Evaluation and Prediction of Evoked Emotions Induced by Image Manipulations

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Abstract

Various image editing tools make our pictures more attractive, and at the same time, evoke different emotional responses. With powerful and easy-to-use imaging applications, capturing, editing and then sharing pictures have become daily life for many. This paper investigates the influence of several image manipulations on evoked emotions for different types of images. To do so, various types of images clustered in different categories, were collected from Instagram and subjective evaluations were conducted via crowdsourcing to gather the emotional responses on different manipulations as perceived by subjects. Evaluation results show that certain image manipulations can induce different evoked emotions on transformed pictures when compared to the original ones. However, such changes in image emotions due to manipulation are highly content dependent. Then, we conducted a machine learning based experiment, in attempt to predict the emotions of a manipulated image given its original version and the desired manipulation method. Experimental results present a promising performance of such a prediction model, which could pave the road to automatic selection or recommendation of image editing tools that can efficiently transform or emphasize desired emotions in pictures.

Introduction

Thanks to wide spread popularity of smart mobile devices with high-resolution cameras, as well as user-friendly imaging and social networking applications, taking pictures, then editing and sharing, have become part of everyday life for many. Photo sharing has been used as a way to share not only stories but also current moods with friends, family and public at large. Modern photo sharing applications equipped with advanced and easy-to-use image editing tools, such as Instagram, provide consumers with very convenient solutions to make their pictures more attractive, and more importantly, to arouse stronger emotional resonances. Different types of image content generate different emotions. Using different photographic techniques, visual filters or editing tools, pictures of the same scene can also evoke different emotions. Motivated by these facts, we attempt to change an original picture's evoked emotion and transform it to new emotions (stronger, weaker, or completely different) by image manipulation. To achieve this goal, we first need to understand the emotional responses evoked by different image manipulations when applied to pictures.

This paper investigates the influence of image manipulations on evoked emotions, and tries to find the potential pattern between image manipulation and generated emotions. To do so, we conducted subjective experiments based on online crowdsourcing. Different types of images were collected from Instagram, and manipulated by a number of typical image editing tools. Crowdsourcing subjects were then exposed to each, and questioned regarding the emotions pictures induced on them. Using the crowdsourced data as groundtruth, we trained and evaluated a model based on machine learning for predicting evoked emotions, taking an original image and desired manipulation as input.

The rest of the paper is structured as follows. The next section introduces the related works by other researchers, followed by a section describing the data collection and user study. Then we analyze and interpret emotional responses obtained from subjects, and report the experiments of emotion prediction upon image manipulation in the followed two sections. Finally, the last section concludes the paper and discusses future work.

Prior Work

Image aesthetic quality estimation, emotion recognition and classification have been largely studied in the field of computer vision [1, 2, 3, 4, 5]. Most previous works use image features for affective image classification and emotion prediction [2, 3, 6, 7, 5]. Such features include color, texture, composition, edge and semantic information. A few researchers have worked on transforming image emotions by editing images. In [8], Wang et al. associate color themes with emotion keywords depending on art theory and transform the color theme of an input image to the desired one. However, in their work, only a few cartoon-like images are used. Peng et al. [9] propose a framework to change an image's emotion by randomly sampling from a set of possible target images, but only show a few examples. Jun et al. [10] show that changing brightness and contrast of an image can affect the pleasure and excitement felt by observers. However, only a limited variation of an input image can be produced by changing the two features. Peng et al. [11] change the color tone and texture related features of an image to transfer the evoked emotion distribution, with experiments conducted on only limited types of image content.

