The Role of Tags and Image Aesthetics in Social Image Search

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ABSTRACT
In recent years, there has been a proliferation of consumer digital photographs taken and stored in both personal and online repositories. As the amount of user-generated digital photos increases, there is a growing need for efficient ways to search for relevant images to be shared with friends and family. Text-query based search approaches rely heavily on the similarity between the input textual query and the tags added by users to the digital content. Unfortunately, text-query based search results might include a large number of relevant photos, all of them containing very similar tags, but with varying levels of image quality and aesthetic appeal. In this paper we introduce an image re-ranking algorithm that takes into account the aesthetic appeal of the images retrieved by a consumer image sharing site search engine (Google's Picasa Web Album). In order to do so, we extend a state-of-the-art image aesthetic appeal algorithm by incorporating a set of features aimed at consumer photographs. The results of a controlled user study with 37 participants reveal that image aesthetics play a varying role on the selected images depending on the query type and on the user preferences.

Categories and Subject Descriptors
H.3.1 [**Information Storage and Retrieval**]: Content Analysis and Indexing—*Indexing methods*; I.4.9 [**Image Processing and Computer Vision**]: Applications; H.1.2 [**Human/Machine Systems**]: Human factors.

General Terms
Algorithms, Human Factors.

Keywords
Consumer Image Search, Re-ranking of Search Results, Image Aesthetics.

1. INTRODUCTION AND RELATED WORK
In recent years, there has been a proliferation of consumer digital photographs taken and stored in personal and online repositories.

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The most popular social multimedia sites (*e.g.* Flickr, Picasa Web Album [18], Facebook, etc.) already have billions of images in their databases [12]. Capturing and storing digital photos is cheap and easy. Therefore, users tend to keep most of the pictures taken. As the amount of user-generated digital media content increases, there is a growing need for tools to search for not only relevant but also *aesthetically appealing* content to be shared with friends and family [22].

Text query-based image search approaches (from now on referred to as query-based search) rely heavily on the similarity between the input textual query and the textual metadata (tags, comments or other related text) added to the images by users. This approach has been somewhat successful in image sharing sites where tags, comments and ratings are typically added on an image-by-image basis by large numbers of users (*e.g.* Flickr), or the image relevance is inferred from its surrounding text (*e.g.* Google Image search). However, image search in consumer shared social repositories is still a challenging task: users do not typically label each image individually, but tend to annotate their pictures in "batch" or "bulk" mode [14], assigning the same tags to groups of images that belong to the same event or photographic session. Moreover, the tags may not necessarily describe the content of the images [11].

In order to solve the relevance problem, image search re-ranking methods have been proposed in the literature. Most of the prior work in this area assumes –through image analysis– that there is one dominant cluster of images within each image set returned by a keyword query, and treats images inside this cluster as the desired ones [5][6][8]. In the area of consumer images, [12] presents a re-ranking method for Flickr images, that fuses tag relevance with location annotation information and visual cues, producing a ranked list of clusters representing different views of a certain location. In this paper we complement the work in [12] by proposing and evaluating the fusion of tag relevance with a visual cue: the aesthetic appeal of the image, such that images that are aesthetically more appealing would be ranked higher. Note that while Luo *et al.* [17] have recently proposed an image aesthetics re-ranking algorithm for Web images (queried from the MSN Live Search), we tackle the problem of social consumer image search on images queried from Picasa Web Album and propose a fusion method integrating query relevance and image aesthetics.

