

Affective Space Exploration for Impressionism Paintings

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Abstract. In this paper, we explore the affective contents of Impressionism paintings. While past analysis of artworks concentrated on artistic concept annotation, like styles and periods, a more perceptual aspect is to investigate the emotions artists projected into. We propose affective space to fuse all affective factors from features. Since the combination of colors is more sensitive and intuitive to emotions, a meta-level feature, color harmony, is introduced to bridge the semantic gaps. By considering the correlation relationships among features and emotions, the affective space is explored through multiple-type latent semantic analysis. Experimental results show the effectiveness of harmonic feature and affective space via multi-label emotion annotation. Some potential applications are demonstrated based on affective space as well, including painting emotionalization and emotion-based slideshow system.

Keywords: Affective space, Color harmony, Emotionalization, Feature clustering, Multiple-type latent semantic analysis, Paintings.

1 Introduction

Arising from the experiences in all their life, artists usually express their personal feelings or draw the common sympathy in the paintings through a series of palettes and brushworks. Especially for Impressionism, based on artists' instinctive perception, this period's paintings convey the affective imagery and product the impression of nature by capturing an instant of subtle shifts among colors and lights.

Basically, painting in digital form is one kind of photo. However, some characteristics are distinguished paintings from photos [2]. Spatial variations of color and number of unique colors in paintings are larger than real scenes. Perceptual edges in photos of real scenes are intensity edges while those of paintings are pure color edges. In particular, paintings have more affective ingredients than photos. Impressionists are more concerned with conveying emotions. Van Gogh had written to his brother, stating "It is emotion, the sincerity of one's feeling for nature that draws us..." Renoir always painted happier aspects of life, expressing joyful emotions and carefree impression. And Paul Gauguin depicted the real emotion and truth found in the primitive cultures of the

islands. These rich emotional compositions from Impressionists inspire us to explore the affective contents for paintings, and focuses on the period of Impressionism.

More recently, artistic concepts like art period, artist name and style were investigated. Marchenko et al. [8] took color usages as cues to analyze paintings. Gunsels et al. [5] extracted statistic features and performed classification via SVM for art movements. By eight given brushwork classes at block level and manually constructed decision hierarchy, Leslie et al. [6] employed transductive inference of concepts to annotate paintings.

In this paper, we explore the affective space for Impressionism paintings. Essentially, paintings with similar emotions could share some kinds of low-level features. However, there exist semantic gaps between low-level features and high-level affective concepts. We propose a new meta-level feature, color harmony, which encodes affective information. Moreover, not only painting features and emotions are correlated but some features are highly correlated by sharing of similar emotions through the nature of paintings. Therefore, to discover the correlation between emotions and painting features, instead of simply concatenating all features as a long feature vector, we take advantage of multiple-type latent semantic analysis to capture these underlying interrelated correlations. Based on the explored affective space, two applications are demonstrated, including painting emotionalization and emotion-based slideshow, which could be regarded as novel forms of aesthetic experience.

The rest of the paper is organized as follows. Section 2 presents the proposed framework for exploration of paintings. In section 3 the harmonic feature and other affective features are processed. Section 4 models the interrelated features through M-LSA and conducts affective space projection for emotion discovery. Section 5 presents the evaluation results and section 6 demonstrates two applications. Section 7 outlines the conclusions and future work.

2 Framework

Figure 1 shows the flowchart of our work. To make the model catch the affective factors scattered in the paintings, these paintings are pre-annotated emotions by 23

