Computational Modeling of Artistic Intention: Quantify Lighting Surprise for Painting Analysis

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***Abstract*—The use of strong lighting contrast to accentuate objects and figures in a painting—called Chiaroscuro—is popular among Renaissance painters such as Caravaggio, La Tour and Rembrandt. In this paper, we propose a new metric called LuCo to quantify the extent to which Chiaroscuro is employed by an artist in a painting. This measurement could be used to assess the capability of any system to fulfill the original artistic intention and consequently ensure minimal disruptions of Quality of Experience. We first argue that Chiaroscuro is a device for artists to draw attention to specific spatial regions; thus it can be understood as a restricted notion of visual saliency computed using only luminance features. Operationally, using a set of local luminance patches we first compute a Bayesian surprise value, where the prior and posterior probabilities are computed assuming a Gaussian Markov Random Field (GMRF) model. Inverse covariance matrices of the GMRF model are estimated via sparse graph learning for robustness. We construct a histogram using the computed surprise values from different local patches in a painting. Finally, we compute a skewness parameter for the constructed histogram as our LuCo score: large skewness means luminance surprises are either very small or very large, meaning that the artist accentuated lighting contrast in the painting. Experimental results show that paintings by Chiaroscuro artists have higher LuCo scores than 19th century French Impressionists, and Rembrandt's self-portraits have increasingly higher LuCo scores as he aged except for his late period—both trends are in agreement with art historians' interpretations.**

Keywords*—*luminance contrast, painting analysis, graph-based statistical learning

I. Introduction

In the working definition of Quality of Experience (QoE) proposed by Qualinet [1], it is stated that QoE "results from the fulfillment of user expectations with respect to the utility and/or enjoyment of the application or service in the light of the user's personality and current state". In the context of creative content such as art paintings, *artistic intention* is another key factor to consider when evaluating the ability of a system to convey the right QoE. Thus the mandate of any technical media delivery system should include *the ability to faithfully convey the original artistic intent*. From this perspective, a computational model of artistic intention would be practically useful. In this paper, we propose to address this challenging topic focusing on one particular painting style[1].

Centuries have passed, and classical paintings by grand masters of yester years like Rembrandt and Vermeer still fascinate us. One notable artistic trend started in Renaissance paintings is *Chiaroscuro*[2]: the use of strong contrasts between light and shadows to accentuate the three-dimensionality of objects and figures in compositions. Though its usage can be traced back to early Byzantine art, it was most famously popularized by Caravaggio (1573-1610), who influenced later painters including Peter Paul Rubens (1577-1640), Georges de La Tour (1593-1652) and Rembrandt van Rijn (1606-1669). As an example, we observe that in *Crucifixion of St. Peter* by Caravaggio in Fig. 1(a), only the figures in the bottom of the painting are well lit. Extreme usage of Chiaroscuro is also called *Tenebrism*[3], which became the signature style for artists like La Tour (see *Smoker* in Fig. 1(b)).

(a) LuCo=1.70 (b) LuCo=3.76

Fig. 1. (a) *Crucifixion of St. Peter* by Caravaggio (1601), LuCo=1.70; (b) *Smoker* by La Tour (1646), LuCo=3.76.

Given the prevalence of Chiaroscuro in classical paintings, in this paper we propose a computational image model to estimate the extent of (Lu)minance (Co)ntrast employed by an artist in a given painting, summarized succinctly in a metric called *LuCo*. We claim that this metric correctly quantifies an artist's intention to manipulate lighting contrast to draw visual attention to local regions; thus preserving LuCo score in a media delivery chain would mean preserving the original Chiaroscuro artistic intent. Compared to previous *visual saliency* models [2], [6], [7], [8] that consider many low-level features and their correlations when constructing a saliency map, our computational model has comparable complexity but focuses exclusively on lighting contrast, resulting in a more sophisticated and in-depth model based solely on luminance features.

Operationally, given an observed network of patches in a local spatial region, we first compute a *Bayesian surprise* value [3], where the prior and posterior probabilities are computed

[1]We focus exclusively on Chiaroscuro in this paper, and leave the computation modeling of other painting styles as future work.

[2]https://en.wikipedia.org/wiki/Chiaroscuro

[3]https://en.wikipedia.org/wiki/Tenebrism

assuming a *Gaussian Markov Random Field* (GMRF) model for the patch network. To ensure robustness, the inverse covariance matrix (precision matrix) for the GMRF model is estimated via learning of a sparse graph with few parameters, leveraging on recent advances in *graph signal processing* (GSP) [4]. We construct a histogram using the computed surprise values per local region. Finally, a skewness parameter is computed from the constructed histogram as the LuCo score for the painting; a skewed histogram means that the luminance surprises are either very small or very large—in other words, the artist accentuated lighting contrast to draw attention to a few spatial areas.

