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A COMPREHENSIVE AESTHETIC QUALITY ASSESSMENT METHOD FOR NATURAL IMAGES USING BASIC RULES OF PHOTOGRAPHY

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ABSTRACT

In this paper we propose a comprehensive photo aesthetic assessment method that represents each photo according to a set of photographic rules. Specifically, our method exploits the information derived from both low- and high-level analysis of photo layout, not only for the photo as a whole, but also for specific spatial regions of it. Five feature vectors are introduced for describing the photo's simplicity, colorfulness, sharpness, pattern and composition. Subsequently, they are concatenated in a final feature vector where a Support Vector Machine (SVM) classifier is applied in order to perform the aesthetic quality evaluation. The experimental results and comparisons show that our approach achieves consistently more accurate quality assessment than the relevant literature methods and also that the proposed features can be combined with other generic image features so as to enhance the performance of previous methods.

***Index Terms*—** No-Reference image aesthetic quality assessment, photography, rules of photography, support vector machine.

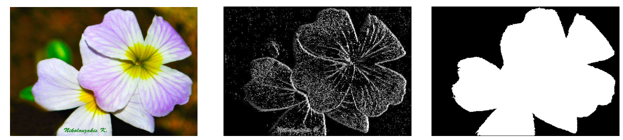
1. INTRODUCTION

Photo aesthetic quality assessment is an emerging task in the field of image processing. The automatic prediction of a photo's aesthetic value constitutes a challenging problem, the solution to which can contribute to applications and tasks such as multimedia preservation, image re-ranking and navigation in big photographic archives, photo collection summarization, image enhancement and others. In the relevant literature there are few methods that examine the re-ranking, search and retrieval of photos based on their aesthetic quality, including [1], [2] and [3]. In [4], [5] and [6], image enhancement methods which take into consideration aesthetic criteria, such as the photo composition, are presented.

In this paper, our aim is to develop a comprehensive and effective aesthetic assessment method based on basic photographic rules. The rest of the paper is organized as follows. In section 2 we review the related work. In section 3 we present the proposed features in detail. This is followed by the presentation of the datasets and the experimental results in section 4 and finally, we draw conclusions in section 5.

2. RELATED WORK

The aesthetic quality assessment of photographic images is a challenging field of research where a variety of methods have been proposed over the past few years. Many of the proposed methods detect the high aesthetic value images by exploiting the information derived from low-level visual features such as brightness, texture and color distribution. For instance, the authors of [7], one of the first approaches in the relevant literature, introduce blurriness, contrast, colorfulness and saliency as a set of low-level features for discriminating images captured by amateurs and professional photographers. A more elaborate method for low-level feature extraction, followed by the implementation of classifiers which are built using SVMs and classification trees, is proposed in [8], where the principle of the rule of thirds is introduced. In [9], at first the subject of the photograph is detected and then a set of visual features, including features for simplicity and the rule of thirds, is used in order to predict the image's aesthetic value.



(a) (b) (c)

Fig. 1: Main subject detection: (a) original image, (b) image edges, (c) main subject

All the above methods are mainly based on low-level feature extraction. Methods that exploit a combination of low- and high-level features to assess image aesthetics include [10]-[13]. High-level features refer to photo layout analysis. In [10], the photo aesthetic value is predicted based on composition attributes, such as salient objects and the rule of thirds; content attributes, which express the concepts and objects depicted in the photo; and sky illumination attributes, which distinguish between photos taken in clear, cloudy or sunset sky. The spatial distribution of edges, the color and hue distribution, as well as the blurriness, brightness and contrast are used in [11] in order to identify high quality professional photos. In addition, in [12] the authors focus on the design of color and spatial features which are not computationally expensive. In [13], it is shown that generic image descriptors can sometimes outperform the aesthetic assessment methods that are based on features specifically designed for this task. Web-based applications exploiting some of the above techniques have also appeared in [14], [15] and [16].

In the relevant literature there are also many content-based methods, which assess the aesthetic quality of a photo based on features extracted from specific regions of the image or for specific content. In [17], the authors present a set of regional features that measure the clarity and the complexity of the subject areas and a set of global features that capture the color and spatial composition of photos using the hue wheel and the Hough transform. Moreover, in [18] specific features are chosen, from a set of region and global features, for each

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individual photo category (e.g., animal, architecture, etc.). A bag-of-aesthetics preserving features for scenic photo aesthetic assessment are proposed in [19], while in [20] the authors focus on the aesthetic assessment of photos that contain faces.