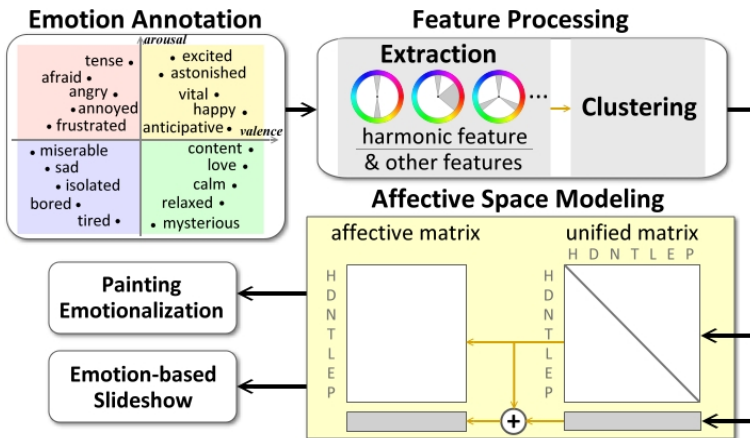


Fig. 1. Flowchart of proposed affective space

persons before the training stage. The emotion we adopt is Russell’s model [11]. At feature processing stage, five features are extracted and clustered to integrate hidden semantics, in which, the harmonic feature is defined and processed. Then all affection-interrelated entities of feature clusters are fused by means of multiple-type latent semantic analysis. They will be represented as unified matrix first and projected to affective space. Given a testing painting, the most relevant emotions can be discovered based on the explored affective space. Hence, painting emotionalization and emotion-based slideshow can be developed afterward.

3 Feature Processing

Painting is mostly characterized by its colors, lights, textures, and lines. Artists essentially pour their emotions through these basic artistic elements. For instance, “The Night of Café” of Van Gogh tried to express with red and green the terrible passions of human nature. In this section, we introduce a new feature scheme, color harmony, which is a meta-level feature, along with four other types of low-level image features to describe the affective contents of paintings.

3.1 Harmonic Feature

The proposed harmonic feature is based on the harmonic model developed by Matsuda [9]. Descended from Itten’s color theory, Matsuda’s harmonic model defines the radial relationships of color combination over the hue channel of HSV color wheel. Ten harmonic types were defined shown in Figure 2. Each type is a distribution of hue colors. Hues fall in gray wedges of one type form the so-called harmony because they meet a balance relationship for human perception.

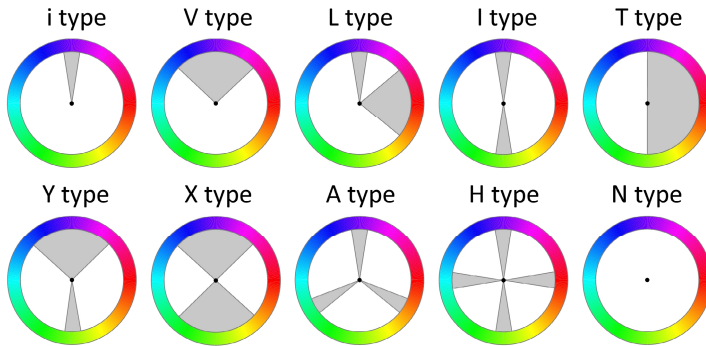


Fig. 2. Harmonic types on the hue wheel

An artist conveys one’s emotion not only by the color harmonic type but also by the orientation in the color wheel. For example, an artist may express specific feelings (emotions) through one orientation of complementary colors (*I* type). Another orientation of complementary colors may convey different emotions. Hence, the shifting of orientation on the wheel can realize color harmony with emotions contained.

Given a painting, we then try to find the fittest harmonic type along with the orientation for the hue histogram of the painting image. In [1], it associates each hue h with one of these sectors by considering the arc-length distance between the hue of pixel and the sector border hue under certain orientation, and chooses the closest one as its harmonic type after summing over all pixels of an image. However, this approach just considers those hues out of these sectors and ignores the area information. Some type which is covered by others may not be selected as the fittest one. For example, I type is covered by Y , X , and H types.

We define a new measure to compute harmony by realizing the orientations of the harmonic types. The basic idea is if more hues of pixels covered by a harmonic type with orientation α , it would be considered to be closer to that type. We define the expected hue distribution $E_{X,t,\alpha}(x)$ of the harmonic type t with orientation α to be a uniform distribution of hues of pixels,

$$E_{X,t,\alpha}(x) = \begin{cases} 0 & , \text{ if } x \text{ does not fall in the sectors.} \\ P_X / \sum_1^{S_t} \theta_t(n) & , \text{ if } x \text{ falls in the sectors.} \end{cases} \quad (1)$$

where P_X and S_t denote the number of pixels of a painting X and the number of sectors of harmonic type t respectively; $\theta_t(n)$ denotes the included angle of the n -th sector of type- t ($t \in \{i, V, L, I, T, Y, X, A, H\}$). Then given a fixed interval of angle Δ_t to shift the orientation, the harmonic features $F_H(X)$ of X is defined as

$$F_H(X) = \max_{\alpha=0}^{(2\pi/\Delta_t)-1} \cap (D_X(x), E_{X,t,\alpha}(x)) \quad (2)$$

where $D_X(x)$ is the hue histogram of the painting X and \cap returns the area of intersection between two distributions.

