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Image Recoloring with Valence-Arousal Emotion Model

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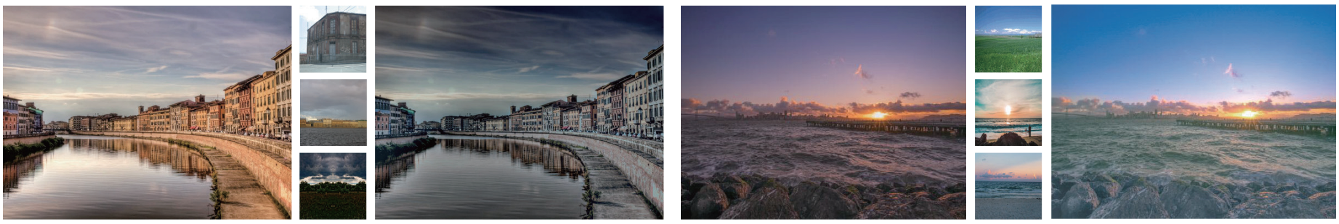

Figure 1: *Given a source image and target emotion (towards more positive or negative), the system recolors the image using reference image segments selected to match the target emotion as well as the labels of the semantically segmented regions.*

Abstract
We introduce an affective image recoloring method for changing the overall mood in the image in a numerically measurable way. Given a semantically segmented source image and a target emotion, our system finds reference image segments from the collection of images that have been tagged via crowdsourcing with numerically measured emotion labels. We then recolorize the source segments using colors from the selected target segments while preserving the gradient of the source image to generate a seamless and natural result. User study confirms the effectiveness of our method in accomplishing the stated goal of altering the mood of the image to match the target emotion level.

Categories and Subject Descriptors (according to ACM CCS): H.3.1 [INFORMATION STORAGE AND RETRIEVAL]: Content Analysis and Indexing—I.4.8 [IMAGE PROCESSING AND COMPUTER VISION]: Scene Analysis—Color

1. Introduction

Color is a powerful tool for conveying mood or feeling in visual communication. When we look at a picture or a drawing, its colors often play a major role in eliciting certain emotional response, whether it is positive, negative, or neutral. The ability to properly select and modify colors is thus one of the basic requirements for successful image processing, which however takes average users considerable time and effort to master. Developing a truly high-level photographic color editing mechanism to facilitate this process remains a challenging goal, as most of the conventional image processing programs still offer nothing more than a bunch of sliders for globally altering hue, contrast, or saturation levels.

There are a number of technical approaches to help ease the task of image recoloring, including ones based on user strokes [LLW04, WHCO08, AP10], color palettes [CFL*15, LRFH13, WYW*10, LZNH15], or examples [RAGS01,PKD05,TJT05,PR10,WDK*13, BPC16, GEB15]. Of particular relevance to our work is the example-based approach, where the system recolors the source image such that it matches the color statistics of the reference image. In this approach, it is basically the user's responsibility to find and provide a proper reference image for obtaining a recolored output that would elicit the desired type/level of emotion.

We aim to develop an image recoloring method that provides a more direct control of the emotion in a quantitatively measurable fashion. In particular, we borrow from the field of psychology a dimensional emotion space called Valence-Arousal (VA) model [Rus80], where the two parameters, V and A, represent the level of pleasure and excitement, respectively, measured on a scale of 1 to 9. The target emotion in our method is thus specified by the values of V and A. We then let the system automatically select reference

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(target) segments that match both the target emotion and the source image semantics.

We first build via crowdsourcing a large collection of images tagged with V-A emotion values, which then serves as the database of reference images (Section 3). Our method then automatically selects the target segments that best fit the target emotion and the semantics of the source segments (Section 4.1), then follows the recoloring of source image to reflect the target emotion (Section 4.2). We also conduct user study to evaluate the effectiveness of our recoloring method (Section 5).