Although the above techniques are related to the present study, each of them uses low-level visual features and also often some high-level features that allow the method to take into account up to three of the basic rules of photography. In this paper we propose the use of five representative feature vectors that correspond to five basic rules of photography and we introduce a novel feature, the pattern, which can effectively capture patterns and symmetry in natural photos. We assess the photo aesthetic quality using these five comprehensive feature vectors which can be used individually to capture the simplicity, the colorfulness, the sharpness, the existence of pattern and the layout composition of the photo. We also concatenate them into one vector, serving as the overall aesthetic quality assessment feature in our method, and we use it in combination with an SVM classifier to estimate whether a given photo exhibits high aesthetic quality or not.

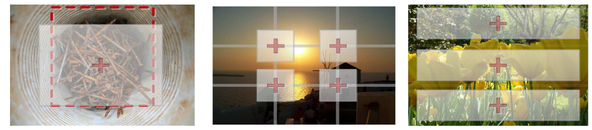
3. PROPOSED AESTHETIC FEATURES

There is a proverb that says "Rules are made to be broken", so also in photography it is often though that the only rule is that there are no rules. However, there are rules or guidelines, which if applied during the capturing process can enhance the aesthetic appeal of the photo. In the proposed approach we try to describe each image according to a set of photographic rules. Therefore, we select five representative photographic rules under which we extract the appropriate image features in order to classify the images as aesthetically pleasing or not. Below, we present the rules in accordance with which we design our features and the corresponding features.

3.1. Simplicity

Simplicity in photography means ideally capturing a single subject on a neutral background, avoiding distractions. Adopting this technique the photographer highlights the subject, leading the eye directly on the desired point.

The simplicity of photo composition plays a crucial role in aesthetic assessment and it depends on two basic rules, the color difference between the main subject and the background, and the spatial arrangement of the main subject. We start by making the assumption that the main subject is the least uniform portion of the image, and based on this we identify our main subject by edge detection (using the image gradient magnitude and orientation), followed by the application of simple morphological operations on a binarized edge mask, so as to result in a limited number of connected regions (Fig. 1). Subsequently, in order to capture color differences, we i) compute the HSV histogram of the main subject and background separately, and we estimate the mean value, the standard deviation, the kurtosis, the skewness and the Kullback-Leibler divergence of both distributions for each color component, and ii) considering two color regions of the image, the main subject and the background, we estimate a 5-bin histogram of the color-difference formula, CIE 1976 (L* a* b*), which is presented in [21]. In parallel, in order to capture the spatial arrangement of the main subject, we compute for it the percentage of its pixels that appear in each of the 9 patches of the rule of thirds grid (Fig. 2b).



(a) (b) (c)

Fig. 2: Composition rules: (a) "fill the frame", (b) rule of thirds, (c) "landscape"

3.2. Colorfulness

Capturing photographs with vibrant colors and intense contrast are among the most powerful ways to arouse viewers' attention. There are several photographic techniques involving the usage of color such as the complementary colors rule, the neighbouring colors rule or the photo-shooting of a colorful object on an otherwise monochromatic background, as described in [22] and [23].

To evaluate the colorfulness of photos we design a comprehensive color feature vector. At first, we perform k-means clustering in order to detect three basic color regions on the image. Subsequently, we exploit the RGB and HSV color spaces, as well as an emotion-based color space consisting of activity, weight and heat dimensions, which is presented in [24]. For each component of the three aforementioned color spaces we estimate a 5-bin histogram; these histograms are then concatenated into one color vector, capturing the color distribution on the three corresponding regions. Now, our aim is to find which single color is dominant in each of these three regions. For this reason we use the aforementioned color vector which is mapped onto a color description matrix of ten dominant colors. In order to quantify the importance of each area we also store the percentage of pixels that each color region occupies.

For each of the 9 patches of the rule of thirds grid we additionally estimate a 5-bin histogram for each color component of the HSV color space and the Correlated Color Temperature (CCT), which is presented in [25] and computed according to Eq. 1, where X, Y and Z are the respective dimensions of the XYZ color space. Finally, we also extract a feature to measure contrast and darkness, following the method presented in [26].

$$CCT = (449 * n^3) + (3525 * n^2) + (6823.3 * n) + 5520.33 \quad where, \tag{1}$$

$$n = \frac{x - 0.3320}{0.1858 - y}, \quad x = \frac{X}{X+Y+Z}, \quad y = \frac{Y}{X+Y+Z} \tag{2}$$

3.3. Sharpness

Sharpness is arguably one of the most important factors that affect the quality of photos. A clear, sharp subject automatically attracts the attention of the eye to the right point, while a blurred subject usually has an adverse aesthetic effect on photos.