We conduct experiments on a wide variety of classical paintings and observe the following two trends. First, among artists known for Chiaroscuro, we observe similar high computed LuCo scores. This is in contrast to paintings by 19th century French Impressionists with lower computed LuCo scores. Second, focusing on portraits by Rembrandt, we observe a gradual increase in LuCo scores as he aged except for his late period. This trend is consistent with commentaries by authoritative art historians [5]. For comparison, we consider two competitor types to detect luminance trends: i) computation of skewness of luminance gradients across multiple scales in a painting, and ii) computation of skewness of saliency values in an obtained saliency map computed using [2], [6], [7], [8]. We observe that none of the competing schemes reveal the same trends we observe in computed LuCo scores, validating the usefulness of our proposal.

The outline of the paper is as follows. We first overview related works in Section II. We then review basic concepts of Bayesian surprise and GSP in Section III. We describe our graph-based metric LuCo in Section IV. Finally, results and conclusions are presented in Section V and VI, respectively.

II. Related Works

Li and Chen [9] extracted color, shape and relative location features to automatically assess the aesthetic quality of a painting. Other stylistic elements like lighting contrast and brush strokes are not considered. In contrast, we propose a computational model to measure how much Chiaroscuro was employed by an artist, which captures one type of artist intention and can be used for QoE evaluation.

To discover correlations among artists, Bressan *et al.* [10] built a graph to connect artists based on their similarities, computed using low-level features by the Fisher kernel [11]: combines discriminative features into a general kernel function. Wang and Takatsuka [12] proposed a Self Organizing Map (SOM) based hierarchical model considering color, composition and line to differentiate among different art periods such as Post-impressionism, Cubism and Renaissance. However, these methods focus only on the clustering of artists, but not on actual painting analysis to quantify artistic styles.

Igor *et al.* [13] studied the use of complementary colors in Van Gogh's paintings. Specifically, they proposed a MECOCO (Method for the Extraction of COmplementary COlours) method to combine an opponent color space representation with Gabor filtering to calculate an "opponency" value, which reflects the usage of complementary color transitions. Johnson *et al.* [14] analyzed brushstrokes of Van Gogh's painting via a computation model. A texture feature vector was first constructed using Gabor wavelet coefficients of different scales and orientations. A Gabor wavelet energy value is then obtained, where larger energy values mean more contours and more visible brushstrokes. However, color and brushstroke are only two characteristics of an artist's style. In contrast, we focus on quantifying the amount of Chiaroscuro employed by an artist for a given painting.

III. Preliminaries

To understand our proposed metric LuCo in Section IV, we first overview two key concepts in this section in order: Bayesian surprise, and graph spectral signal decomposition.

A. Bayesian Surprise

Informally, surprise is the arrival of an unexpected event or observation, one that is incongruent to the previous set of expectations. Itti and Baldi formalized one notion of surprise, called *Bayesian surprise* [3], as a general information-theoretic concept. It measures the difference between the observer's prior belief constructed based on previous observations, and his posterior belief based on previous *and* new observations.

First, denote by $P_{\mathbf{X}_1^N}(\mathbf{y})$ the prior probability distribution of a signal $\mathbf{y}$, $\mathbf{y} \in \mathbb{R}^M$, constructed from a set of N previous observations $\mathbf{X}_1^N = \{\mathbf{x}_1, \ldots, \mathbf{x}_N\}$. Denote by $P_{\mathbf{X}_1^{N+1}}(\mathbf{y})$ the posterior probability distribution of $\mathbf{y}$, constructed from previous observations $\mathbf{X}_1^N$ and *new observation* $\mathbf{x}_{N+1}$. Bayesian surprise is computed as the Kullback-Leibler (KL) divergence [15] between the prior and posterior probabilities:

$$S(\mathbf{X}_1^N, \mathbf{x}_{N+1}) = \mathrm{KL}(P_{\mathbf{X}_1^{N+1}}(\mathbf{y}), P_{\mathbf{X}_1^N}(\mathbf{y})), \\ = \int P_{\mathbf{X}_1^{N+1}}(\mathbf{y}) \log \frac{P_{\mathbf{X}_1^{N+1}}(\mathbf{y})}{P_{\mathbf{X}_1^N}(\mathbf{y})} \, d\mathbf{y}. \quad (1)$$

The definition in (1) is general; we discuss our definitions of prior and posterior probabilities $P_{\mathbf{X}_1^N}(\mathbf{y})$ and $P_{\mathbf{X}_1^{N+1}}(\mathbf{y})$ in Section IV-A.

