB image was first converted to HSI space, with hue (H) and saturation (S) channels representing color information and intensity (I) corresponding to brightness, as follows [5]:

$$\begin{aligned} H(R,G,B) &= \arctan\left(\frac{\sqrt{3}(R-B)}{(R-G)+(R-B)}\right), \\ S(R,G,B) &= 1-\frac{\min(R,G,B)}{R+G+B}, \\ I(R,G,B) &= 0.299R+0.587G+0.114B. \end{aligned}$$

The intensity channel was set to a constant value, identical for all pixels to make sure that no intensity information can possibly influence the color edge filter's performance. Then, the image was converted back to RGB space, resulting in a "de-intensified" version of the original color image. Figure 1 displays an example of an image with the intensity information removed by this technique. The de-intensified image contains no intensity edges, and its color edges are therefore pure color edges.

To extract pure color edges a gradient-based color filter, described in [6], was applied to the de-intensified image. For each of the R, G and B channels, the image derivative in the horizontal, vertical and two diagonal directions was computed.

At each pixel the maximum value of the gradient was chosen. The edge map for each channel was obtained by thresholding edge intensity image, with pixels valued above some $T$ being edge pixels and the rest being non-edge pixels. $T$ was chosen so as to maximize the sum of the entropies for two pixel classes: edge-pixels and non-edge pixels. Finally, an overall edge map was obtained by combining edge map for separate channels using logical $OR$ operator.

**Fig. 1**. Removing intensity information from a color image. *(Left:)* Original image *Right:* De-intensified image (all pixels are of equal intensity)

#### 3.2.2. Intensity edges

The edges of the images were obtained by converting the RGB images to gray-scale and applying the Canny edge detector.

### 3.3. Quantifying the relation between pure color and intensity edges

Consider a color input image – photograph or painting. Let $E_c$ denote the set of pure color edge pixels and $E_g$ denote the set of intensity edge pixels obtained as described in Section 3.2 .

Consider the edge pixels that are pure color edge but not intensity edge: these edge pixels will be termed *color-only* edges.

Let $e_{c\setminus g}$ denote the fraction of the total number of edge pixels in the image that are color-only:

$$e_{c\setminus g} = \frac{|\{E_c \setminus E_g\}|}{|\{E_c \cup E_g\}|}. \quad (1)$$

$A \setminus B$ denotes set difference of sets A and B and $|S|$ denotes the cardinal of set S.

Similarly, the fraction of the edge pixels that are intensity edge but not pure color edge is called *intensity-only* and is given by:

$$e_{g\setminus c} = \frac{|\{E_g \setminus E_c\}|}{|\{E_c \cup E_g\}|}. \quad (2)$$

## 4. EXPERIMENTAL RESULTS

### 4.1. Color-only and intensity-only differences between photographs and paintings

The test images described in Section 3.1 were processed as outlined above and the following results were obtained. The most obvious differences between paintings and photographs were observed on the high resolution images (Table 1). $e_{c\setminus g}$ is on the average larger for paintings, while $e_{g\setminus c}$ is on the average larger for photographs. As can be seen in the Table, the difference between the mean is significant considering the standard deviations of the quantities. Another distinguishing feature is the amount of each type of edge pixel normalized by the total number of pixels in the image (the quantities $|E_{c,g}|/|A|$ in Table 1). The gradient color edge detector, applied with the same parameters to the images from both classes finds almost eight times more pure color edge pixels in paintings than in photographs. The difference between the means $\mu(|E_{c,g}|/|A|)$ is more than three times the largest of the two standard deviations $\sigma(|E_{c,g}|/|A|)$.

| | paintings | photographs |
|---|---|---|
| $\mu(e_{c\setminus g})$ | 0.8166 | 0.4991 |
| $\mu(e_{g\setminus c})$ | 0.1522 | 0.4301 |
| $\sigma(e_{c\setminus g})$ | 0.1153 | 0.0874 |
| $\sigma(e_{g\setminus c})$ | 0.0921 | 0.0895 |
| $\mu(\|E_c\|/\|A\|)$ | 0.1136 | 0.0147 |
| $\mu(\|E_g\|/\|A\|)$ | 0.0152 | 0.0130 |
| $\sigma(\|E_c\|/\|A\|)$ | 0.0423 | 0.0057 |
| $\sigma(\|E_g\|/\|A\|)$ | 0.0125 | 0.0053 |

**Table 1**. Results for the hi-res PNG database. $\sigma$ denotes standard deviation, $\mu$ denotes mean

On the images of lower resolution (500 by 500 pixels) in lossy JPEG format (see Table 2), the difference between classes is still evident although is slightly reduced. In high quality paintings the percentage of color edges normalized by the image size $|E_c|/|A|$ is 11.36%, whereas in low quality JPEG images just 7.36%, which reflects the fact that finer edges corresponding to brush strokes are "blurred away" by the compression algorithm and reduced resolution. The increase in the percentage of color edges in photographs (almost 5% in JPEG comparing to only 1.5% in PNG) can be explained by the artifact 8x8 pixel block structure created by the JPEG algorithm for the higher compression rates. We

| | paintings | photographs |
|---|---|---|
| $\mu(e_{c\setminus g})$ | 0.5729 | 0.4701 |
| $\mu(e_{g\setminus c})$ | 0.3183 | 0.4426 |
| $\sigma(e_{c\setminus g})$ | 0.1689 | 0.1717 |
| $\sigma(e_{g\setminus c})$ | 0.1651 | 0.1821 |
| $\mu(\|E_c\|/\|A\|)$ | 0.0736 | 0.0490 |
| $\mu(\|E_g\|/\|A\|)$ | 0.0394 | 0.0130 |
| $\sigma(\|E_c\|/\|A\|)$ | 0.0490 | 0.0399 |
| $\sigma(\|E_g\|/\|A\|)$ | 0.0189 | 0.0053 |

**Table 2**. Results for the low-res JPEG database. $\sigma$ denotes standard deviation, $\mu$ denotes mean

found that in photographs the color and intensity edges tend to coincide, while in paintings there are significantly more color edge pixels than intensity ones (see Figure 2).