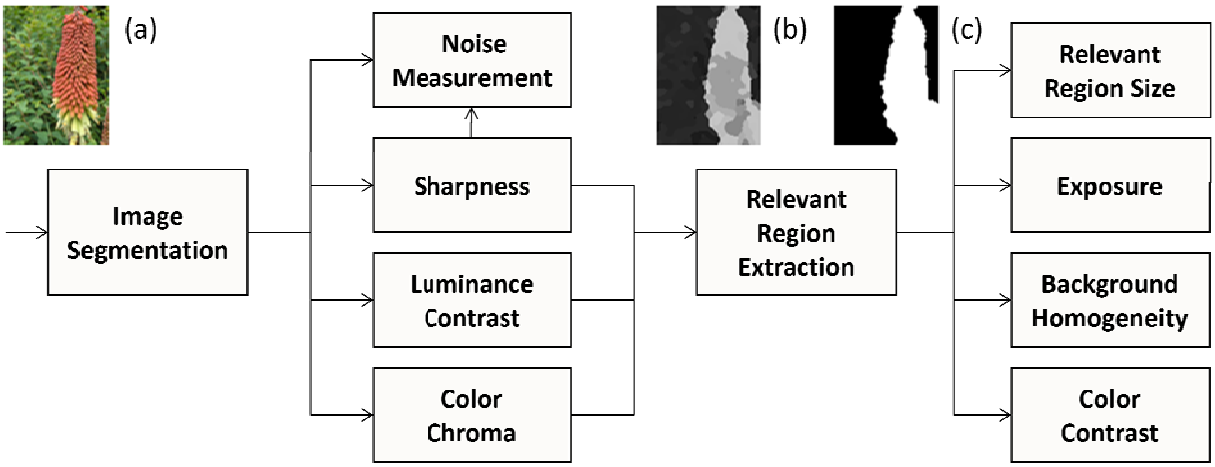


Figure 1. Diagram of the image aesthetics model used in this paper. Region based sharpness, contrast and color chroma are used to extract the image appeal map (b); from the image appeal map, the appealing region, or relevant region, is extracted through thresholding (c). This relevant region is used to calculate other features (e.g., relevant region size, relevant region exposure, background homogeneity and color contrast).

Image aesthetic appeal may be defined as the interest that a photograph generates when viewed by human observers, and it incorporates both objective and subjective factors [23]. Some of the image features that have been used in the literature include sharpness and colorfulness [16][27], contrast and saliency [26]. In [4], a classifier is used to classify high and low rated photographs using 15 features that incorporate a low depth-of-field indicator, a shape convexity score and a familiarity measure. The spatial distribution of edges, color distribution and hue count are incorporated in [10] in order to classify between high quality photos and low quality photos. Obrador showed in [19] that there is no need for all regions in an image to be aesthetically appealing in order for the image to be considered appealing. Similarly, a region-based image aesthetics measure is introduced in [17] where clarity, contrast and simplicity features are considered in addition to lighting, composition geometry and color harmony. Note that [4][10] and [17] train a classifier (good aesthetics vs. bad aesthetics) with images and ratings obtained from photo forum sites, where the average aesthetic appeal of images is usually above the average [28] and also the number of ratings is higher for good photos that for bad photos [28], *i.e.*, users usually rate only images they like.

Interestingly, none of the previous approaches tackle common problems in consumer photography such as highlight clipping on the CCD/CMOS sensor, and image noise. In this paper we introduce an image re-ranking algorithm that takes into account the aesthetic appeal of the images retrieved by a consumer image sharing site search engine (Google's Picasa Web Album) and at the same time we extend the algorithms in [19][20] by incorporating a series of features aimed at tackling the problems just mentioned. We perform a controlled user study with 37 participants that were asked to select images retrieved from 10 different image search queries in Picasa Web Album.

This paper is organized as follows: Section 2 presents the image aesthetics measure in some detail, including a set of novel features; and Section 3 describes the fusion algorithm that combines image aesthetics with the relevance ranking given by a text-based search engine. The user study and its results are presented in Section 4 and 5, respectively. Finally, the conclusions and lines of future work are summarized in Section 6.

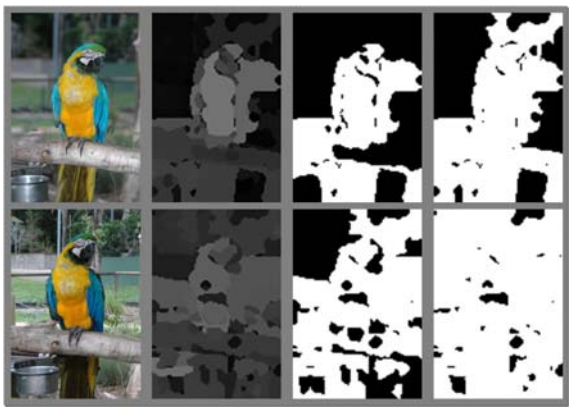
2. IMAGE AESTHETICS MODEL

The image aesthetic measure used in this paper is an extension of the work of [19][20]. This method, which is briefly described below, postulates that an image is aesthetically appealing if it has a large relevant region that is sharp, colorful, well illuminated and well contrasted with the background. In this paper, we present an aesthetics measure that improves the sharpness and color features extracted from consumer photographs, in addition to introducing a new feature to measure image noise.

