SELECTIVE REMOVAL OF EXTRANEOUS PHOTOGRAPHS

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ABSTRACT

In this paper, we propose a method for selecting the most representative high-quality images from a set of user photographs. To prevent redundancy arising from many similar images, we find all sets of near-duplicates. We then rank images based on three technical qualities: exposure, blur, and color harmony. Finally, we provide an ordering of the images which accounts for both quality and uniqueness. Our goal is not to rank images based on subjective aesthetic qualities, but instead to help a photographer filter out technically flawed photographs and focus on objectively high quality shots.

Index Terms— image processing, quality screening, exposure, meta data, color content

1. INTRODUCTION

The ease of using digital cameras allows for a large number of photographs to be taken at any given event. This increase in photograph quantity can lead to many unneeded low-quality photographs which need to be filtered by the user, which can be time-consuming and repetitive.

To automate this process, an aesthetics ranking technique could be implemented to find the appeal each image has, but this method would discard many images with potential to be fixed through retouching.

Implementing a technical quality ranking technique will keep the photographs suited for retouching, but does not take into account redundancy of similar images, and the user would be left with a set which does not span the entire event.

We thus propose a technique which ranks images based on their technical qualities with a bias for unique images.

To focus our research and determine which image qualities are relevant to technical image quality, we assume three general steps a photographer takes between shooting and using a picture, which we call the Photographer's Process:

1. Remove: Sort through the imported images and remove the ones least suited for retouching.

2. Retouch: Modify the raw files just selected to stylize and enhance them.

3. Retrieve: Select the retouched images most suitable to a given task.

We implement three modules to assess technical quality. The blur detection looks at the gradient magnitude of edges and the similarity to a predicted out-of-focus image. Exposure is measured by finding the balance in brightness throghout the image. Color harmony is based on Cohen's model[1]. Similar-images are clustered into groups using the color content and timestamps of an image. Finally, a reordering of the set is provided based on how suited they are for removal (the "Importance Order"). A user study has shown 86% accuracy in our absolute ranking of photographs and 78% accuracy in determining which photographs belong to the same set.

2. RELATED WORK

Previous works have classified images based on a professional vs. amatur photographer binary with high accuracy[2][3][4], which is useful for search engines' retrieval of high quality images. Others have focused on personalized aesthetic rankings of photographs[5][6]. These works focus on finalized images, while we focus on images that are still raw and may be retouched afterward.

Event classification has been explored in order to choose the best images from an entire event[7][8], while we choose the best images from each scene within event- images with the same subject content related rather than the same event context.

Kormann, Dunker, and Paduschek[9] describe a promising method of automatically rating and ranking images based on image content and time-metadata, with results better than random. We improve upon their work with more accurate algorithms.

3. QUANTIFYING IMAGE QUALITY

To find the Importance Order of the user's photographs, we first use interest points to find the subject, which will be used for both quality assessment and similarity clustering. Quality is determined by the rankings of the blur, exposure, and color harmony modules. Groups of similar images match the color content and timestamp of every pair of images. We combine them to get the final ordering1.

The blur, exposure, and color assessment modules will provide a ranking between zero and nine, with larger numbers indicating higher quality. Because an image which ranks
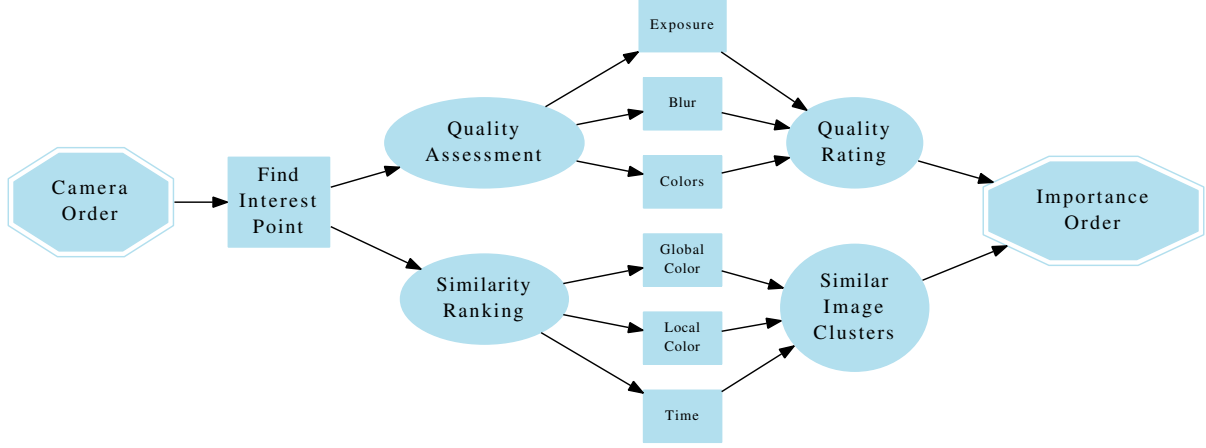
Fig. 1. Interest points are used to find the subject. Blur detection, color harmony, and exposure algorithms calculate an image's quality rating. The color distribution of the local subject and global image, coupled with the timestamp, cluster images into groups. A reordering of the input results, allowing the user to remove images at the end of this ordering.