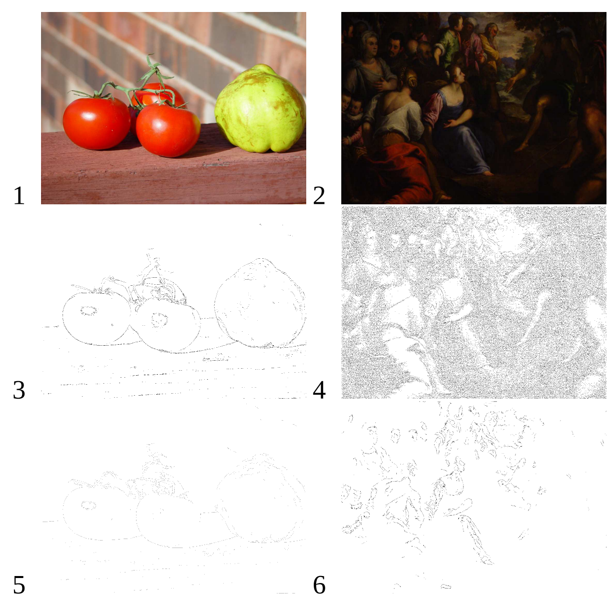


**Fig. 2**. *(1)* Photograph *(2)* Painting *(3)* Color edges in photograph *(4)* Color edges in painting *(5)* Intensity edges in photograph *(6)* Intensity edges in painting

### 4.2. Color edge strength in paintings and photographs

We compared the strength of the color edges in the two image classes. The results are illustrated in Figure 3, which displays the distribution of the color edge pixels as a function of edge strength. We found that there are more color-smooth areas in photographs, i.e areas where color edge intensity is zero. These areas usually correspond to walls and other smooth objects n the indoor scenes, sky in the photographs of nature and are not realistically represented by artists, because the roughness of the painting tools (brushes) often creates unnatural edges in the areas indented to be smooth. We also found that there are more abrupt edges in photographs, i.e sharp changes in color in very short spatial interval (this corresponds to color edge intensity $> 200$ in the plot in Figure 3).

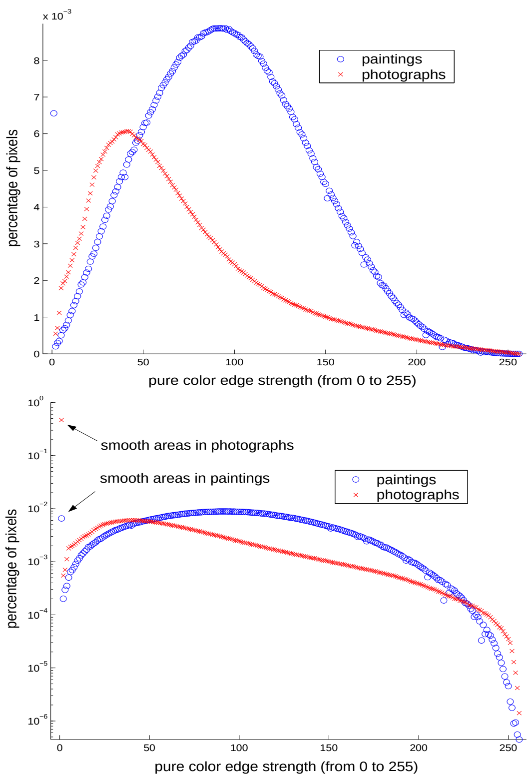


**Fig. 3**. Distribution (histogram) of the edge pixels as a function of edge strength. "o": paintings; "x": photographs. *Top:* Linear scale. *Bottom:* Log scale. Horizontal axis: color edge strength. Vertical axis: fraction of image pixels that are color edge pixels. Each point in the graphs represents the average over the painting, respectively, photograph set.

### 4.3. Intensity edges in paintings and photographs are structurally similar

We examined the spatial variation of image intensity in the vicinity of intensity edges in paintings and photographs. The intensity edges were determined by applying the Canny edge detector to both paintings and photographs followed their conversion to gray-scale. We examined the 1-D change of image intensity along a direction orthogonal to the intensity edge (i.e. along the image gradient), on a distance of 20 pixels of either side of the edge. We did not find significant differences between paintings and photographs in the shape of these image intensity profiles.

## 5. SUMMARY AND CONCLUSIONS

We found that photographs and paintings (even realistic) differ substantially in their edge properties. These differences were quantified, and our results indicate that they can be effectively used to automatically differentiate paintings from photographs. In a photograph of a real-world scene, the variation of image intensity is substantial and systematic, being the the result of the interaction of light with surfaces of various reflectances and orientations. In the real world, color is not essential for recognition and navigation and color-blind visual systems can function quite well. Painters, however, appear to primarily use color—rather than systematic changes of image intensity—to represent different objects and object regions.

## 6. REFERENCES


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