Bajcsy [2] stated that when humans look at a photograph they tend to focus their attention on the region that is most aesthetically appealing within that photograph, and then, based on the properties of this region they will decide whether the image is useful for their task at hand, *i.e.*, whether the image is aesthetically appealing or not. The aesthetics model proposed in this paper takes advantage of these findings by identifying the region in the photograph that is most aesthetically appealing – from now on referred to as the *relevant* region. This is accomplished by (see Figure 1) performing an image segmentation, and within each of the image segments, calculating the segment's sharpness (*S*) –described below in Section 2.1–, the segment's average contrast (*CN*) using the root-mean-square contrast –as in Equations 6 and 7– over all pixels belonging to that image segment, and the segment's average color chroma (*CC*) – calculated as the chroma magnitude μ_{ab} in the CIE-L*ab* color space. These are combined in order to obtain the aesthetic appeal map (*AMap*) at each pixel location (i,j) of the image given by:

$$AMap_{i,j} = S_{i,j} + \alpha(S_{i,j}) \cdot CN_{i,j} + \beta(S_{i,j}) \cdot CC_{i,j} \qquad (1)$$

where α and β are inversely proportional to the sharpness of that specific image segment (*i.e.,* if the specific object is out of focus, the more important its contrast and color chroma are). They also



(a) (b) (c) (d)

Figure 2. (a) Example of same subject with different levels of isolation from the background; top image taken with low depth of field and flash strobe yields homogeneous background; bottom one taken with high depth of field and available light yields less homogeneous and more distracting background; (b) their appeal map; (c) appeal map thresholded at MaxAppeal/2; (d) appeal map thresholded at MaxAppeal/4. Notice how the top (c) and (d) images are quite similar (i.e., homogeneous background), while the bottom (c) and (d) images are not (i.e., less homogenous and more distracting background).

depend on how reliable the sharpness feature may be measured in that region, being inversely proportional to the amount of structure in that image segment (*i.e.*, the less structure, the more important contrast and color chroma are). The areas of the image with a certain degree of structure are detected by an image matting algorithm so that sharpness can be accurately measured on them.

One important feature in assessing the aesthetic appeal of an image is the isolation of the relevant region from background distractions (corroborated by [17]); examples of this can be found in low depth of field photography, or portraits with a flat background, where observers can easily focus their attention on the relevant region. This background homogeneity feature is calculated as the difference between the outcome of thresholding *AMap*, at two different levels (see Figure 2 for an example, where the top image has a relevant region well isolated from its background, as opposed to the bottom image).

The relevant region is finally calculated by thresholding *AMap* to one half of its maximum value. Key features in the proposed aesthetic model are: (1) The average of *AMap* on the relevant region; (2) the relevant region size in order to account for good composition, such that smaller relevant regions are penalized; and (3) the average luminance and its standard deviation within the relevant region, penalizing poorly lit images.

The Color features have been modified from [20] by calculating color chroma (*CC*) within each region, as described above, instead of colorfulness. Note that colorfulness takes into account color contrast, which does not make sense within a specific image segment. Color contrast (*CCN*) is, instead, computed on the entire relevant region ($CCN_{relevantR}$) and on the whole image ($CCN_{overall}$). It is calculated in CIE-L*ab* color space as the length of the standard deviation of the *a* and *b* coordinates:

$$CCN_i = \sqrt{\sigma_a^2 + \sigma_b^2} \tag{2}$$

The final color contrast measure is given by:

$$CCN = \max(CCN_{relevantR}, CCN_{overall}) \tag{3}$$

accounting in this way for both a colorful relevant region and a colorful background.

As described in Section 2.3, the overall aesthetic measure is composed of a main term, and a set of penalty and reward factors, where each of these factors either increase or decrease the overall aesthetic measure of the photograph. Accordingly, a Color Contrast reward Factor (*CCNF*) is defined as:

$$CCNF = \begin{cases} 1, & for \quad CCN < 14 \\ \frac{33}{1000} \cdot CCN - 0.53, & for \quad 14 \le CCN < 26 \\ 1.4, & for \quad CCN \ge 26 \end{cases} \tag{4}$$

after training this measure on 200 images with varying degree of color content.

Unfortunately, the features described above do not take into account important artifacts which are common in consumer photography, such as sensor highlight saturation a.k.a. *clipping*,

and high image noise (often found in camera-phone images, which are very popular in social sharing sites).

We describe next the features that we designed to tackle the previously mentioned artifacts. Finally, we present the aesthetic measure that incorporates these new features.

2.1 Sharpness measure

As stated above, each image segment is assigned a representative sharpness value [20]. The actual sharpness measure for each pixel (i,j), *S(i,j)*, is based on a multi-resolution Laplacian filter bank approach calculated on the luminance channel of the image, such that all 4 levels of the Laplacian pyramid are combined in order to be resilient to image noise. This formulation is actually inaccurate along high contrast edges which are well known to generate a much higher sharpness measure than the one perceived by humans. Therefore a local contrast correction function was implemented based on [7]. Unfortunately, sensor highlight clipping generates very high contrast edges in regions that may be out of focus rendering once more, an incorrect sharpness measure. We describe next how to improve the presented formulation in order to take care of this artifact.