Evaluating image's evoked emotions after image manipulation is not a trivial task. Many well-established image manipulation and editing tools have been widely used in online photo sharing and social networks, as ways for users to enhance their image content either to draw better attention or to evoke stronger emotions. Popular image editing tools include image enhancement [12], grayscale conversion, vintage processing, cartoonizing [13], and more recently addition of stickers[1] [14]. However, most image manipulation methods have been studied merely from the perspective of image processing and not so much on their emotional impact.
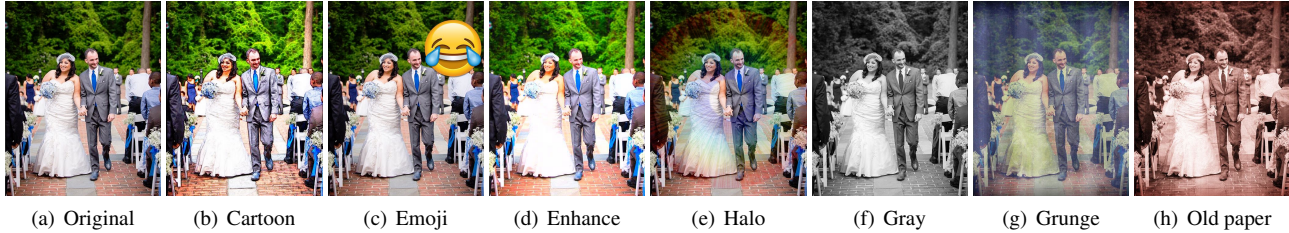
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[1] https://www.facebook.com/help/1597631423793468

(a) Original	(b) Cartoon	(c) Emoji	(d) Enhance	(e) Halo	(f) Gray	(g) Grunge	(h) Old paper

Figure 1. *Example image manipulated by different methods.*

Several affective image databases have been created in previous works, including artistic photos or abstract paintings used in [2], International Affective Picture System (IAPS) [15], The Geneva affective picture database (GAPED) [16] and Emotion6 [11]. In our research, we are more interested in the emotions of everyday photographs, especially those images that are widely shared by online users. Unfortunately, most existing affective image datasets contain either extremely emotional images, or images without much natural high-level semantic features like human face. All those types of images do not fit our requirements. Therefore we decided to collect our own dataset using Instagram, one of the most popular online photo sharing services.

To measure emotions, different types of models have been designed by psychologists. One of the most popular is the valence-arousal (VA) model (proposed by Russell [17]), characterizing emotions in two dimensions, where valence measures attractiveness in a scale from positive to negative, while arousal indicates the degree of excitement or stimulation. In terms of categorization of emotions, Ekman's six basic emotions (anger, disgust, fear, joy, sadness and surprise) [18] are widely known. In our work, we used both models similar to works in [16, 11].

Image Dataset and User Study

This section describes in detail the image dataset creation and crowdsourcing experiment.

Image Collection and Processing

We collected images from Instagram. According to a previous study by Hu et al. [19], images shared within Instagram can be classified into the following eight basic categories in terms of their content: *Friends*, *Food*, *Gadget*, *Captioned photo*, *Pet*, *Activity*, *Selfie* and *Fashion*. Therefore, we collected image dataset by searching for the eight category keywords or their synonyms via Instagram #tag. This was mainly motivated in order to have a wider variety of image content. At the end 13 color images were selected manually for each category resulting in 104 images in total. All selected images have the same size of 640×640 pixels.

For each image, seven different manipulations were applied to create different visual effects. We will refer to these manipulations as the following names:

- *Cartoon*: Applies a cartoon effect to an image.
- *Emoji*: Adds an Emoji on top-right corner of an image.
- *Enhance*: Applies brightness/contrast/colorization enhancement on an image via LAB colorspace.
- *Halo*: Applies a circular halo effect to an image.
- *Gray*: Converts an image to gray scale.

- *Grunge*: Applies a classic vintage effect with a grunge background to an image.
- *Old paper*: Applies another heritage style vintage effect with an old paper background to an image.

The reason of selecting the seven particular manipulations is that the changes of an image caused by these operations cover different aspects of image information, e.g. color, texture, composition, and higher-level image semantics. The emoji sticker "Tear of Joy" was selected as it has been in the top 10 most popular emojis on Emojipedia for all of 2015[2], and the emotion it expresses is not that obvious. The seven manipulations were implemented by using ImageMagick software[3]. An example image processed by the 7 different manipulations is illustrated in Figure 1. Summing up, a grand total of 832 (104×8) images were generated, including the original versions of each image. The image dataset is publicly accessible at `http://mmspg.epfl.ch/emotion-image-datasets`.