The contributions of our work are summarized as:

- A novel semantic image recoloring method that gives direct control to change/enhance the emotion elicited from the image
- Introducing a psychologically-modeled Valence-Arousal emotion chart into image recoloring
- An automatic method for selecting target image segments to match both the target emotion and the source semantics
- Use of crowdsourcing to build image database tagged with V-A emotion values and to evaluate the proposed method against others

2. Related work

Many of the early image color transfer methods perform global color transfer from the target image to the source image [RAGS01, CUS04, CSUN06, PKD05, PR10, XM09]. In the seminal work of Reinhard et al. [RAGS01], they described a global color transfer technique based on color statistics, that is, mean and standard deviation of the entire source and the target images. Chang et al. [CUS04, CSUN06] instead incorporated the characteristics of human color perception to generate results that are perceptually more meaningful. Pitie et al. [PKD05] and Pouli et al. [PR10] modeled the problem as probability density function transfer and histogram reshaping. Xiao et al. [XM09] solved it as an optimization problem to further enhance the quality of recoloring. Global color transfer however may produce unnatural recoloring when color statistics differ significantly from region to region.

To overcome this limitation, Tai et al. [TJT05] proposed a local color transfer method using probabilistic image segmentation and parametric region matching. Yoo et al. [YPCL13] used mean-shift algorithm for region-based color transfer. To further avoid color transfer between mismatched regions, Cusano et al. [CGS12] used semantic image segmentation and obtained more meaningful region pairings for color transfer. Wu et al. [WDK*13] similarly performed semantic content analysis to associate regions with predefined semantic classes, then allow color transfer only between semantically compatible regions. All of these global or local color transfer techniques do not provide means, other than through the user-provided reference image itself, to directly control type or level of emotion that the recolored output should elicit.

Word-based recoloring approach [CSMS11, WJLC12, MSMP12, HQZ14] takes as input a source image and a target word representing specific mood such as “romantic”, “cool” or “serene”, then recolors the image to match the target word. Csurka et al. [CSMS11] associated 15 affective words with groups of colors, then performed color transfer referencing the established color groups. Murray et al. [MSMP12] proposed a concept transfer method that uses a given concept word (e.g. romantic, earthy and luscious) associated with specific color palettes. He et al. [HQZ14] adopted Pantone color scheme that contains 27 emotions as well as 24 three-color combinations for each emotion. Many of these approaches focus on transferring colors based on the predefined link between colors and emotions, while largely neglecting the semantics of the source image. Our method, on the other hand, chooses a set of colors to transfer that matches not only the target emotion, but also the semantics of the image region that it goes to. Moreover, we provide means to express the target emotion as a quantitative measurement, rather than just a word, through the incorporation of Valence-Arousal (VA) emotion model. While word-based descriptions can be intuitive to use, they are often too abstract and insufficient to cover the full range of possible emotional states elicited by stimuli [Rus80, GS13]. The use of V-A model allows for a rigorous representation of each emotional state, mapping and exploring of all possible emotions in recoloring, as well as incremental/decremental adjustment of emotion.

3. Building image dataset

3.1. Image data with semantic annotations

The first task is to collect and build a set of images with per-pixel semantic annotations. Following [LYT09, ML13], we use the LabelMe image database [RTMF08] that has a large collection of outdoor scenes and their associated semantic annotations. Liu et al. [LYT09] analyzed the per-pixel frequency of the semantic labels in the LabelMe images, and found the top 34 most-labeled object categories. Among them, we used the top 16 categories (e.g. sky, mountain, building, tree, road, sea, field, grass, plant, car, sand, rock, sidewalk, window, and desert) as the search keywords, then obtained 700 images containing the selected semantic labels. Then additional 173 images were collected from on-line image communities (e.g. Flickr, PhotoPin and Unsplash), which however do not have per-pixel semantic labels, and thus we conducted semantic segmentation [ML13] on those images. Consequently, our image database consists of a total of 873 semantically annotated images.

3.2. Assigning V-A emotion values

The next step is to tag each image in the dataset with V-A emotion values, for which we use on-line crowdsourcing. The Valence-Arousal model [Rus80] is a dimensional emotion space widely used in the field of psychology (Figure 2). Valence represents the pleasantness of an emotional stimulus, which we assume to scale from 1 to 9 (1 means “negative” and 9 “positive”). Arousal is the intensity of emotion provoked by a stimulus, which also ranges from 1 (“calm” and “inactive”) to 9 (“excited” and “active”).

We use Amazon Mechanical Turk (AMT) to assign V-A emotional values to the collected images. Each subject (user) is presented an image with a representation of V-A dimensional scales called Self Assessment Manikin (SAM) [BL94], with which to enter their V-A values based on how they feel about the given image. While the emotion elicited from each image may vary among subjects, we utilize the AMT function that filters out extreme outliers.