2.1.1 Imaging Sensor Highlight Clipping

Digital cameras have a limited dynamic range to sense the brightness of incoming light. If the incoming light is too bright at a pixel position, thus exceeding the camera's dynamic range, it will not be correctly recorded, yielding what is known as color clipping [21]. Color clipping is common in consumer photographs, and it produces non-linearities that generate a high energy output from the sharpness filter bank, creating inaccuracies in the final aesthetic measure. Two main sources of clipping were found to be particularly problematic when computing the sharpness metric:

Figure 3. Original out of focus and motion blurred image, with specular highlight in the boy's left eye (left), amplified sharpness maps before contrast based correction (middle), and after contrast based correction (right).

1. Out-of-focus areas, where each point of light becomes a disc (*i.e.,* circle of confusion). The sharpness measurement algorithm may detect that circle as a sharp object.

2. Highlight specularities, produced by mirror-like reflections from glossy surfaces.

2.1.2 Contrast Based Sharpness Measure

Ferzli and Karam [7] showed that the perception of sharpness is a function of the local contrast. Hence, we have optimized the non-linear factor δ', which is a function of the luminance contrast in order to avoid the influence of highlight clipping:

$$\delta'(i,j) = \begin{cases} -0.0042 \cdot CN'(i,j) + 1, & for \quad 0 \le CN'(i,j) \le 50 \\ 0.8 \cdot e^{-0.0336(CN'(i,j)-50)}, & for \quad 51 \le CN'(i,j) \end{cases} \tag{5}$$

where *CN'(i,j)* is the luminance contrast as defined below.

In order to solve the blooming problem that exists with certain camera sensors (*i.e.*, when electrons of a saturated pixel flow into the neighboring cells), the contrast function *CN'(i,j)* has been implemented in a multi-resolution approach, in order to capture both high and low resolution contrasts. The contrast at each resolution is measured using the root-mean-square contrast $CN_k(i,j)$:

$$CN_k(i,j) = \left[\frac{1}{k \cdot k - 1} \sum_{(l,m) \in W_k} (x_{l,m} - \bar{x}_k)^2 \right]^{1/2} \qquad \bar{x}_k = \frac{1}{k \cdot k} \sum_{(l,m) \in W_k} x_{l,m} \tag{6,7}$$

$$CN'(i,j) = \max\left(CN_3(i,j), CN_7(i,j), CN_{11}(i,j)\right) \tag{8}$$

where $x_{i,j}$ is the luminance value at pixel (i,j), and W_k is a square of size k^2 centered at pixel (i,j). Finally, the sharpness measure, *S(i,j)*, given by:

$$S(i,j) = \delta'((i,j)) \cdot f\left(FB_{LL}(i,j), FB_{LH}(i,j), FB_{HL}(i,j), FB_{HH}(i,j)\right) \tag{9}$$

as introduced in [20], where FB_{mn} is the output of the *mn* filterbank stage, and *LL, LH, HL* and *HH* are the band-pass filters from lowest to highest frequency bands, and *f()* is the function that combines all the filterbank outputs. See Figure 3 for an example.

2.2 Noise measure

Noise in digital pictures has become a serious problem as the pixel size in the image sensors has been shrinking to allow for high megapixel counts. This fact is exacerbated by low quality optics and low quality sensors in camera-phones. Accurate modeling of the image noise at the device output is hard, due to various image processing steps such as local and global contrast enhancements, various non-linear transformations and compression[13].

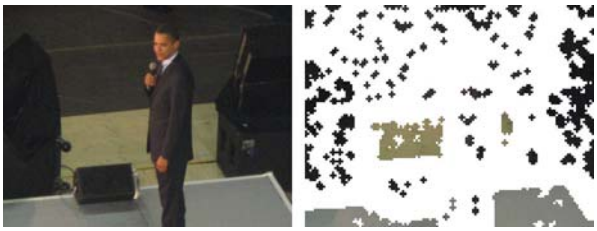


Figure 4. Original noisy image (left), and luminosity-homogeneous regions, larger than 320 pixels each, (right).

Measuring noise in digital images is usually done as a two step process [13][1]: first, the intensity-homogeneous blocks (*i.e.,* blocks with the lowest structure variation) of the image are identified; second, the noise is measured within each of these intensity-homogeneous blocks. In [1] they try to estimate the noise variance for the whole image. However, as [13] showed, in many cases of practical interest the noise is not spatially stationary over the image.