To this end, we apply the no-reference image blur detection scheme described in [27] so as to extract features that can describe the blurriness of the image, resulting in a 500-element sharpness feature vector, according to the Algorithm 1 of [27]. In addition, in order to detect more complicated forms of blur, such as motion blur, that are difficult to be captured on the power spectrum of the Fourier transform, we use the Haar wavelet transform. We estimate the horizontal H, vertical V and diagonal D detail coefficients for three levels of the Haar wavelet transform and we compute a 5-bin histogram of the edge map ($Emap = \sqrt{H^2 + V^2 + D^2}$) for each of the 9 patches of the rule of thirds grid (Fig. 2b).

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Fig. 3: Pairs of half-image patches, for pattern assessment

3.4. Pattern

The world is full of patterns, symmetry and textures. Photographers seem to appreciate this kind of beauty that surrounds us, as patterns and symmetry exude a sense of harmony and rhythm which makes the photographs appealing. This feature is one of our contributions to the field of photo aesthetic assessment, since to our knowledge such a feature has not appeared before in the relevant literature.

In order to extract the appropriate information to describe the aforementioned characteristic of images we divide the image in multiple half-image parts, as shown in Fig. 3. For every pair of half-image patches we detect SURF interest points and subsequently we perform point feature matching, capturing the similarities of these patches. In addition, our aim is to examine the presence of intense edges and if these edges are distributed in the same manner in both half-image patches, for each of the four pairs (Fig. 3). In order to achieve this, we estimate the mean value, the standard deviation and the Kullbak-Leibler divergence after applying the Haar wavelet transform on both half-image patches of each pair (Fig. 3).

3.5. Composition

Composition is also an important aesthetic factor, since the appropriate arrangement of the objects on the photographic canvas can add balance and harmony, while a poor composition can distract the viewer's eye out of the intended point of interest.

In the proposed approach we examine three composition rules: the "fill the frame" (Fig. 2a), the rule of thirds (Fig. 2b) and the "landscape" composition (Fig. 2c), as presented in [28] and [29]. To achieve this, we use the objectness measure, presented in [30], in order to detect eight objects on each photo. Then, our aim is to estimate the relative position of each object with respect to the center of each of the shaded image patches, that is marked with a cross in Fig. 2. For assessing the "fill the frame" composition, we compute the euclidean distance and the angle of the object's center with respect to the center of the shaded patch depicted in Fig. 2a, as well as the spatial overlap between the shaded patch and the detected object's area (as an example, the latter area is marked with a dashed line in Fig. 2a). For the rule of thirds and the "landscape" composition we similarly estimate the euclidean distance, the angle and the spatial overlap of the object with respect to the shaded patches presented in Fig. 2b and Fig. 2c. For the "landscape" composition, we additionally estimate the color distribution on the 3 patches of the "landscape" grid (Fig. 2c), based on the HSV color format.

3.6. Overall aesthetic assessment feature

Having computed the aforementioned feature vectors, we concatenate them in one final, comprehensive, 1323-element vector. The overall procedure of the proposed aesthetic quality assessment method is presented in Fig. 4. The code for the proposed method has been made publicly available [1].