low on any part would be considered poor, we have proposed an algorithm which penalizes low scores more than it rewards high scores, because our primarily goal is to weed out poor images. We use a scale which penalizes low quality images more than it rewards high quality images for this overall ranking:

$$\left(\sum_{i=1}^{n} W_i \left(Q_i + t \right)^{\frac{2}{3}} \right)^{\frac{3}{2}} \tag{1}$$

Where there are n modules, W_i represents the weight of module i, Q_i is that module's rating for the image, and t is a leniency threshold to balance each module's output, empirically chosen to be 4. Weights are assigned as follows:

- $W_{exposure} = 30\%$

- $W_{blur} = 60\%$

- $W_{color} = 10\%$

3.1. Subject Recognition

Using a Harris Interest Operator (utilizing NASA's Vision Workbench[10]), interest points are obtained for each image. To extract a bounding box from these points, the most dense rectangle is calculated by maximizing the ratio of interest points to rectangle area. We assume this to be the primary subject. It is used in detecting similar images and calculating blur levels.

3.2. Similar-Image Clustering

To find similar images, we perform three steps of increasing complexity for high confidence. First, we use the timestamp to obtain a similarity index between all pairs of images. Based

on an algorithm which segments a set based on gaps in the timestamps[11], we have derived a formula which finds temporal closeness between every pair of images. So, instead of finding gaps in sets, we find the similarity $S_{i,j}$ between two images i and j on a 0-9 scale. This allows nonconsecutive images to be grouped together:

$$S_{i,j} = \frac{G_{i,j}}{A_{i,j}} \tag{2}$$

Where $A_{i,j}$ is the average gap within a window size of 8 images before i and after j, and $G_{i,j}$ is the log of the time gap between the two images taken at time T_i and T_j:

$$G_{i,j} = \log(|T_i - T_j|) \tag{3}$$

The calculated similarity index $S_{i,j}$ is used to weight the results of the next two steps.

The image is then divided into a 4x4 grid of average luminosity values. To compare two images, we find the luminosity difference of each square and deduct from the similarity score if the difference is greater than a threshold of 15% luminosity. Because this is sensitive to subject and camera movement, we then take the bounding box derived in 3.1 and rerun the luminosity difference algorithm with stricter threshold of 10%.

Clusters are formed by first putting each image into its own group, then iteratively merging the two most similar groups until a threshold is reached. In this way, a group votes for other similar groups, rather than each image voting for another, resulting in a noise-resistant clustering. This method is similar to a Quality-Threshold clustering algorithm.

3.3. Blur Detection

Using the foreground bounding box, the blur detection algorithm quantifies the contrast between the edges and background. Using the Image Gradient Model proposed in [12],
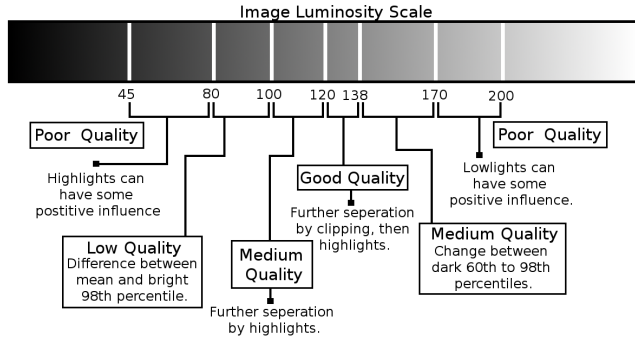
Fig. 2. The Exposure process: This figure shows the inital segmentation of images by mean (values 0 to 255), then the further segmentation of images of medium and good quality (mean ranges 100-120, and 120-138 respectively).

we obtain a value for the sharpness. To increase accuracy and reduce the adverse affects that acceptable background blur may have, we constrain detection to the bounding box.

Next, we compute the difference in pixel values between the original image and a Gaussian blurred image. Though this provides little insight with independent images, it correlates well with blur amount when comparing the subject of similar images.

3.4. Exposure

Image exposure is a measure of how appropriate the lighting is in a given image. While traditionally measured in-camera with light meter over the area, our exposure algorithm evaluates how the lighting in the result image appears to a human observer. Images are ranked according to various measures of their brightness.

Based on the idea that the mean value of image brightness is an approximate indication of how well-exposed an image is, images are first segmented based on their average brightness value.

The categories of mean brightness value (mean) correspond roughly to a parabolic mapping of exposure values, with well exposed photographs having a mean of $130 < p < 140$: the further towards the extreme high and low means, the worse quality the image is. These divisions are used as the starting point of analysis.