The proposed approach performs an image matting step in order to identify the areas of the image with a certain degree of structure variation. This result is used to isolate the regions that have very little structure variation (see Figure 4), where the pixels are assumed to be independent and identically-distributed (iid). Note that the signal in these intensity-homogeneous regions should be nearly constant such that the variation is mainly due to noise. As local noise estimates should not be influenced by distant data samples, we calculate the noise variance within each intensity homogeneous region as the average of all variances calculated on a 3x3 support. In addition and in order to have a reliable estimate, we need to use sufficient data samples. Therefore, we only calculate the noise variance in intensity-homogeneous regions larger than a threshold size (*i.e.*, 320 pixels in the current implementation).

Since the SNR in the chrominance (Cb and Cr) channels is typically lower than that of the luminance channel [15], we compute the noise variance in the Cb and Cr channels only, and keep the maximum of the two per intensity-homogeneous region. The final noise measure (*INoise*) is calculated by ordering the noise measures, based on their value, of all intensity homogeneous regions that were large enough for the task, and selecting the median value of the top 5, in order to avoid outliers.

The noise penalty factor (*NOF*) is defined as:

$$NOF = \begin{cases} 1, & for \quad INoise < 1 \\ 1.235 - 0.235 \cdot INoise, & for \quad 1 \le INoise < 3.125 \\ 0.5, & for \quad INoise \ge 3.125 \end{cases} \tag{10}$$

The NOF determines in what measure the overall aesthetic appeal measure will be decreased (see Section 2.3). All thresholds and constants have been optimized over a 200 image training set of images with a wide range of noise levels.

2.3 Overall Aesthetic Measure

Note that each image is first downsampled, so that the longest side of the photograph will be 1024 pixels, in order to normalize the sharpness and noise measures across images.

The final Image Aesthetic Appeal measure is defined as:

$$AM = \left[\frac{1}{N} \sum_{\substack{i,j \\ \text{in relevant region}}}^{N} AMap_{i,j} \right] \cdot SZ \cdot E \cdot H \cdot CCNF \cdot NOF \quad (11)$$

where the main contribution to the measure is the first term, *i.e.,* the average of the appeal map over the appealing region. This factor is modified by penalty and reward factors [20], where *SZ* is the size of relevant region factor, *E* and *NOF* are the exposure and noise factors, *H* is the background homogeneity factor, and *CCNF* is the color contrast factor. Note that SZ, *E* and *NOF* are penalty factors, *i.e.*, *SZ* <1 if size of relevant region is below a threshold, *E*<1 if relevant region is badly exposed (either overexposed or underexposed), *NOF*<1 if noise is visible in image; conversely *H* and *CCNF* are reward factors, *i.e.*, *H*>1 if background is homogeneous and *CCNF*>1 if the relevant region or the overall image present high color contrast. Note that all factors have a Max and a Min cap (see Equations 4 and 10 for examples).

3. SCORE AGGREGATION FUNCTION

Given an input query *k,* we propose the combination of two rankings or scores by using an aggregation function [24]: *relevance* (R_k), provided by a standard text query-based search engine, where it corresponds to the retrieval position of a specific image (*i.e.,* 1 for the top retrieved result, 2 for the next, etc.); and *aesthetic appeal,* provided by the previously described algorithm (A_k). These two measures are normalized into $Rnorm_k()$ and $Anorm_k()$.

We define an aggregation function, $FA_k(n)=f(Anorm_k(n), Rnorm_k(n))$ that re-scores each item *n* by taking into account both the aesthetics and text-based scores. Desired properties of the aggregation function include: (a) images with highly relevant tags to the input query should receive a high score after the aggregation; (b) highly aesthetically appealing images should receive a high score after the aggregation; (c) images that are *both* highly relevant and aesthetically appealing should receive a higher score after the aggregation than in the 2 previous cases; and (d) the weights given to relevance and aesthetics in the final ranking would be user and task dependent. As a first approximation, we propose a simple aggregation function:

$$FA_k(n) = f\left(A_{norm_k}, R_{norm_k}\right) = \left[\alpha\left(A_{norm_k}\right)^m + (1-\alpha)\left(R_{norm_k}\right)^m\right]^{\frac{1}{m}} \quad (12)$$

where the optimal settings α of and *m* depend on the user, the particular image collection and the task at hand. In the experimental results presented in this paper, we use α=½, *i.e.*, aesthetics are as important as relevance. Dynamic optimization of this parameter is left for future research. In preliminary experiments, we implemented and validated three different aggregation functions, corresponding to m=1, m=2 and m=3. After experimentation, it was found that the best combination of relevance and aesthetics was accomplished with m=2, which would strike a balance between images that are either relevant or aesthetically appealing, and images that are both relevant and aesthetically appealing.