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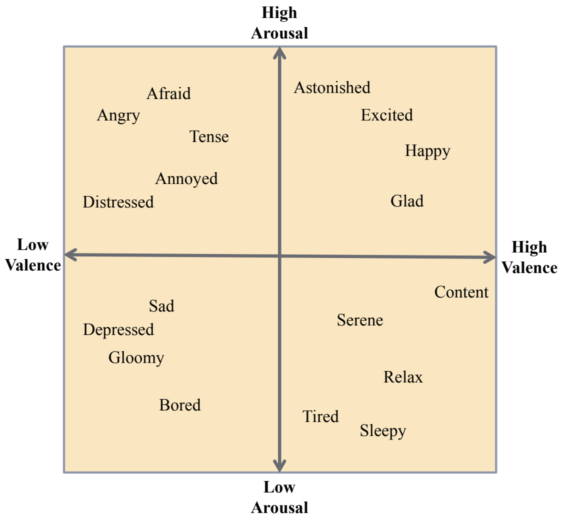

Figure 2: *Valence-Arousal emotion space*

We also limit the number of questions for each subject to 100 to keep them focused throughout the test. A total of 11,934 responses were collected from 408 different subjects. On average, each image was evaluated by more than ten subjects. Figure 3 shows some example V-A responses[†].

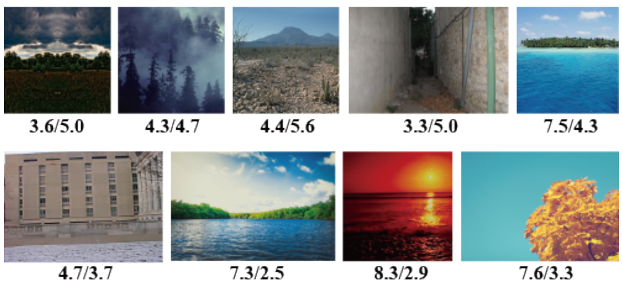

Figure 3: *Example images with Valence/Arousal values collected on Amazon Mechanical Turk. Both values range from 1 to 9.*

4. Recoloring algorithm

Figure 4 shows the overview of our recoloring method. To the best of our knowledge, this is the first image recoloring method which ensures that the recolored output matches both the target emotion and the semantics of the source image. Given a source (input) image S, we first perform semantic segmentation [ML13] on S to generate K semantic segments. For each of these source segments, our system then searches the image database and finds the best matching target semantic segment via energy minimization (Section 4.1). Then the source image is recolored, segment by segment, referencing the colors in the corresponding target segments (Section 4.2).

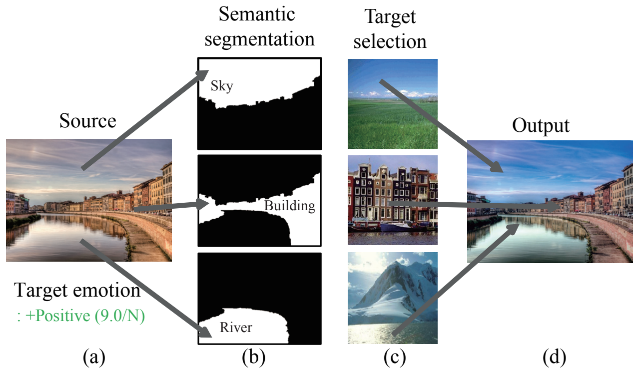

Figure 4: *Given a target emotion (a), the source image is first semantically segmented (b). The target (reference) segments are then automatically selected from the image database by minimizing the objective function in Eq. (1) (c). The source image is recolored using the colors from the target segments (d).*

4.1. Selecting target segments

We use energy minimization to automatically select target semantic segments that best match the target emotion and the source semantics. Given a source image S consisting of K semantic segments $S = \{s_1, ..., s_K\}$ and target emotion (V-A values), our method finds via exhaustive search a set of target segments $T = \{t_1, ..., t_K\}$ from the image database, where t_i is a target segment with matching semantic label as s_i, that minimizes the following:

$$\underset{T}{argmin} \sum_{i=1}^{K_s} E_i(s_i, t_i), \quad (1)$$

subject to

$$label(s_i) = label(t_i), \quad (2)$$

where

$$E_i = w_e E_e + w_l E_l + w_s E_s + w_p E_p. \quad (3)$$

Emotion term $E_e = \|t_e - u_e\|^2$ is the penalty for the difference between the target emotion (denoted u_e) and that of the target segment (denoted t_e). Since an emotion is represented by (V, A) coordinates, this equation computes the 2-D distance on the V-A space. In case only one of the two parameters is used, it degenerates to 1-D distance.

