

# Automatic photo quality assessment

Taming subjective problems with hand-coded  
metrics

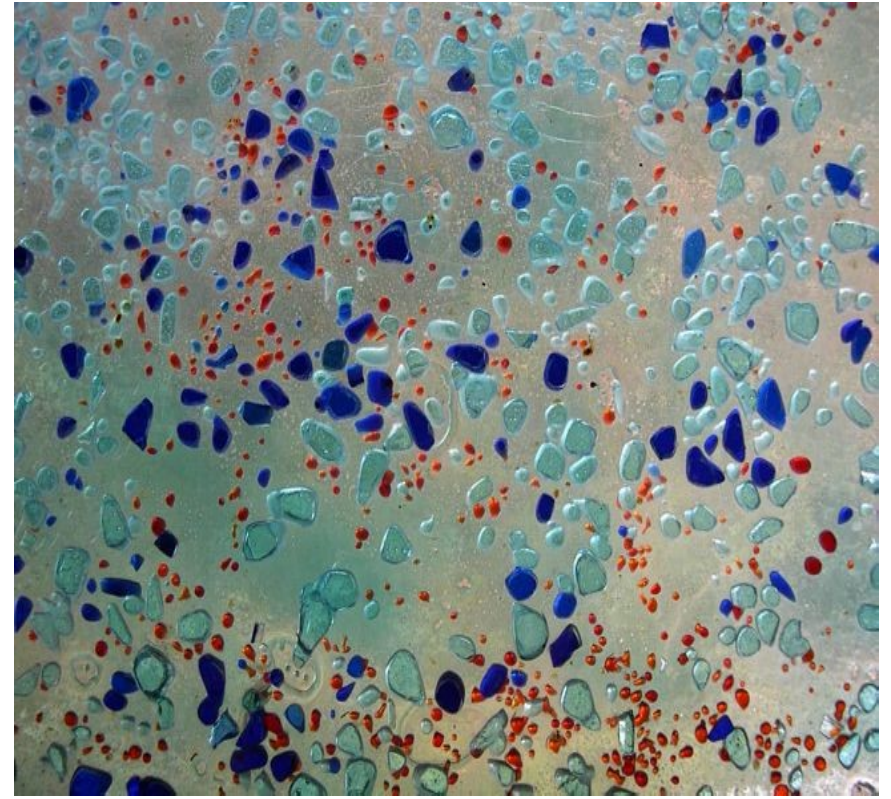
# How do you measure a subjective quality quantitatively and objectively?

- Find a consensus -
- Only look at things that everyone agrees on
- Get people to vote, and average the results
- Get people to pass judgments multiple times
- Discard outliers
- Ignore ambiguous cases, and focus on cases where you can be more certain

# What are some subjective qualities of images?

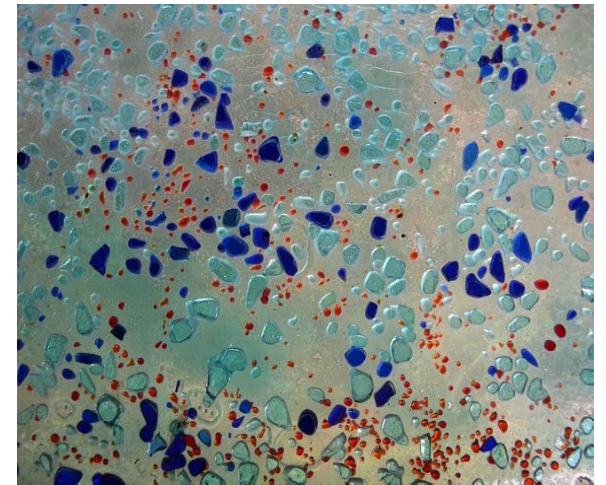
- Professional or “snapshot”?
- Aesthetically pleasing, or not?
- Photorealistic or not?
- “Original” or not?
- “Familiar” or not?