4. USER STUDY

A user study was conducted in order to answer the following research questions:

R1: Are users influenced by image aesthetics when searching for images in the context of shared consumer photographs?

R2: What are the factors that play a role in determining the importance of image aesthetics in consumer image search tasks?

We performed our user test on images queried from a popular consumer image sharing site: Picasa Web Album [18].

We carried out a controlled study with 37 volunteers (27 male) whose ages ranged from 23 to 49 years old (mean 30.6 years). Seven participants (19%) had one or more children. They were all computer literate and held a variety of occupations, including researchers, administrative assistants, engineers, accountants, infrastructure specialists, students, financers, people managers, front desk clerks and human resources specialists, from a diverse set of nationalities. All participants filled out an online demographic pre-study questionnaire that included questions about their digital picture taking and image search habits and expertise. Participants were audio recorded during their experiments.

Participants were shown the results of ten image search queries (see Table 1) : nine that had been generated with popular tags and one personal query that they had previously selected. The participants were presented with the top 15 results of executing the ten queries, one at a time. They were asked to inspect each image at full screen resolution, and then select the *best 3 photos* of the result list in response to each query; they also entered the reasons for those selections in a text box. Without their knowledge, the 15 images belonged to three different rankings (treatments): (a) the original relevance ranking provided by Picasa Web Album (*Picasa*); (b) the image aesthetics-based ranking (*Aesthetics*); and (c) the ranking resulting from applying the aggregation function (*Fusion*). The top five images from each treatment were presented to the user at the same time in a randomized manner, which means there was a chance to have *collisions*, *i.e.*, images that appear in the top five of more than one treatment. In the case of a collision, the image was only shown once, and if selected the performance measures would take that into account (see below). Three performance measures were used for the evaluation:

Treatment winner (TM): It quantifies the *number of times* that the selected photos came from each of the 3 treatments, as given by Equation 13, with $\sum TM_i = 1$, where *i* is the treatment under consideration. In order to take into account collisions between treatments, a second term is added to the right of the equation, such that when there is a collision, the reward is equally split between the treatments that generated that collision. For example, if one of the selected images appeared in the top 5 of both the Picasa and Aesthetic rankings, *i.e.*, *collisions(j)*=1, their corresponding TM measure would be halved.

$$TM_i = \sum_{\substack{j \epsilon Photos\ in \\ Treatment\ i}} \frac{PhotoWasSelected(j)}{3} \cdot \frac{1}{collisions(j)+1} \quad (13)$$

where *PhotoWasSelected(j)* returns 1 if photo was selected by the participant, and 0 otherwise; and *collisions(j)* is 0 if image appeared only in this treatment, 1 if it appeared in this treatment and another one, and 2 if it appeared in all treatments.

Re-ranking performance (RM): It quantifies *how well* each treatment ranked the images that were selected by the user. For instance, one of the selected images might have been ranked in

position #6 by a treatment –and hence did not get any points from the TM measure. However, its RM would be significantly higher than the RM of another treatment that would have ranked the same image in position #100. To this effect, we propose the following RM formula for treatment i:

$$RM_i = \frac{1}{3} \cdot \left[\frac{S - Pos_i(Ph1)}{S-1} + \frac{S - Pos_i(Ph2)}{S-2} + \frac{S - Pos_i(Ph3)}{S-3} \right] \quad (14)$$

where *Pos(Ph)* is the position that each photo occupies in the treatment's ranking such that *Pos(Ph1)>Pos(Ph2)>Pos(Ph3)*, and *S* is the scope or maximum rank considered. In our user study, the largest portion of our participants (N=16; 43%) is satisfied with the search results after inspecting the second page of results – *i.e.,* 40 images, followed by those who only look at the first page (N=7; 19%) – *i.e.,* 20 images. Hence, *S*=40 in Equation 14. This scope has also been reported in the image search literature [9] as one of the most common ones.

Note that $RM_i = 1$ if all the selected photos are ranked at the top for treatment *i*, and $RM_i = 0$ when the selected photos are ranked at the bottom for treatment *i* (at or below the scope).

Overall performance (OM): It averages the TM and RM measures into a single measure that provides the overall performance for a specific treatment and query: $OM_i = \frac{TM_i + RM_i}{2}$.

5. RESULTS AND DISCUSSION

In this section, we summarize the first qualitative feedback provided by participants, as it is helpful in understanding the quantitative performance results that are reported next.