Lightness term $E_l = \|L_s - L_t\|^2$ encourages their lightness ranges to match, where L_s and L_t denote the lightness range of the source and target segments, respectively.

Size term $E_s = \|A_s - A_t\|^2$ is the size constraint that forces the size

† The database is publicly available at http://cga.yonsei.ac.kr/publications/Image_Recoloring_with_Valence-Arousal_Emotion_Model

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of the target segment (denoted A_t) to be similar to that of the source segment (denoted A_s).

Position term $E_p = \|P_s - P_t\|^2$ encourages finding target segments from the area where the source segments are (e.g., sky tends to exist near the top of the image almost all the time). P_s and P_t denote centers of source and target segments, respectively.

Weights For all experiments, we use the weights that have been empirically determined: $w_e = 0.3, w_s = 0.2, w_p = 0.2, w_l = 0.2$.

4.2. Recoloring

Once the set of best matching target segments has been found, the colors are transferred from each target segment to the corresponding source segment. We rely on color statistics [RAGS01] to perform segment-to-segment color transfer. Our method however ensures that the color transfer occurs only between semantically compatible segments (e.g. sky-to-sky and tree-to-tree). Given the source image I, the color of each pixel p in the output image O is obtained by:

$$O(p) = \mu_{t_i} + \frac{\sigma_{t_i}}{\sigma_{s_i}}(I(p) - \mu_{s_i}), \tag{4}$$

where i denotes the segment index that p belongs to. μ and σ are the mean and the standard deviation of all colors of segment i, respectively.

One possible danger of such segment-to-segment color transfer is that the gradient of the source image may not be preserved, which may lead to visual artifact at the segment boundaries. We alleviate this by post-applying the gradient preservation technique [XM09]:

$$\min \sum_{p_i} \left(O'(p_i) - O(p_i)\right)^2 + \lambda \sum_{p_i} \left(\frac{\partial O'}{\partial p_i} - \frac{\partial S}{\partial p_i}\right)^2, \tag{5}$$

where λ controls the balance between preserving gradients vs. preserving the transferred color. Using Eq.(5), the final output image O' is obtained separately on each channel of *Lab* color space. We set $\lambda = 30$ for L channel and $\lambda = 1$ for a and b channels, reflecting the fact the human visual system is particularly sensitive to the lightness contrast.

5. Results

Figure 1 and 5 demonstrate our recoloring results on some example images and target emotions. Figure 6 shows the case where emotion words are used as target emotion. Given the emotion word, we extract the corresponding V-A values from the V-A dictionary of words [WKB13]. Figure 7 illustrates colorization of a greyscale source image using various target emotions. As shown in Figure 8, our method allows partial recoloring where color transfer applies only within the selected region, which is possible due to the semantic segmentation. In Figure 9, we show nine different recoloring results using the top-3 ranked target segments for each source segment.

Considering the subjective nature of emotion, we conducted two user studies to evaluate our affective recoloring method. All the experiments were conducted on Amazon's Mechanical Turk.

Experiment 1 In the first user study, we compare the source image with the recoloring result. We set four types of target emotions: +negative (1.0/N), +positive (9.0/N), +calm (N/1.0) and +exciting (N/9.0). Here, N stands for "not used". We used a total of 32 source images (eight source images for each target emotion) and thus generated 32 recolored images. In each question, human subjects were presented with a pair of images (source and recolored) and they were asked to answer which one they preferred by choosing one of the four options: our recoloring result, source image, both, or neither. A hundred subjects participated in this test. As shown in Figure 10(a), over 80 percent (on average) of the participants reported that they preferred recolored images. Considering the V-A numbers we used for the target emotions in this experiment are extreme ones in the V-A chart, this result appears to show that people tend to favor images that elicit strong emotions, rather than neutral. The preference of the recolored image is slightly lower for the arousal compared to the valence. We presume that the change of colors more affects the valence than arousal.