3.2 Other Affective Features

Dominant Color. The histogram of a painting is calculated first. Those colors occur below 10% of area would be omitted. Impressionists are good at showing color shift by complementary colors, such as “*Wheatfield with Crows*” by Van Gogh. Therefore, the dominant color is represented in LSLM color space formulated by Ewald Hering based on artistic concepts, in which L, S, and LM denote luminance, red-green, and yellow-blue channels respectively.

Edge Histogram. In general, the lines’ directions in a painting can express a variety of feelings. Strong and vertical lines present tense scenes while horizontal ones are more tranquil. We employ edge histogram to model the line property, and specify the spatial distribution of five types in $4*4$ blocks, namely four directional edges and one non-directional edge.

Texture. The granularity is also a factor to deliver emotions. The exposure of details makes the scene more real while the coarse-grained appearance gives a smooth mood. We take log-Gabor filter [3] to capture localized frequency information, which make the bandwidth optimized to produce a filter with minimal spatial extent. The scale and orientation are set to 4 and 6 respectively.

Color Layout. Besides color palettes, the context of color regions may form different concepts if considering neighborhoods. By using YCbCr space, we partition a painting to 8×8 blocks and derive the average color of each block. After applying DCT, we adopt those coefficients of high frequency, which benefits structural similarity due to perceptual sensitivity of human vision.

3.3 Feature Clustering

To keep the features more evident for latent semantic analysis of affective concept, each feature is discretized by clustering similar feature values. For the harmonic feature, each painting is first classified into one of the ten harmonic types according to equation (2). Then, the number of clusters of each harmonic type is determined to be proportional to the number of paintings belonging to. For each of the other four features, the number of clusters is a fixed number (we set it to 18 in this work). A state-of-the-art unsupervised clustering algorithm, *affinity propagation* [4], is employed to group similar feature values. After feature clustering, for each feature, a $|P| \times |C|$ matrix, where $|P|$ is the number of painting while $|C|$ is the number of clusters, is constructed to indicate the existence of clustered feature value in each painting. In other words, for example, if the color layout of a painting p belongs to the q -th feature cluster, the element m_{pq} of matrix M_{PL} will be 1.

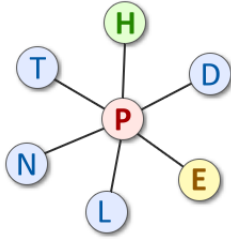
4 Affective Space Exploration

To explore the affective space, for each painting, we have five features and annotated emotions. Conventional vector-based approaches for feature representation of an image concatenate all types of features into a feature vector. The correlations among features are not considered. To explore the hidden affective correlations among features and emotions, we employ and modify the *multiple-type latent semantic analysis* (M-LSA) [12]. Emotion discovery can be conducted based on the affective space constructed by M-LSA.

4.1 M-LSA Modeling

Given n types of entities $\{X_1, X_2, \dots, X_n\}$ and between two types of entities, there could exist a pairwise co-occurrence relationship. M-LSA represents the entities along with the correlations by a *multiple-type graph* $G(V, E)$, which is an undirected graph where each vertex corresponds to a type of entities. There exists an edge $e_{ij} \in E$ that connects the i^{th} and j^{th} vertices if the X_i and X_j have a correlation relationship where the co-occurrence information is represented by a $|X_i| \times |X_j|$ correlation matrix M_{ij} , in which $|X_i|$ is the number of entities of type X_i . M-LSA identifies latent semantic concept by exploiting all the pairwise co-occurrence relationships.