5.1 Qualitative Feedback

All users in our study provided feedback on the reasons why they picked or did not pick specific images in the experiment. Most users (N=32; 86%) provided detailed feedback. After careful analysis of their audio and textual feedback, we identified five variables that users take into account when searching for consumer images:

- *Presence of people in the photo*: A few participants enjoyed seeing happy people in the pictures ("she's happy/surprised") and candid pictures of people that tell a story in a daily activity setting (not posing). However, the majority of participants (N=32; 86%) were not interested in photos with people they did not know.

- *Emotional content in the photo*: Fifteen participants (41%) enjoyed the pictures that made them feel better (*e.g.* "peaceful", "smile") while a few (N=4; 11%) mentioned liking images that evoke a place that they long to be.

- *Preferences or personal experiences*: Twelve participants (32%) liked the pictures that depicted something they enjoy in real life, and another subset (N=4; 11%) liked images that sparked fond memories. Conversely, they did not like the pictures that were very different from those they would typically take themselves.

- *Expectations about search results*: Most of the participants (N=35; 95%) felt reassured when they could understand the relationship between the retrieved images and the input query. Conversely, they did not like the images if they could not recognize an object or landmark that confirmed the query (*e.g.* "this could be anywhere", "I cannot see the park").

- *Importance of image aesthetics*: The majority of the subjects (N=33; 89%) mentioned aesthetic properties of the images at one point or another during the experiment. Comments about the image's composition (*e.g.* "the main subject is nicely isolated from the background"), good lighting, bright colors and sharpness were amongst the most frequent (N=18; 49% in average). Conversely, almost all participants (N=35; 95%) mentioned not liking low quality images with high levels of noise (*e.g.* "taken with a camera-phone") that were over/under exposed or out of focus –particularly the object of interest.

5.2 Quantitative Results

Table 1 summarizes the results of the statistical analysis for each treatment, and for each of the queries considering the overall performance measure (OM) described above. Descriptive statistics with different subscripts (*e.g.* a, b, c) in the same row differ significantly for p<.05, *i.e.,* if the subscripts are the same, then there is no statistically significant difference between the measures. For example, for Query #1 in Table 1, there is *significant* difference between *Aesthetics* and *Fusion*, but there is neither a significant difference between *Picasa* and *Aesthetics*, nor between *Picasa* and *Fusion* since they share the same subscript.

According to the results presented in Table 1, the *Picasa* treatment performed better in more queries, followed by *Aesthetics* and, finally *Fusion*.

5.3 Implications for Design

From the analysis of both qualitative and quantitative results, we shall highlight the following implications for the design of consumer image search tools:

- *More relevant tags are needed*: Previous work [12] has successfully combined tags with location metadata and visual cues in order to boost performance. Content-based analysis techniques are particularly relevant in this domain, in order to automatically or semi-automatically label the high percentages of unlabeled images that are stored in consumer sharing sites.

- *Relevance is more important than pure Aesthetics*: When the results of the query-based search engine are poor (as mentioned by participants in Q4 and Q5), images with high aesthetic appeal are likely to be irrelevant to the user.

- *Personalization and context are needed*: User modeling

Table 1 . Comparison between the treatments' Overall Score (OM) for each condition: Mean [std] score, (*p<.05). Descriptive statistics with different subscripts (*e.g.,* a, b, c) in the same row differ significantly for p<.05.

Query	1. Picasa	2.Aesthetics	3. Fusion	P
1. Birthday party	**0.41 [0.18]$_{ab}$**	**0.44 [0.16]$_{a}$**	0.30 [0.18]$_{b}$	*
2. Inauguration of Barack Obama	0.36 [0.18]$_{b}$	**0.49 [0.19]$_{a}$**	**0.39 [0.15]$_{ab}$**	*
3. Trip to Japan	0.20 [0.20]$_{c}$	**0.66 [0.18]$_{a}$**	0.29 [0.19]$_{b}$	*
4. New York buildings	**0.73 [0.26]$_{a}$**	0.19 [0.19]$_{b}$	0.13 [0.19]$_{c}$	*
5. Wedding in the park	**0.62 [0.27]$_{a}$**	0.29 [0.24]$_{b}$	0.15 [0.14]$_{c}$	*
6. Hawaii beach	0.38 [0.23]$_{a}$	0.36 [0.21]$_{a}$	0.46 [0.18]$_{a}$	
7. Mountains of China	**0.62 [0.26]$_{a}$**	0.21 [0.18]$_{c}$	0.42 [0.19]$_{b}$	*
8. Summer in Paris	**0.38 [0.25]$_{ab}$**	0.35 [0.17]$_{b}$	**0.51 [0.20]$_{a}$**	*
9. Vacation in Italy	0.49 [0.29]$_{a}$	0.40 [0.24]$_{a}$	0.34 [0.20]$_{a}$	
10. Personal	**0.55 [0.29]$_{a}$**	0.24 [0.20]$_{b}$	**0.41 [0.23]$_{a}$**	*

techniques would greatly help in understanding to which degree aesthetics is important for each user.