The other measures of image quality are also based on brightness, and were determined by taking various measurements on a deliberately chosen pool of images that had a wide variety of exposure problems. The measures are as follows: clipping, highlights, lowlights, the upper 60th and 98th percentiles, the lower 60th and 98th percentiles, and variance. Each of these measures are calculated on both the foreground and the background of the image, relative to the area over which they are calculated.

Overexposure of an image can lead to large areas in the

photo in which the human eye cannot discern any form (note that this definition can also indicate areas of a solid white value that contains absolutely no data about the form present). However, as the program is primarily concerned about how humans perceive images, the number of pixels in the highest five perceived values are used to calculate the highlights present in the image.

The most extreme mean brightness values are images of very poor quality, and are rated as such based solely on the mean value, although having a bright 98th high percentile can provide enough contrast to make a discernible image, though certainly nothing of quality. Means between 80 and 170 encompass nearly all images of medium through excellent exposure, and thus require the most analysis. After being subdivided into mean categories, they are again subdivided into further categories (see figure 2) before analysis.

3.5. Color Harmony

To determine the quality of a photograph's color content, we use Cohen's seven types of color harmony[1] to determine which, if any, is contained in the photograph. For each image, we find the hue which is most represented across the seven types, as well as the percent of pixels which match any of the harmonies.

We then separate the pixels by their saturation content, using user-study data from Amazon Mechanical Turk to determine the boundaries of each saturation bin. We then look for the most closely matched harmony type within each bin, ranking the bin based on how far it is from the closest type. We combine the bins' rankings for a final quality ranking.

4. RESULTS

We have run our algorithm on several publicly available datasets as well as our own. We used Amazon Mechanical Turk and gathered a total of 454 users rankings across trials.

Enumerated below are the results and comparisons to similar works.

4.1. Similar Image Detection

We asked Turk users to group together photographs within four sets of twenty images. Our similarity ranking module agreed with Turk users with 78% accuracy.

4.2. Image Rating

Separate trials were run to compare our algorithm to previously ranked images: 48 from Ke, Tang, and Jing[2], and 100 from Luo and Tang[4]. We then compared 459 of our own images to Turk users. Here we compare against an absolute rating of each image without regard to uniqueness.
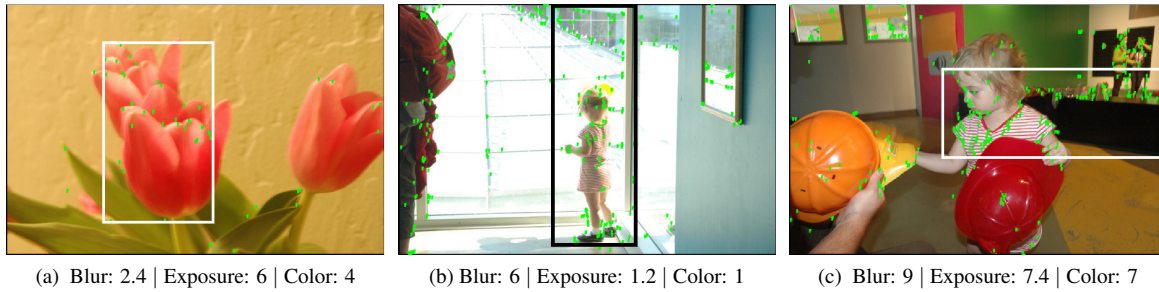
(a) Blur: 2.4 | Exposure: 6 | Color: 4   (b) Blur: 6 | Exposure: 1.2 | Color: 1   (c) Blur: 9 | Exposure: 7.4 | Color: 7

Fig. 3. Examples of (a)(b) low quality and (c) high-quality images. The dots are interest points found; the square is the bounding box considered to be the subject. Despite the too-inclusive box in (c), each algorithm worked properly.

We took a random sample of 100 images from Luo's and Tang's 11,981 images [4]. We asked 44 Turk users to rank 50 images each on a scale from one to ten.

Using the 48 image data set from Ke, Tang, and Jing[2], and Amazon Turk ratings as a ground truth, we achieve a correlation coefficient of .340, which is comparable to the authors' correlation coefficient of .495. Similarly, with a sample from Luo and Tang's public data set of high-quality images[4], we achieve a correlation coefficient of .311. These numbers show that our algorithm provides positive absolute results when comparing photographs independently, despite our goal of culling images within a set of related images.

5. CONCLUSION AND FUTURE WORK

We propose a method of applying current research to automate another step of the Photographer's Process. By focusing on obtaining an ordering which is representative of all photographs taken, we obtain a diverse set of high quality images similar to what a user would have chosen manually. We derive a novel algorithm for analyzing exposure quality. We improve upon previous algorithms which find temporal gaps between images to obtain a metric for temporal nearness. The final ordering depends on both the quality ranking and the number of similar images which have already appeared.

Our work focuses on a small portion of the Photographer's Process. In the future, we would like to see the idea of relative rankings applied to the second Retouching step. (It has already been extensively applied to the third Retrieval step.) Retouching can use relative processing to increase creativity between similar images or combine data from multiple images. With this, we would be able to automate the Photographic Process.

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