User Study

We used Microworkers[4] platform to collect emotional responses from subjects. A questionnaire was designed where four emotion-related questions are asked for each image. The first two questions are about the valence and arousal ratings respectively, where a 9-point scale was used, same as [11, 15]. For valence, 1, 5, and 9 mean very negative, neutral, and very positive emotions respectively, in terms of attractiveness. For arousal, 1 and 9 mean emotions with very low and very high stimulating effects respectively. In the questionnaire, instead of directly asking subjects to provide VA scores, questions were rephrased to be similar as in [11]. The third question is about the emotion distribution of the image, based on Ekman's six basic emotions [18]. Similar to [11], 7 emotion keywords (Ekman's six basic emotions and "Neutral") were used and subjects were asked to select the keywords that best describe their emotions after seeing a particular picture. In the last question, subjects were asked to select the content related factors that have the most impact on their emotional decisions. The 7 pre-defined factors are *Face*, *Color*, *Scene*, *Object*, *Text*, *Emoji* and *Halo* respectively, and their meanings are shown in `http://grebvm2.epfl.ch/lin/emotion/ImageEmotionEvaluation2.pdf`. This could further help understanding how the image content and manipulation jointly influence evoked emotions. Furthermore, in every questionnaire, a number of CAPTCHA questions (e.g., "$56 + 78 =$?" and "If the

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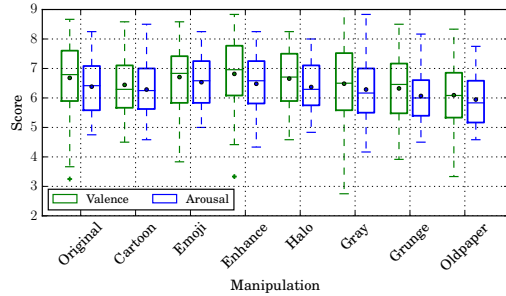**Figure 2.** *Boxplot of VA scores for each image manipulation method.*

(a) Valence   (b) Arousal

Figure 3. *Difference VA scores for different image content and manipulations. Value in the map = original score − score after manipulation.*

Figure 4. *VA score changes due to "Old paper" manipulation, versus original VA scores.*

arm is green, what color is it?") were included to detect and remove subjects who provided sloppy answers.

Each questionnaire contains eight images, selected in a semi-random way such that the following constraints are satisfied: i) the eight images in each questionnaire came from eight different categories respectively; ii) the order of image manipulations appearing in each questionnaire was randomized. Therefore it ensured that subjects saw different image content in each questionnaire with manipulations in different orders. We aimed at collecting twenty answers for each questionnaire, meaning that every image was to be rated by 20 different answers. Therefore, a total of 2080 $(20 \times 832/8)$ questionnaires (implemented using internal template by Microworkers) were distributed online.

Thanks to Microworkers' rating system, we kept tracking the results and ruling out answers from dishonest subjects while task campaigns were running, based on their answers to CAPTCHA questions and the time spent on each questionnaire (for those who spent less than 120 seconds to answer a questionnaire, their answers were removed). The vacated positions were then taken by new subjects until their answers satisfied the above requirement. Finally, answers from 590 unique subjects were collected, each rating 28.2 images in average. We offered 0.3 US dollars to reward the subjects successful completion of each questionnaire. A screenshot of the questionnaire can be found on `http://grebvm2.epfl.ch/lin/emotion/ImageEmotionEvaluation2.pdf`.

Evaluting Emotions induced by Image Manipulation

This section analyzes the emotional responses obtained from crowdsourcing experiment, with respect to the answers to each question.