B. Graph Spectral Signal Decomposition

A undirected graph $\mathcal{G}$ is composed of nodes $\mathcal{N}$ and undirected edges $\mathcal{E}$ that connect nodes in $\mathcal{G}$. A graph-signal $\mathbf{x}$, $\mathbf{x} \in \mathbb{R}^M$, is a signal on a M-node graph $\mathcal{G}$. $\mathbf{x}$ can be decomposed into its graph frequencies via *graph Fourier transform* (GFT) [16]. Denote by $\mathbf{W}$ the *adjacency matrix*, where $w_{i,j} \geq 0$ is the weight of the edge that connects nodes i and j. Denote by $\mathbf{D}$ the *degree matrix*, where $d_{i,i} = \sum_j w_{i,j}$. The *graph Laplacian matrix* $\mathbf{L}$ is defined as the difference matrix between the two:

$$\mathbf{L} = \mathbf{D} - \mathbf{W}. \quad (2)$$

$\mathbf{L}$ is real and symmetric and can be eigen-decomposed as $\mathbf{L} = \Phi^T \Lambda \Phi$, where Λ is a diagonal matrix with eigenvalues λ's of $\mathbf{L}$ (graph frequencies) along the diagonal, and Φ contains the corresponding eigenvectors as rows. A graph-signal $\mathbf{x}$ can be decomposed into its frequency components z_k's using Φ:

$$\mathbf{z} = \Phi \mathbf{x}. \quad (3)$$

A graph-signal $\mathbf{x}$ is *smooth* with respect to graph $\mathcal{G}$ if its energy is concentrated in the low frequencies, *i.e.*, most coefficients z_k's are near-zero for large λ's. More precisely, it can be shown [16] that a smooth signal $\mathbf{x}$ leads to a smaller *graph smoothness regularizer* $\mathbf{x}^T\mathbf{L}\mathbf{x}$:

$$\mathbf{x}^T\mathbf{L}\mathbf{x} = \sum_{i,j} w_{i,j}(x_i - x_j)^2 = \sum_k \lambda_k z_k^2. \quad (4)$$

We will show how the smoothness regularizer $\mathbf{x}^T\mathbf{L}\mathbf{x}$ can be used for sparse graph learning in Section IV-B.

IV. Luminance Contrast Metric

We now describe our proposed computational model to compute a LuCo score for a painting. We assume that a painting photo has first been rescaled (with no change to its aspect ratio) to a digital image of roughly the same pixel count as input to our algorithm.

A. Contrast Definition via Bayesian Surprise

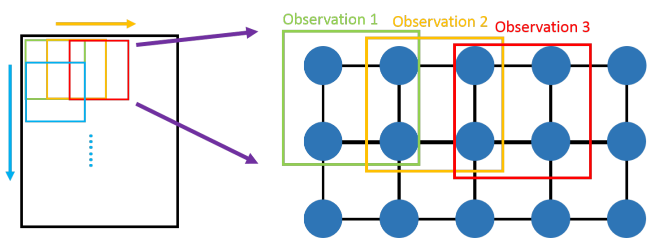


Fig. 2. An example of sliding windows. Observations 1 (green) and 2 (orange) are the previous graph-signals to compute the prior distribution. Together with new observation 3 (red), one can compute the posterior distribution. Observation block slides horizontally and vertically with overlaps.

Bayesian surprise has been used for visual saliency detection [3]. Since we focus on lighting contrast to compute a LuCo score, we compute Bayesian surprise using the luminance channel only. Specifically, when an observer scans a painting, an expectation of what luminance observation $\mathbf{y}$ should come next—described by the prior distribution $P_{\mathbf{X}_1^N}(\mathbf{y})$—is generated naturally after seeing N local observations $\mathbf{X}_1^N = \{\mathbf{x}_1, \ldots, \mathbf{x}_N\}$. If a new luminance observation $\mathbf{x}_{N+1}$ drastically alters the resulting expectation $P_{\mathbf{X}_1^{N+1}}(\mathbf{y})$—*i.e.*, the KLD between prior $P_{\mathbf{X}_1^N}(\mathbf{y})$ and posterior $P_{\mathbf{X}_1^{N+1}}(\mathbf{y})$ is large—then this constitutes a large Bayesian surprise.