- *Image aesthetic measures are not universal*: Different types of topics have completely different aesthetic connotations, *i.e.,* buildings *vs.* weddings. Therefore, we believe that a general image aesthetics measure is unable to represent *all* parameters that might play a role in defining the aesthetic appeal of an image. Hence, we are working on a user and category-dependent aesthetic measure. The work presented here represents a first step in the characterization of image aesthetics.

- *Fusion is not straight-forward*: The proposed fusion algorithm performed poorly when compared to the *Picasa* treatment. However, our experiments suggest that *Fusion* may be appropriate in the cases of queries that produce highly relevant results – *Fusion* actually performed better than the other two treatments for RM (Re-ranking performance, see Section 4) in 2 of the queries.

- *Sensitivity to the Presence of People:* Finally, participants in our study vastly preferred images without unknown people. An exception is the case of travel-related queries to exotic countries, where participants preferred images that showed native people of the countries related to the queries. In the case of running the experiment on the personal collections of the participants, we would expect users to be more interested in photographs with *familiar* (*e.g.* friends) people in them [23].

Figures 5 through 7 show actual image examples for three of the queries, where images have been ranked left (highest ranked image with this treatment) to right (lowest ranked image with this treatment), for each of the treatments.

6. CONCLUSIONS AND FUTURE WORK

In this paper we have introduced an image re-ranking algorithm that takes into account the aesthetic appeal of the images retrieved by a consumer image sharing site search engine (Picasa Web Album). We have also extended a state of the art image aesthetic appeal algorithm by incorporating a series of features aimed at consumer photographs. The results of a controlled user study with 37 participants have revealed that Image Aesthetic plays a varying role on image preferences depending on the query type and the user preferences. Future work includes optimizing an image aesthetic metric for specific image categories, looking into other features such as color harmony and image composition and carrying out a more comprehensive study with personal images from the participants.

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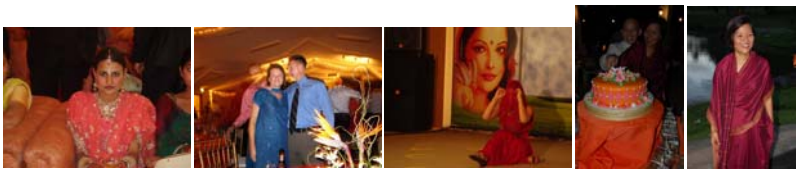
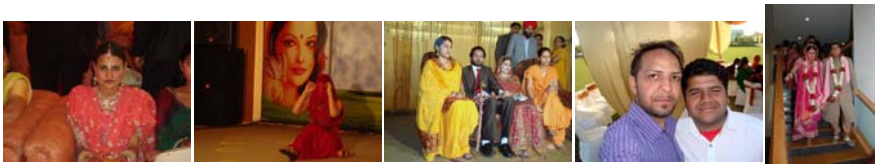
Aesthetics



Fusion

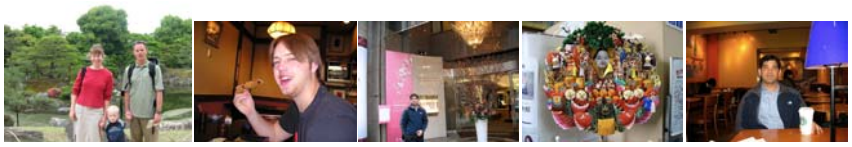


Pic,asa

Figure 5. Ranked results for query #5: "Wedding in the park". *Picasa* performed better than *Aesthetics* and *Fusion*.

Aesthetics

Fusion

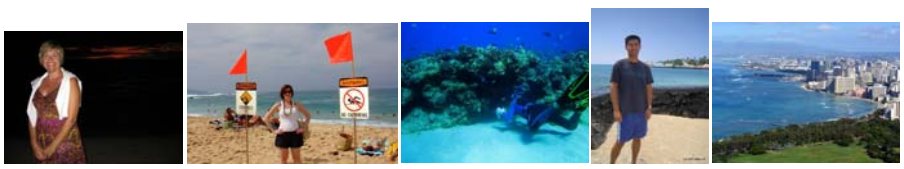


Picasa

Figure 6. Ranked results for query #3: "Trip to Japan". *Aesthetics* was better than *Fusion* and *Picasa*.

Aesthetics

Fusion



Picasa

Figure 7. Ranked results for query: "Hawaii beach". All three methods performed equally well.