Valence-Arousal Score Analysis

Firstly, for each image, the mean valence and arousal scores were computed, by averaging all the rated VA scores. Then for each image manipulation (including the original), distributions of all images' mean VA scores are gathered and plotted with box plot in Figure 2. Among all the manipulations, vintage processing with *Grunge* and *Old paper* generated the lowest VA scores. Besides, for certain methods such as *Gray*, VA scores show a higher variance than that of other methods. We take as working hypothesis that manipulating an image in a certain way leads evoked emotions to change along a certain direction, but the change of emotions due to image manipulation highly depends on image content.
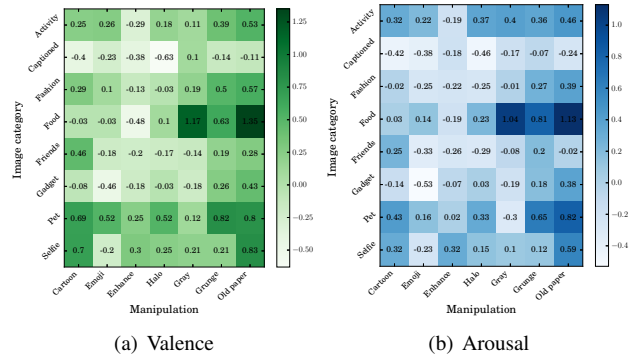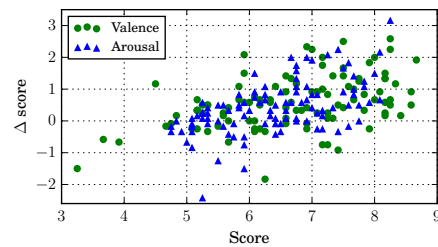
To verify this assumption, we investigated the influence of the two factors (image content and manipulation) on evoked emotion, with respect to VA scores. We computed the mean VA scores of each image category for different manipulation methods, by averaging the scores of 13 pictures belonging to each category for each method. Then we present the difference VA score between original and manipulated images, with respect to different image categories, as heat maps shown in Figure 3. From the results, one observes that certain image manipulations have great impact on the VA scores of certain types of images. For example, manipulations *Grunge* and *Old paper* greatly lower the VA scores of most image content, especially for *Food* and *Pet* images. In addition, other manipulations like *Emoji* and *Halo* both increased the VA scores of *Gadget* and *Captioned photo*.

We then plot the Δ VA scores of every image (difference score between original and manipulated version by *Old paper*), versus the their original VA scores, as a scatter plot shown in Figure 4. Here, we observe that images with higher original valence or arousal scores are more likely to generate higher difference VA scores, indicating that images with higher VA scores are prone to be impacted by the manipulation *Old paper*.

Emotion Distribution Analysis

We then assessed the evoked emotions in terms of probability distribution of emotional keywords. To obtain the emotion distribution of each image, we counted the occurrence of each emotion keyword voted by subjects on each image, and generated a normalized distribution over the 7 keywords, by dividing the number of keyword with the total number of voted keywords. The average emotion distribution corresponding to each manipulation method is shown in Figure 5. Again, one observes slight changes on the
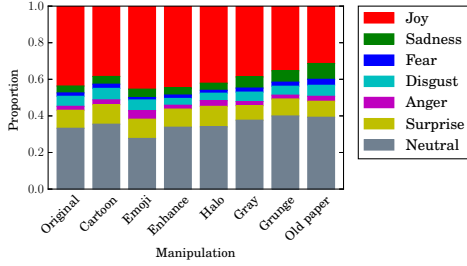
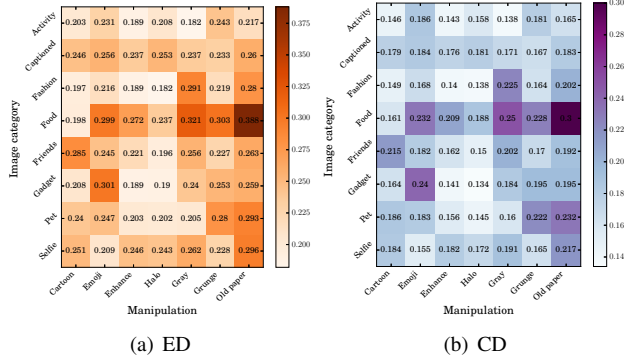**Figure 5.** *Average emotion distribution of different manipulation methods.*

(a) ED (b) CD

Figure 6. *Difference in emotion distributions between manipulated and original images measured by ED and CD.*

Figure 7. *Emotion distribution distance (CD) between original and manipulated image ("Old paper"), versus original VA scores.*

Figure 8. *Distribution of influential factors for different manipulations.*

emotion distributions over different manipulation methods. The most obvious observation is that the proportion of *Joy* for images processed by the two vintage filters (*Grunge* and *Old paper*) is much reduced compared to the original images. At the same time, subjects have been evoked more *Sadness* and *Neutral* emotions by the two methods.