In our context, we define an observation $\mathbf{x}_n$ as follows. We first group $\sqrt{K} \times \sqrt{K}$ adjacent luminance pixels on a 2D grid into a patch, and group $\sqrt{M} \times \sqrt{M}$ neighboring non-overlapping patches into a network of M patches. Each patch is represented by a node in a graph, and is connected to nodes representing other patches in the same network. As an example, in Fig. 2, we see that an observation is composed of four patches in a network. Two neighboring observations have an overlap of two patches.

Each node i in the graph is associated with the average luminance x_i of the pixels in patch i. Thus $\mathbf{x} = [x_1, \ldots, x_M]^T$ is a length-M vector of average patch luminance in one observation. We assume observation $\mathbf{x}$ is an instance of a GMRF generative model; *i.e.*, $P(\mathbf{x})$ follows a Gaussian distribution with precision matrix $\mathbf{L}$:

$$P(\mathbf{x}) = \exp\left(\frac{-\mathbf{x}^T\mathbf{L}\mathbf{x}}{\sigma^2}\right), \quad (5)$$

where σ is a parameter for the GMRF model.

However, one does not know the important precision matrix $\mathbf{L}$ *a priori*, and hence it is important to estimate $\mathbf{L}$ accurately using only observations $\mathbf{X}_1^N$. Once $\mathbf{L}$ is estimated, the prior $P_{\mathbf{X}_1^N}(\mathbf{y})$ can be expressed using (5). The posterior $P_{\mathbf{X}_1^{N+1}}(\mathbf{y})$ can be computed similarly using observations $\mathbf{X}_1^{N+1}$. We discuss the robust estimation of $\mathbf{L}$ given $\mathbf{X}_1^N$ next.

B. Robust Learning of Precision Matrices

One naïve method to estimate the precision matrix $\mathbf{L}$ in a GMRF model is to first compute a $M \times M$ covariance matrix $\mathbf{C}$ for M samples x_i given N observation vectors $\mathbf{x}_n$, then compute $\mathbf{L} = \mathbf{C}^{-1}$. However, when the number of observations N is small relative to the number of samples M, the estimated $\mathbf{C}$ is not robust, potentially resulting in a precision matrix $\mathbf{L}^*$ that deviates significantly from the true matrix $\mathbf{L}$.

To robustly estimate $\mathbf{L}$, we take a *sparse graph learning* approach. It is known [17] that a GMRF model with precision matrix $\mathbf{L}$ has a corresponding graphical representation: weight $w_{i,j}$ of an edge connecting nodes i and j in the graph is assigned $-L_{i,j}$; if $L_{i,j} = 0$ then there is no edge connecting nodes i and j. The graph Laplacian of the corresponding graph, as discussed in Section IV-B, is in fact the precision matrix $\mathbf{L}$. Hence a sparse graph with few connected edges would mean a sparse precision matrix $\mathbf{L}$ with few non-zero entries. Given observations $\mathbf{x}_n$, if we now estimate a sparse graph, it would mean that we are estimating only a few non-zero entries in $\mathbf{L}$, which in general is more robust than estimating all entries in a $M \times M$ matrix.

There are several approaches to estimate a sparse graph Laplacian $\mathbf{L}$ given observations $\mathbf{x}_n$, each one is now viewed as a *graph-signal*. Friedman *et al.* [18] proposed *graphical lasso*, an extension of the l_1-norm regularization popular in the sparse coding literature to graphs. Rotondo *et al.* [19] first identified a suitable *graph template* with only edges in two different directions based on the computed structure tensor, then estimated two weight parameters for edges of the two different directions robustly. In this paper, we employ instead the method in [20] for sparse graph learning, which in addition assumes that the signals $\mathbf{x}_n$ projected to GFT basis computed from $\mathbf{L}$ are mostly low frequencies.