[1] The CERTH image aesthetic method, http://mklab.iti.gr/project/IAQ

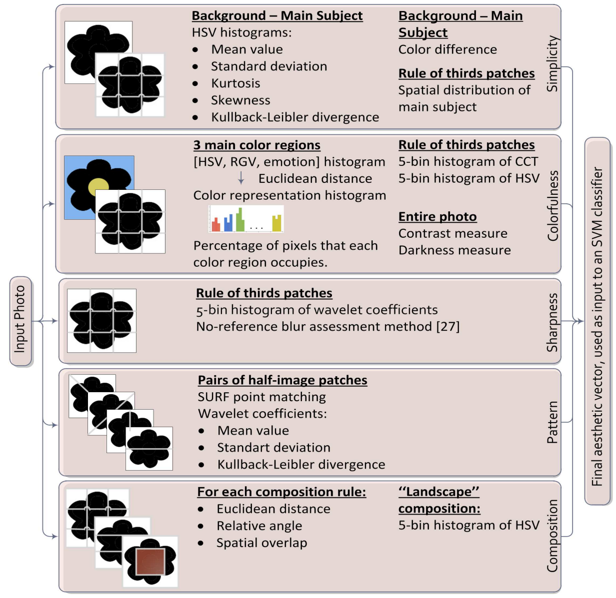

Fig. 4: Overview of the proposed method

4. EXPERIMENTAL RESULTS AND DISCUSSION

4.1. Datasets and Evaluation

Most of the photo aesthetic assessment techniques evaluate the performance of their features on publicly available datasets which consist of photos acquired from on-line photography communities. There are hundreds of amateur and professional photos uploaded and rated by the community members. These photos are appropriate for aesthetic assessment tasks due to their content and the diversity of the ratings submitted by both amateurs and professionals. The former tent to judge the photos based on emotion while the latter pay more attention to technical details.

To evaluate the proposed approach we use three different datasets, CUHKPQ [17], CUHK [17] and AVA [31]. The CUHKPQ dataset is divided into seven thematic categories, and each photo has been classified by members of the photography community as a high-aesthetic or low-aesthetic quality photo. Similarly to the methodology of [12], we randomly partition ten times the photos of each category, assigning half of them as training and the rest as testing set. Afterwards, we train a single linear SVM classifier for each individual category and the average results are reported. In addition, the contributors of [17] collected 12000 images from all categories (this subset is denoted as the CUHK dataset), on which we also perform experiments following the same experimental design. On the other side, the AVA dataset contains photos derived from a photo contest community, the www.dpchallenge.com, which are associated with their mean aesthetic scores. This dataset has already been divided in training and testing set by the authors of [31], so for both of these sets, following the experimental design of [11], we choose the 10% and 20% top ranked photos as high-aesthetic ones and the 10% and 20% bottom ranked as low-aesthetic photos, respectively. In this way, the images with score in the middle of the score range are excluded as in [11], since they could introduce noise in the classification process.

Finally, the performance of our aesthetic assessment approach is evaluated calculating the classification accuracy and the Area Under

Table 1: Experimental results (AUC) on the CUHKPQ dataset

	Features	Animal	Architecture	Human	Landscape	Night	Plant	Static	Overall
Lo et al. [12]	**Concatenated**	0,9160	0,8414	0,9209	0,9065	0,8633	0,9330	0,8972	0,8974
Tang et al. [17]	Dark channel	0,8393	0,8869	0,7987	0,8575	0,7062	0,7858	0,8335	0,8189
	Complexity Combined	0,8212	0,7219	0,7815	0,7516	0,7284	0,8972	0,7491	0,7817
	Hue Composition	0,7861	0,8376	0,7909	0,8936	0,7214	0,8316	0,8367	0,8165
	Scene Composition	0,7003	0,6781	0,7923	0,6979	0,7477	0,5966	0,7057	0,7056
	Concatenated	0,8712	0,9004	0,9631	0,9273	0,8309	0,9147	0,8890	0,9044
Luo et al. [9]	Clarity Contrast	0,8074	0,5348	0,6667	0,5379	0,6297	0,7439	0,7309	0,6738
	Lighting	0,7551	0,6460	0,7612	0,6226	0,5311	0,7752	0,7430	0,7032
	Geometry Composition	0,7425	0,5806	0,6828	0,4393	0,6075	0,7308	0,5920	0,6393
	Simplicity	0,6478	0,5582	0,7752	0,7454	0,6918	0,7450	0,7849	0,6865
	Color Combination	0,8052	0,7194	0,6513	0,7280	0,5873	0,7846	0,7513	0,7244
	Concatenated	0,8712	0,9004	0,9631	0,9273	0,8309	0,9147	0,8890	0,7792
Ke et al. [11]	Blur	0,7566	0,7981	0,7381	0,7785	0,6665	0,7963	0,7662	0,7592
	Brightness	0,6993	0,8138	0,7801	0,7848	0,7244	0,7337	0,6976	0,7464
	Hue Count	0,6260	0,7082	0,7027	0,5964	0,5537	0,6920	0,5511	0,6353
	Concatenated	0,7751	0,8526	0,7908	0,8170	0,7321	0,8093	0,7829	0,7944
Proposed method	Simplicity (section 3.1)	0,8547	0,8155	0,8924	0,8787	0,7839	0,8961	0,8323	0,8206
	Colorfulness (section 3.2)	0,8215	0,8661	0,9112	0,9182	0,7947	0,9084	0,8605	0,8407
	Sharpness (section 3.3)	0,9451	0,8721	0,9615	0,8674	0,9042	0,9248	0,9066	0,9085
	Pattern (section 3.4)	0,8966	0,8312	0,8614	0,8562	0,8954	0,8950	0,8184	0,8434
	Composition (section 3.5)	0,8831	0,8859	0,8845	0,9210	0,8932	0,9063	0,8778	0,8610
	Concatenated (section 3.6)	**0,9542**	**0,9208**	**0,9731**	**0,9410**	**0,9426**	**0,9603**	**0,9407**	**0,9460**

the ROC Curve (AUC) measures [32].