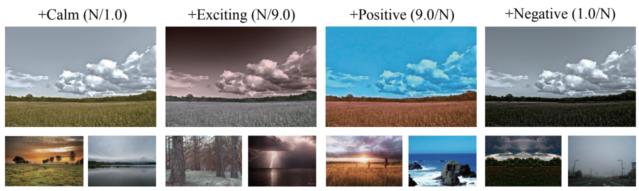

Figure 7: *Coloring of a greyscale source image using four different target emotions.*

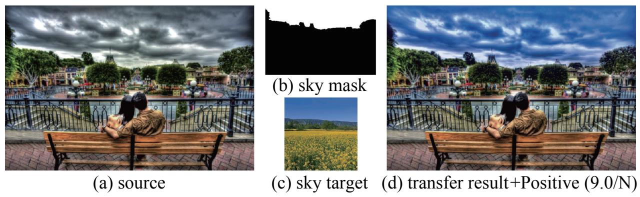

Figure 8: *Partial recoloring. (a) source image. (b) source sky segment. (c) target sky segment. (d) recolored sky.*

Experiment 2 We have also compared our method with the previous word-based recoloring techniques, [CSMS11] and [HQZ14]. Here we selected five emotional words (elegant, delicate, classic, spiritual and earthy) as target emotions and assigned the predefined V-A values for each word [WKB13]. For each word, we used ten different source images to generate ten recolored results using the two previous methods and ours (therefore a total of 50 comparisons). In each case, we presented three recoloring results and asked two questions: First, which result best represents the target emotion word? Second, which result looks most natural? Again, a hundred subjects participated in this test. On the first question, our results were picked by the majority of the participants on all target emotions except "spiritual" (Figure 10(b)). As for the second question, our results were consistently preferred in all cases (Figure 10(c)). Figure 11 shows some example cases and how they were ranked by the subjects.

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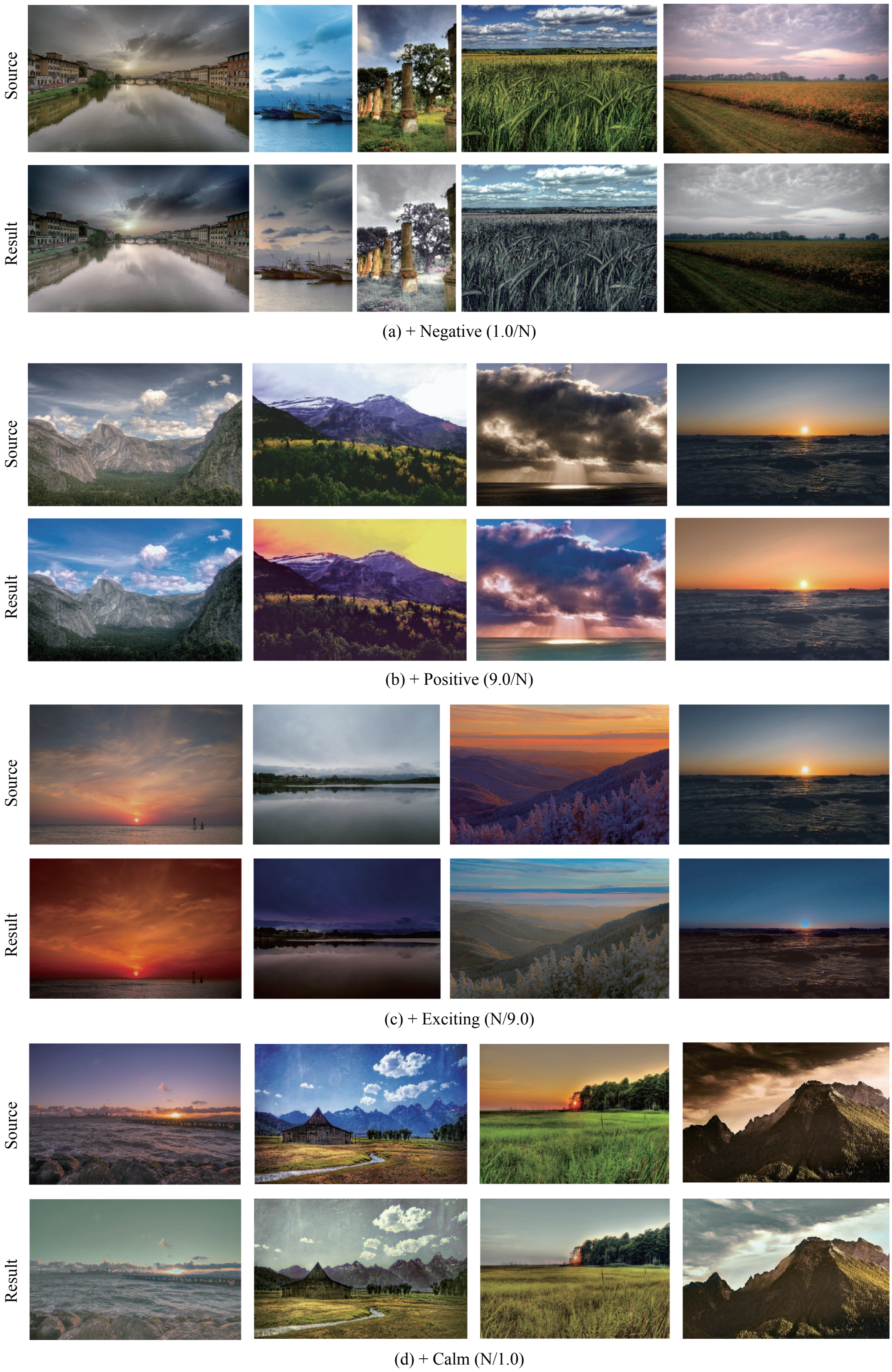