Denote by $\mathbf{X}$ a $M \times N$ matrix containing the N observations $\mathbf{x}_n$ as columns. Similarly, denote by $\mathbf{Y}$ a matrix containing the N "denoised" signals $\mathbf{y}_n$. The term $\mathbf{Y}^T\mathbf{L}\mathbf{Y}$ thus computes a sum of $\mathbf{y}_n^T\mathbf{L}\mathbf{y}_n$, each computing the smoothness of signal $\mathbf{y}_n$ with respect to $\mathbf{L}$:

$$\mathbf{Y}^T\mathbf{L}\mathbf{Y} = \sum_{n=1}^N \mathbf{y}_n^T\mathbf{L}\mathbf{y}_n = \sum_{n=1}^N \sum_{i=k}^M \lambda_k z_n(k)^2, \quad (6)$$

where λ_k is the k-th graph frequency, and $z_n(k)$ is the k-th GFT coefficient for signal $\mathbf{y}_n$.

The optimization in [20] seeks $\mathbf{Y}$ and $\mathbf{L}$ simultaneously with the following objective that contains two regularization terms: i) a smoothness term $\mathbf{Y}^T\mathbf{L}\mathbf{Y}$ as described previously; and ii) a sparsity term $\|\mathbf{L}\|_F^2$ that promotes zero entries in $\mathbf{L}$:

$$\min_{\mathbf{L},\mathbf{Y}} \|\mathbf{X}-\mathbf{Y}\|_F^2 + \alpha\,\mathrm{tr}(\mathbf{Y}^T\mathbf{L}\mathbf{Y}) + \beta\,\|\mathbf{L}\|_F^2\,,$$
$$\text{s.t. } \mathrm{tr}(\mathbf{L}) = M, \quad L_{i,j} = L_{j,i} \leq 0, i \neq j, \quad \mathbf{L}\cdot\mathbf{1} = \mathbf{0}, \qquad (7)$$

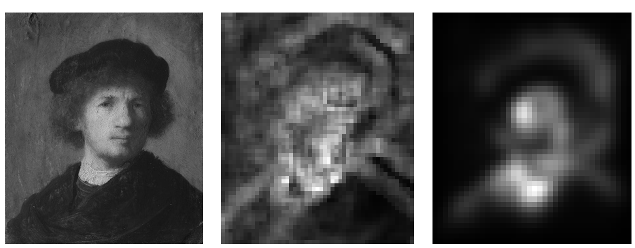
where α and β are parameters for the two regularization terms. The constraints restrict the matrix $\mathbf{L}$ to be a valid graph Laplacian. (7) can be solved via an alternating scheme; see [20] for details.

C. Approximating the Surprise Map

Given that the precision matrices $\mathbf{L}$ and $\mathbf{L}'$ for the prior $P_{\mathbf{X}_1^N}(\mathbf{y})$ and the posterior $P_{\mathbf{X}_1^{N+1}}(\mathbf{y})$ can be robustly estimated, in theory we can now compute the Bayesian surprise $S(\mathbf{X}_1^N, \mathbf{x}_{N+1})$ using the definition in (1). However, (1) is difficult to compute directly, so we approximate it as follows. Bayesian surprise, calculated as (1), in our context is measuring the distance between two exponential probability distributions with precision matrices $\mathbf{L}$ and $\mathbf{L}'$ respectively. So we compute the distance $s(\,)$ between the matrices instead, by computing the Frobenius norm of difference matrix $\mathbf{L}-\mathbf{L}'$:

$$s(\mathbf{X}_1^N, \mathbf{x}_{N+1}) = \|\mathbf{L}-\mathbf{L}'\|_F. \qquad (8)$$

To compute the surprise value for the entire painting, we use a sliding window that moves horizontally and then vertically to estimate horizontal and vertical luminance surprises, and then combine them together to acquire a *surprise map*, which is in a smaller scale compared to the original image. An example surprise map corresponding to *Self Portrait* by Rembrandt (Fig. 3(a)) is shown in Fig. 3(b).



(a) (b) (c)

Fig. 3. (a) *Self Portrait* by Rembrandt (1630); (b) Corresponding computed surprise map. (c) Corresponding saliency map by Itti's method [2]. Surprise and saliency maps are rescaled to the same size as the image.

D. Calculating the Skewness

After computing a surprise map, we construct a histogram with Q bins and measure the skewness G using the following formula [21]:

$$G = \frac{\sqrt{Q(Q-1)}}{Q-1}\frac{\sum_{i=1}^{Q}(H_i-\bar{H})^3}{Q\epsilon^3}, \qquad (9)$$

where H_i is the height of the i-th bin while the width of each bin is 0.1. $\bar{H}$ is the mean height value of bins, and ϵ is the standard deviation. This skewness value is our LuCo score for the painting.