In our work, we have seven types of interrelated entities, harmony (H), dominant color (D), edge histogram (N), texture (T), color layout (L), emotions (E) and painting (P). The left of Figure 3 shows the graph. For the P -type, each entity corresponds to one painting image while for the E -type, each entity corresponds to one type of emotion. For the other five types, each entity corresponds to one feature cluster. Moreover, we also exploit those indirect relationships between entities, which have no



$$U = \begin{bmatrix} 0 & M_{HD} & M_{HN} & M_{HT} & M_{HL} & M_{HE} & M_{HP} \\ M_{DH} & 0 & M_{DN} & M_{DT} & M_{DL} & M_{DE} & M_{DP} \\ M_{NH} & M_{ND} & 0 & M_{NT} & M_{NL} & M_{NE} & M_{NP} \\ M_{TH} & M_{TD} & M_{TN} & 0 & M_{TL} & M_{TE} & M_{TP} \\ M_{LH} & M_{LD} & M_{LN} & M_{LT} & 0 & M_{LE} & M_{LP} \\ M_{EH} & M_{ED} & M_{EN} & M_{ET} & M_{EL} & 0 & M_{EP} \\ M_{PH} & M_{PD} & M_{PN} & M_{PT} & M_{PL} & M_{PE} & 0 \end{bmatrix}$$

Fig. 3. Multiple-type graph and the unified matrix U

direct correlations in G . For example, to capture the co-occurrence relationship between harmony and emotion, matrices $M_{HE} = M_{HP} \times M_{EP}^T$. Consequently, a unified matrix U , shown in the right of Figure 3, is produced to capture all affective information of these entities. Moreover, an importance factor α_{ij} is associated to each matrix M_{ij} to denote the relative importance of matrix M_{ij} .

4.2 Affective Space Projection

The basic idea of M-LSA is to capture the most significant concepts hidden in the interrelated entities. The significance of concepts can be identified based on the mutual reinforcement principle. In our work, this means that significant entities of one feature co-occur often with significant entities of other features or emotions. Based on the mutual reinforcement principle, the significance of each type of entities X_i , denoted as the significance vector r_i , can be expressed as the following equation and rewrite it by U

$$r_i \approx \sum_{\forall j: j \neq i} \alpha_{ij} M_{ij} r_j \Rightarrow r \approx U \cdot r \quad (3)$$

It can be observed that r will meet the eigenvector of the unified matrix U . The significance vector r implicitly encodes the latent semantics behind the correlations. Each entry of r corresponds to a feature cluster and its value can be regarded as the significance with respect to one basis in affective space. The top k eigenvalues $\lambda_1 \geq \lambda_2 \geq \dots \geq \lambda_k$ of U corresponds to k most salient concepts. The corresponding eigenvectors $[v_1, v_2, \dots, v_k] = U_k$ can span a k -dimensional latent affective space, which can be represented as an affective matrix $A = [\lambda_1 v_1, \lambda_2 v_2, \dots, \lambda_k v_k]$.

4.3 Emotion Discovery

The affective space has condensed all the hidden semantics of feature clusters of training set to an affective matrix. It provides a potential that fusing all affective factors to discover emotions.

To determine which emotions are discovered for a query painting, first, a query vector q is obtained by feature processing. It is projected onto the affective space where $q_c = q^t \times U_k$. After the projection, q_c is compared with each of those P -type

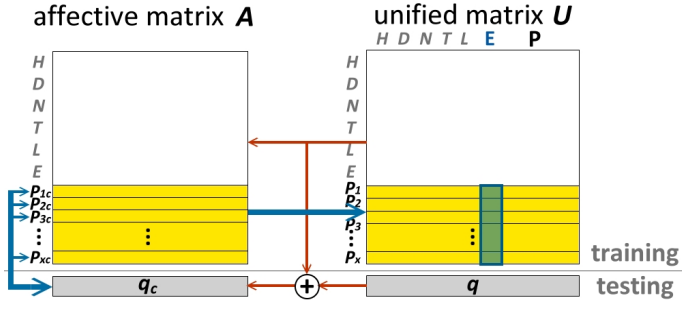


Fig. 4. Affective space projection and emotion discovery

entities p_{ic} in affective space by cosine measure. As a result, the top m relevant candidate paintings are found. The most relevant emotions are generated according to the ranking of emotion counts among these top m candidate paintings. Figure 4 shows the procedure.