Figure 5: *Recoloring results. Target emotions are more negative (a), more positive (b), more exciting (c), and more calm (d). N denotes "not used"*

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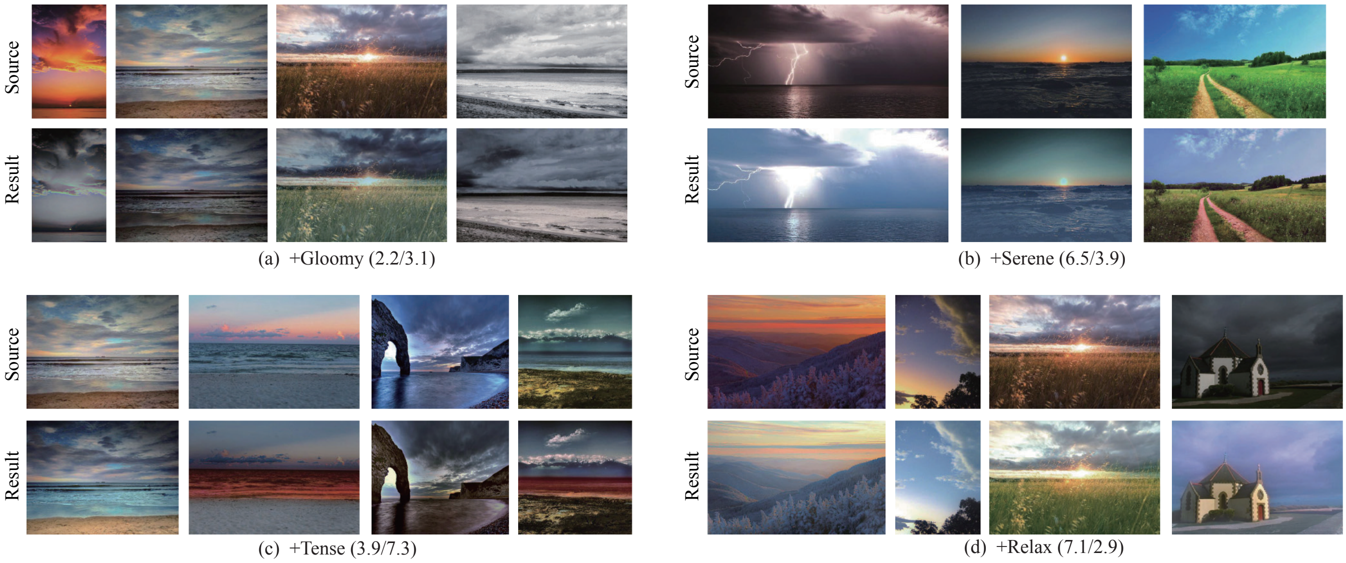

Figure 6: *Recoloring using target words.*

Figure 9: *Nine different recoloring results using top three target segments for each source segment.*