# Can you spot the CG image?





# It's the one on the left



# What makes a photograph memorable?

- Humans prefer colorful things (look for color saturation)
- Good photographs should have good composition (What is that?)
- Technicalities (focus, contrast and exposure levels)
- Images can also have interesting semantics (What is going on in the image?)

# How do we use this?

- Look at distribution of colors – Variance? Homogeneity? Contrast? Local gradients?
- Composition – Similar to Saliency; image should have a clear subject – higher concentration of sharp edges close to the center of the image
- Technicalities – Look for variations in intensity, signs of blurring
- Semantics – Don't worry about that just yet

# Past approaches

- Ignore semantics – the state of the art just isn't ready for it yet
- Focus on low-level details, which can be detected by hand-coded metrics
- Get lots and lots of metrics
- Train a classifier on them with labeled examples



# Low vs. High Level Features

- The papers distinguish between “low level” and “high level” features without defining the terms
- We use “high level” to describe features which correspond directly to some camera property, or some human response to the image as a whole
- Low level features thus refer to those which operate on, or close to, a per-pixel basis

# Low Level Features

- Mean pixel intensity
- Contrast
- Color distribution (compared with dist. Metric)
- Mean color saturation and Hue variance
- All of the above, but restricted to the center of the image
- Texture variations
- Edge densities

# Mean pixel intensity

- Proxy for brightness
- Used to detect over or under exposure

$$\frac{1}{XY} \sum_{x=0}^{X-1} \sum_{y=0}^{Y-1} I_v(x, y)$$

# Contrast

- Compute gray level histograms for R,G,B channels
- Sum into combined histogram  $H$
- The measure of contrast is the width of the middle 98% mass

# Color distribution

- Can look at distribution of pixels in color space
- The types of colors used can tell something about the image.
- Use a distribution distance metric to compare distributions of different images.

# Rule of thirds

- If you think of the image as a 3x3 grid, then the center square should have the most interesting things in it.
- Take separate mean values there.

$$\frac{9}{XY} \sum_{x=X/3}^{2X/3} \sum_{y=Y/3}^{2Y/3} I_{H,S,V}(x, y)$$



# Image size

- Professionals might use different aspect ratios in their film or final presentation, so look at size and shape of images; Nothing fancy
- Can use  $(X + Y)$  as size rather than  $X*Y$
- $X/Y$  for shape

# High level features

- Familiarity (by nearest neighbor method)
- Blur level
- H,S,V values of  $n$  largest patches (objects?)
- Depth of Field indicators
- Shape convexity
- Perceptual edges (intensity vs. color, spatial distribution)
- Saturation variation, hue count, color palette
- Spatial edge distribution, color variation

# Familiarity

- Unique pictures are thought to be more original, and thus more interesting to look at.
- See how much the image resembles other known images; the less it looks like known images, the more unique and original it is.

$$\frac{1}{K} \sum_{i=1}^K q(i)$$

Where  $q(i)$  is a distance measure from the  $i^{th}$  image in the top  $K$  nearest neighbors.

# Blur Level

- Estimating blur is a difficult problem
  - G. Pavlovic and A. M. Tekalp. [Maximum likelihood parametric blur identification based on a continuous spatial domain model](#). *IEEE Transactions on Image Processing*, 1(4), 1992
  - H. Tong, M. Li, H. Zhang, J. He, and C. Zhang. [Blur detection for digital images using wavelet transform](#). In *Proceedings of International Conference on Multimedia and Expo*, 2004.
  - One approach: assume  $I_b = G_\sigma * I_s$ , and find an estimate for  $\sigma$

# Regional Composition

- Could also look at the largest object in the image
- Use clustering algorithm to do segmentation, then look at mean Hue/Sat/Intensity for each of the top 5 clusters bigger than 1% of the image size. (More hand-coded parameters.)