5 Evaluations

To evaluate the effectiveness of the proposed affective space with harmonic features, we take the accuracy of multi-label emotion annotation for the performance evaluation. The emotion we adopt is Russell's model [11], which is a combination of arousal and valence components. The corresponding list of emotions is shown in Figure 5. At the training stage, affective space is constructed based on pre-annotated emotions. And then we could discover the relevant emotions for the testing painting inputs through aforementioned emotion discovery module. Five-fold cross-validation is performed on 624 paintings, which were created by 17 artists, including the periods of impressionism (10 artists), and post-impressionism (7 artists). These paintings are mostly collected from <http://www.artchive.com>. The emotion types that our experiment utilize can be divided to two categories: 1) the four quadrants of Russell's emotion model, totally 4 emotion types; and 2) the detailed terms of the four quadrants, totally 20 emotion types. The number of pre-annotated emotions per painting for training is 1.89 for four emotion types and 3.74 for twenty emotion types. The performance measure is defined as

$$average_score = \left(\sum_{i=1}^N |E_i \cap E_q| / \sqrt{|E_i| \times |E_q|} \right) / N \quad (4)$$

where N is the number of top- N returned candidate paintings, $|E_i|$ is the cardinality of set E_i of i^{th} returned painting and $|E_q|$ of the query, \cap is intersection operation.

Figure 6 shows the effectiveness of affective space (with top-30 affective concepts and top-5 candidate painting returned) for our emotion annotation. We can observe it performs much better for both categories if we adopt harmonic feature. Besides, other

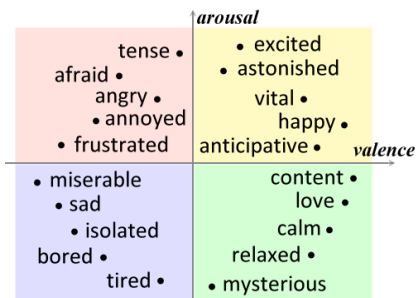


Fig. 5. Russell's emotion model

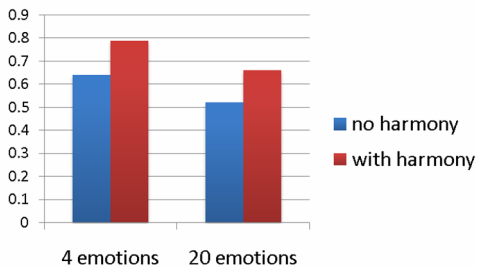


Fig. 6. Experimental results based on affective space

than the average score for four emotion types is near 80%, the score for twenty emotion types is near 70% as well. Because it is almost equal to the multi-label classification problem, it reveals the effect of affective space.

In the other hand, some interesting mappings between harmonic types and emotions are discovered. For example, tense and miserable are related to *Y* and *I* type around blue and yellow sectors. The *i* type around yellow area is related to emotions of 2nd quadrant in Russell's model while the *V* type around yellow area is related to emotions of 3rd quadrant.

6 Applications

6.1 Painting Emotionalization

Affective space is also able to easily recommend paintings considering emotion and harmony simultaneously. It is beneficial for generate a novel form of art, that is, painting emotionalization. This idea comes from *color transfer* [10], which is to take the characteristics of color usages from a referred image and apply it to the target image. In our framework, we could not only recommend paintings based on emotions of the given source paintings, but integrate harmony composition of painting to perform affection-based transfer. The sample results we render are illustrated as Figure 7. Given the left paintings, the middle ones are recommended through our affective space. The results of painting emotionalization are rendered as the right ones.

6.2 Emotion-Based Slideshow System

In our previous work [7], an emotional-based slideshow system was proposed, which automatically accompanied with music. By taking advantage of affective space, it will be more flexible since we can not only conduct painting-emotion association discovery but also the clustering and linear arrangement procedure can be done simultaneously according to the ranking in affective space. A sample is as illustrated in Figure 8, as user gives seed paintings, their emotions are discovered correspondingly. Then paintings with the similar emotions are grouped and inter-cluster arrangement is performed via the ranking in affective space.



Fig. 7. Example of painting emotionalization



Fig. 8. Emotion clustering and arrangement for slideshow

7 Conclusions

In this paper, we present a generic model to encode the affective factors for Impressionism paintings in a unified affective space. Since the combination of colors is well-affected on human perceptions and emotions. A meta-level feature, color harmony, is introduced and its computation is defined. We project these affection-interrelated features into an affective space by multiple-type latent semantic modeling. Not only given new paintings, we can discover the corresponding emotions, but given emotions, it is feasible to recommend paintings. Experimental results show the average score achieves near 70% for multi-label emotion annotation on twenty emotion types and near 80% for four emotion types using affective space. Two applications are demonstrated.

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