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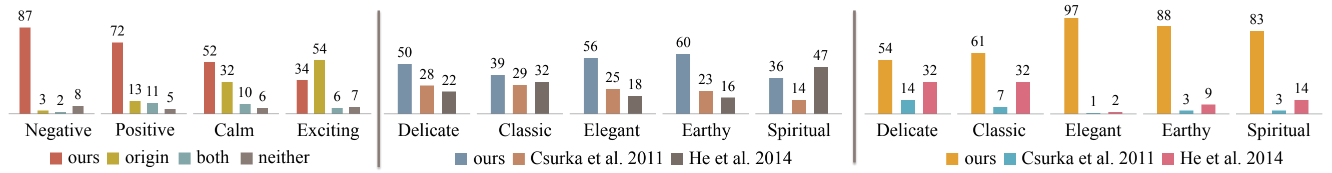


(a) Four targets (b) Emotion (c) Naturalness

Figure 10: *(a) The preference statistics over source image vs. recolored image. (b) Comparison with [CSMS11, HQZ14] on how well the result matches the target emotion. (c) Comparison with [CSMS11, HQZ14] on how natural the result looks.*

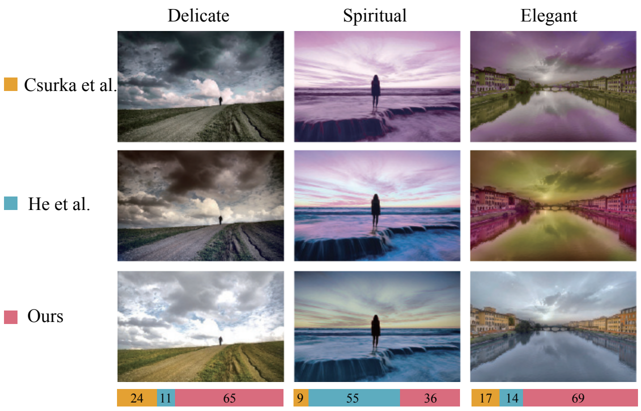
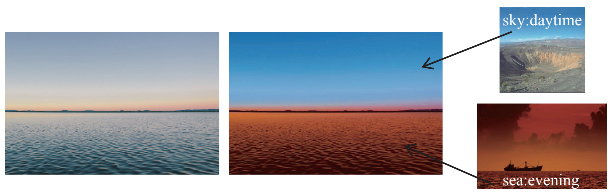


Figure 11: *Comparison with Csurka et al. [CSMS11] and He et al. [HQZ14]. The numbers at the bottom represent the numbers of people who chose ours vs. others.*

(a) source (b) wrong segmentation (c) transfer result

Figure 12: *Limitation: incorrect segmentation leads to unnatural recoloring*



(a) source (b) transfer result (c) target: sky, sea

Figure 13: *Limitation: semantics across regions may be inconsistent*

We used Matlab to implement our recoloring method. The entire process for an image of size 640×480 with two semantic segments took around 23 seconds, including 8 seconds for finding the two target segments and 15 seconds for recoloring.

6. Discussion and Future work

We have presented a semantic image recoloring method that directly manipulates the emotion elicited by the image. As with any semantic image recoloring techniques, the accuracy of semantic segmentation has a direct impact on the quality of recoloring. As shown in Figure 12, an incorrect segmentation may lead to an unnatural color transfer. With the recent advances in deep learning along with ever-increasing computing power, it is expected that the accuracy of object recognition and semantic segmentation would continue to improve [CPK*14, LSD15, NHH15]. Another limitation is that while our method performs semantic analysis of the source image, it does not consider inter-segment semantics such as time or season and thus may end up with inconsistent semantics across segments (Figure 13). It is certainly feasible to incorporate into our current framework a wider variety of intra- or inter-segment semantics as well as some image features (e.g. texture).

Our current system mostly deals with outdoor scenes that contain sky, mountain, sea, building, car, field, grass, road, plant, etc. As future work, we will expand our database to include a wider variety of semantic classes and images, such as indoor scenes, animals, humans and man-made objects. Our system relies on searching the image database to find the target images. Content-based pre-clustering of the database would help speed up the search process [LZLM07]. Another interesting future research direction would be to facilitate incremental emotion enhancement by analyzing the emotion level in the source image.

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