Table 2: Classification accuracy on the CUHK dataset

	Feature Dimensionality	Accuracy
Datta et al. [8]	56	75,85
Ke et al.[11]	7	76,53
Lo et al. [12]	24	77,25
GIST [33]	512	67,96
BOV-SIFT-SP [13]	8192	81,36
BOV-Color-SP [13]	8192	82,13
FV-Color-SP [13]	262144	**89,90**
Proposed features (section 3.6)	1323	82,41
FV-Color-SP	4000	78,16
FV-Color-SP+Proposed	5323	85,02

4.2. Results and Discussion

At first, we test the performance of the proposed method on each of the seven categories of the CUHKPQ dataset [17] and we compare our features with previously proposed methods. Moreover, in order to demonstrate that our results do not depend a lot on the photo subject, we further evaluate our method over all categories. For comparison we use the aesthetic assessment method proposed by Lo et al. in [12], for which the corresponding code has been released, the region-based and global aesthetic features proposed by Tang et al. in [17], the subject oriented method proposed by Luo et al. in [9] and the high-level attributes proposed by Ke et al in [11]. The corresponding results of the last three methods are taken from [17]. The performance evaluation using the AUC measure is shown in Table 1. As can be seen, the proposed method achieves the best results, both for each of the different subject categories and overall, followed by the algorithm of Tang et al. and in some categories by the method of Lo et al. Furthermore, our individual features present promising performance in comparison to similar features of the other methods.

We continue with results on the CUHK dataset [17], consisting of 6000 high-aesthetic and 6000 low-aesthetic images. In this case, we compare with the related methods [8], [11], [12], [13], [33], whose corresponding results were presented in [13]. The feature dimensionality and the accuracy of these methods are presented in Table 2, where we can see that our method outperforms most of the others. The generic image features with Fisher Vector encoding and spatial pyramidal decomposition of [13] provide the highest accuracy, but these features exhibit extremely high dimensionality, consequently also excessive computational complexity when it comes to using them for training an SVM classifier (the results of [13] were obtained by learning linear SVMs with a hinge loss using the primal formulation and a stochastic gradient descent algorithm [34]). At this point, we also implemented the most efficient generic descriptor of [13], the FV-Color-SP, and tested it with a linear SVM, to demonstrate that the combination of our photographic-rule-based features with generic descriptors can boost the overall performance. For the FV-Color-SP feature vector we employ dimensionality reduction to 4000 elements, for computational efficiency purposes. It is clear from the experimental results shown in Table 2 that our features can indeed improve the results obtained using generic low-level features, when combined with the latter.

Finally, the performance of the proposed method in comparison with the algorithm provided by Lo et al. on the "overall" category of the AVA [31] dataset is presented in Table 3. The corresponding results demonstrate that our method achieves good performance on another challenging dataset and that its results are consistently better than the results of [12]. In addition, in this dataset, which includes mostly professional photos, we can see that the proposed pattern feature is one of the most effective individual features.

Table 3: Overall classification accuracy on the AVA dataset

	Features	Accuracy on 10%	Accuracy on 20%
Lo et al. [12]	**Concatenated**	0,6660	0,6214
Proposed method	Simplicity (section 3.1)	0,6361	0,6005
	Colorfulness (section 3.2)	0,6503	0,6348
	Sharpness (section 3.3)	0,7594	0,7242
	Pattern (section 3.4)	0,7692	0,7180
	Composition (section 3.5)	0,7264	0,6983
	Concatenated (section 3.6)	**0,7708**	**0,7435**

5. CONCLUSION

In this paper, we proposed a new comprehensive photo aesthetic assessment method which exploits five basic photographic rules to extract rule-specific low- and high-level visual features. The experimental results of this approach, and of the combination of these features with previously-proposed generic ones, demonstrate the importance of taking basic photographic rules into account when designing an aesthetic quality assessment method.

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