To quantify the changes in emotion distributions induced by different manipulations, we used two metrics Euclidean distance (ED) and Chebyshev distance (CD) to compute the difference between emotion distributions of original images and their manipulated versions. The average distances for different image categories and manipulations are plotted as heat maps shown in Figure 6. This time, one observes again that different types of image content are influenced by image manipulation methods in different degrees. Similar as previous results on VA scores, methods *Gray* and *Old paper* generate higher distances in emotion distributions of many types of images, especially *Food* and *Pet*. In some types of images such as *Fashion*, *Food*, *Gadget* and *Pet*, manipulations on those images have greater impact on evoked emotion distributions than other types of content.

We then plotted the distances (CD) in emotion distributions versus the absolute difference in VA scores, between original images and manipulated images by *Old paper*, as scatter plot shown in Figure 7. From the result, one observes that when a manipulation has more impact on VA scores, it also tends to create higher differences in emotion distributions. This shows a good degree of correspondence between the emotional changes measured by the two metrics: VA scores and emotion distributions.
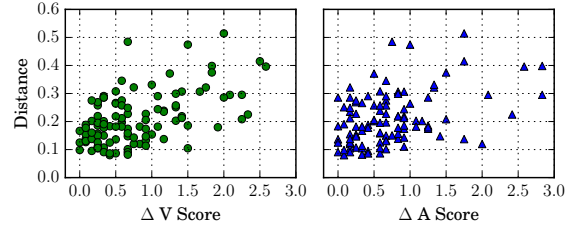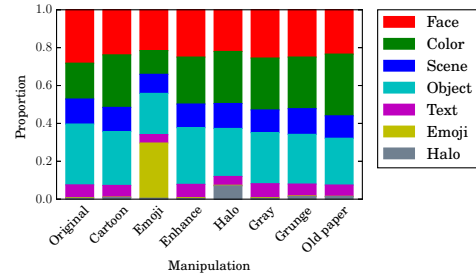
Factors Influencing Evoked Emotion

Furthermore, we investigated the content related factors that influence subjects emotional responses. We computed the probability distributions of subjects selected factors that influenced their decisions, in the same way as computing emotion keyword distribution, and plot the average distribution of each manipulation in Figure 8. In all manipulations, factors like *Face*, *Color* and *Object* highly influence subjects' evoked emotions. However, certain image manipulations that modify image's regional visual information can draw subjects' attentions and facilitate their decision making as well. For instance, in images manipulated by *Emoji* and *Halo*, the influential degree of Emoji sticker and halo effect is much increased. In addition, we also notice that the factor *Color* has a greater influence in most manipulated images (except for *Emoji*). This is because most manipulations largely change the color information of images, which impacts subjects emotion in a high degree.
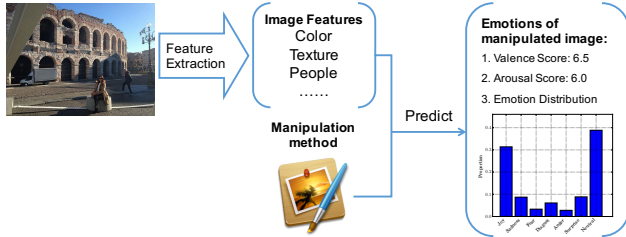
Predicting Emotions induced by Image Manipulation

In this section, we report the experiment of predicting emotions of manipulated images using machine learning. The purpose of conducting this experiment is to investigate the feasibility of accurately predicting image emotions induced by image manipulation before applying the manipulation, and find the potential pattern between image manipulation and evoked emotions.

We propose a predictor which can estimate the emotions of the manipulated version of an image given only the original image and the target manipulation method as input. The targets to be predicted include: the i) valence score, ii) arousal score and iii) emotion distribution. The framework of such a prediction model is illustrated in Figure 9. Such a predictor provides us with at least two benefits. First, it can predict the emotions of desired manipulated image without actually applying any manipulation, which is especially good for computational costly operations, such as

Table 2. The feature set used for predicting image emotions.