# Low Depth of Field detection

- Large aperture can blur everything outside of a certain range of depth.
- Some photographers actually do this on purpose, and it can look good.

$$\frac{\sum_{(x,y) \in M_6 \cup M_7 \cup M_{10} \cup M_{11}} w_3(x, y)}{\sum_{i=1}^{16} \sum_{(x,y) \in M_i} w_3(x, y)}$$

Where  $M_i$  is the  $i^{th}$  square in the 4x4 grid, and  $w_3(x, y)$  is the 3rd band wavelet coefficient at  $(x, y)$



# Color Edges vs. Intensity Edges

- Determine intensity edges and count pixels
- Normalize RGB components by pixel intensity and rerun edge detection to determine color edges
- Pure intensity edges are not present in the normalized image. Hue does not change substantially over an intensity edge

$$E_g = \frac{\# \text{ pixels: intensity, not color edge}}{\# \text{ pixels: all edges}}$$

# Variation in Color and Saturation

- Unique color count
  - $U = \# \text{ of unique colors} / \# \text{ of pixels}$
- Pixel saturation
  - Convert image to HSV color space
  - Make a saturation histogram with 20 bins
  - $S$  is the ratio between the count in the highest and lowest bins

# Color Palette

- Quantize RGB channels into 16 values
- Make a 4096 bin histogram and normalize to unit length
- Find closest matches among known professional photos and snapshots
- Intuitively, looks for photos with closest color palettes

# Hue Count

- Convert image to HSV
- Consider pixels with brightness in  $[0.15, 0.95]$  and saturation  $> 0.2$
- Construct 20-bin histogram on hue values
  - $m$  = maximum value in histogram
  - $N = \{i \mid H(i) > \alpha m\}$
  - $\alpha$  sets noise sensitivity
- $20 - ||N||$  is the number of “unused” hues.

# Spatial Edge Distribution

- Apply a Laplacian filter to the image to detect edges
- Can compare a normalized Laplacian image to mean Laplacian for high and low quality images
- Can also calculate area of bounding box enclosing a fixed percentage of edge energy
  - Cluttered backgrounds produce larger bounding boxes

# Spatial Color Variation

- For each pixel, fit a plane to a 5 x 5 neighborhood in normalized R, G and B.
- Obtain three normals  $\mathbf{n}_R$ ,  $\mathbf{n}_G$ ,  $\mathbf{n}_B$ . They define a pyramid; sum the areas of the facets as a measure of local color variation.
- $R$  is the average summed area over all pixels.



## Which were the good features?

- In “Studying aesthetics in Photographic images using a computational approach” the best features were:
- Mean saturation for biggest patch
- Mean pixel intensity
- Mean saturation in middle square
- 3<sup>rd</sup> wavelet band for saturation
- Top 100 familiarity score
- LDOF saturation
- Size ( $X + Y$ )

# Paintings vs. Photographs



From

<http://www.the-romans.co.uk/painting.htm>



From <http://www.collectiblesgift.com/images/>

# Qualities of a Painting

- Perceptual edges are color edges
- High spatial variation in color
- Large color palette
- High saturation
- We can use these features to measure “photorealism”

# Another Approach: RGBXY Space

- Each pixel is a point in 5-D space
- An image defines a  $5 \times 5$  covariance matrix of the RGBXY point cloud
- Represent each image as a length 5 vector of the singular values of its covariance matrix
- Paintings typically use larger color palettes and have larger spatial color variations

# Professional Photo vs. Snapshot



Waiting in line! by Imapix



pot\_goldfinger\_lrg from [www.cleanleaf.ca](http://www.cleanleaf.ca).

# Qualities of a Professional Photo

- Simplicity
  - Easy to distinguish subject from background
- Surrealism
  - Professional photos tend to be distinctive
- Technique
  - Less blur
  - Higher contrast
- We can frame “professionalism” in terms of these qualities

# Simplicity and Surrealism

- Subject should be easily distinguished
  - Edges should be spatially concentrated
  - Cluttered images will have many more unique hues
- Distinctive color palettes
  - Professional photos may have similar palettes

# Technique

- Professional photos will be higher contrast
- Most cameras adjust brightness to 50% gray
  - Professional photographers will typically adjust for a 50% gray subject, disregarding the background
  - An overall deviation from 50% gray results
- Some part of a professional photo will be in focus; we can expect less overall blur