Feature Type	Dimension	Description
Color	1	A global factor measuring the colorfulness of a natural image [20].
	1	A global contrast factor of an image [21].
	48	Color histogram of image YCbCr colorspace (16-bin histogram for each channel).
Texture	22	Features from Gray-Level Co-occurrence Matrix (GLCM) including the mean, variance, energy, entropy, etc [2].
Semantic	1	Number of people in the image.
Manipulation	1	Manipulation method to be applied on the image.

Figure 9. *Framework of the emotion prediction system.*

Table 3. Prediction results of cross validation experiments.

Method	Valence		Arousal		Emotion Distribution	
	MSE	R^2	MSE	R^2	MSE	R^2
Baseline	1.21	~ 0	0.75	~ 0	0.0132	~ 0
LR	0.78	0.369	0.57	0.311	0.0092	0.325
SVR	0.51	0.589	0.37	0.529	0.0060	0.559
RFR	0.45	0.639	0.34	0.571	0.0056	0.585

the recently popular image editing app Prisma[5] that uses artistic style image morphing. Second, the proposed predictor extracts image features only once from the original image, which does not require the system to extract features each time from newly manipulated images.

To train and evaluate the proposed predictor, we utilized the image dataset used in crowdsourcing experiment. In our dataset, there are 104 images, each manipulated by 7 different methods, resulted in 728 manipulated image samples. To train the predictor, we extracted a set of features (color, texture and semantic information) from each original image, and then took another feature indicating the selected manipulation method. It finally resulted in a 74-dimension feature vector for each image. The detailed descriptions of the features are listed in Table 1.

To train and test our models, we used Scikit-learn library [22], within which we experimented with four methods: linear regression (LR), support vector regression (SVR) with Radial basis function (RBF) kernel, random forest regression (RFR), and a baseline method where the predicted value is simply the mean of the training set corresponding to each manipulation method (just for comparison). To avoid over-fitting, we conducted training and testing in 10-fold cross validation, with 90% images used for training and the rest for testing in each fold. To evaluate the performance of trained predictors, two metrics were used: mean squared error (MSE) and coefficient of determination (denoted R^2). Particularly, for emotion distribution, the MSE value was obtained by averaging the squared differences between predicted distribution and groundtruth distribution over all the 7 dimensions. For each prediction target, we tuned the parameters of each predictor to obtain as good result as we could. The final average results of cross validation tests are shown in Table 2.

From the results, one observes that the random forest regression outperforms the other three methods. It resulted in the maximal R^2 scores higher than 0.5 in predicting all the three targets: 0.639 for valence, 0.571 for arousal and 0.585 for emotion distribution, which are much higher than that of random guessing ($R^2 \leq 0$) or the baseline method. When compared to the results

of VA score prediction in [5], where the minimal MSE of 1.27 for valence and 0.82 for arousal were obtained, our model in prediction of VA scores seems promising, although different datasets were used. With random forest regression, we also checked the importance of features in decision making, and found that the manipulation method, number of people and energy of GLCM are the three most important features. This again indicates that image manipulation indeed influences image emotion in a high degree, and that high-level semantic features like the existence of people also have great impact on evoked emotion, in addition to other low-level image features such as color and texture.

Conclusion

This paper investigates the influence of image manipulation on evoked emotions for different types of images. An image dataset was created by collecting different types of images from Instagram, and subjective experiments were conducted via online crowdsourcing, to examine subjects emotional responses on different images processed by different manipulation methods. Experimental results show that certain image manipulations induce evoked emotions very different from those experienced on original images. However, such manipulation methods do not always perform the same on different types of images. In other words, emotion changes due to image manipulation are highly dependent on image content. A further experiment based on machine learning was conducted, in attempt to predict the emotions of a manipulated image given only its original version and the manipulation method. Experimental results show a very promising accuracy of using such a model for predicting emotions. These results provide us with insights to design of advanced image emotion transformation systems that can recommend the type of manipulation to apply, based on the content of a picture and the desired emotion to express, which is a future direction of our work.

Acknowledgments

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