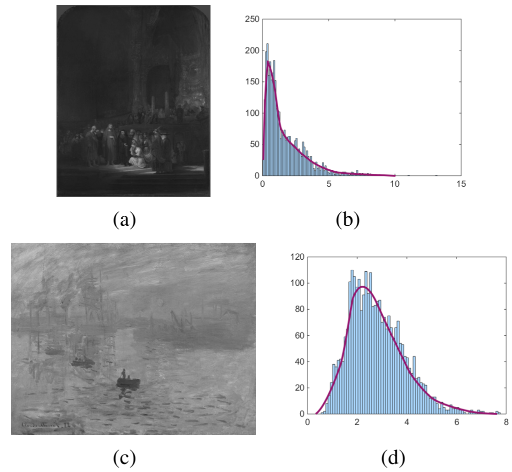


Fig. 4. Comparison of skewness between two paintings. (a) *The Woman Taken in Adultery* by Rembrandt (1644); (b) Histogram of the surprise map of (a), LuCo=2.38; (c) *Impression* by Monet (1872); (d) Histogram of the surprise map of (c), LuCo=0.66.

As examples, two constructed histograms are shown in Fig. 4. We see that if the LuCo score is large, then the luminance Bayesian surprises tend to be either very large or very small, which means that the artist accentuated lighting contrast in the painting. The complete LuCo computation procedure is summarized in Algorithm 1.

Algorithm 1 Computing LuCo score:

Input: One scaled painting image with fixed number of pixels
for each sliding window of $N+1$ observations $\mathbf{X}_1^{N+1}$,
  Step A: Learn $\mathbf{L}$, $\mathbf{L}'$ from observations $\mathbf{X}_1^N$, $\mathbf{x}_{N+1}$.
  Step B: Compute $\|\mathbf{L}-\mathbf{L}'\|_F$.
end for
Construct histogram and compute skewness G.
Output: LuCo score G.

V. Experimentation

A. Experimental Setup

To evaluate the effectiveness of our proposed metric, we collected many high-resolution photos of paintings of old masters from Google Art Project[4] and re-scaled them to roughly the same pixel count (100000) without changing the aspect ratio. We conducted experiments on the luminance channel of these images. In our experiments, we set the patch size K to be 5×5, while the number of patches M in a graph was 25. The number N of observations counted for the prior distribution was 5, and the overlap of patches between observations was 20. α and β were set to 10^{-2} and $10^{-0.2}$ respectively, while the number of bins Q in the histogram was set to 100.

We compare our method with a gradient-based method and several saliency-based methods. For the gradient-based method, we reimplemented Itti's method [2] calculating only the gradients in the luminance channel of the painting and obtain a gradient map. We then built a histogram and computed a skewness parameter using (9). For the second scheme we first computed a saliency map using [2], [6], [7], [8], with only the

[4]https://www.google.com/culturalinstitute/project/art-project

luminance channel for a fair comparison. Then, as done in the previous scheme, we computed the skewness parameter of the saliency histogram.

B. Comparison Between Chiaroscuro And Impressionism

In the first experiment, we utilized 20 paintings each in the Chiaroscuro style and Impressionist style. The resulting average LuCo scores are shown in Table I. We observe that the LuCo scores of the Chiaroscuro paintings are generally higher than the Impressionist paintings. Further, the variances in the two styles are relatively small, showing consistency of LuCo scores among paintings in each style. Thus, we can conclude that artists employed stronger lighting contrast in these Chiaroscuro paintings than Impressionism paintings, which is in agreement with art historians' interpretations [22].

For illustration, representative paintings from Chiaroscuro and Impressionism styles are shown in Fig. 5 and Fig. 6 respectively. We see that in general Chiaroscuro paintings have larger luminance contrast both visually and in LuCo scores.

TABLE I. LuCo Scores of Different Styles

Styles	Mean	Standard Deviation
Chiaroscuro	1.47	0.42
Impressionism	0.73	0.29

C. Analysis of Rembrandt's Paintings

Rembrandt van Rijn is well known for strong lighting contrast via his dexterous usage of light and shadows in his paintings, thus is a good candidate for us to evaluate the effectiveness of our luminance contrast computational model. According to the biographical analysis of Rembrandt in [5], Rembrandt's artistic career can be divided into five periods:

1) The Leiden period (1625-31, Period 1),
2) First Amsterdam period (1631-35, Period 2),
3) Second Amsterdam period (1635-42, Period 3),
4) Third Amsterdam period (1643-58, Period 4), and
5) Fourth Amsterdam period (1658-69, Period 5).

It is argued that Rembrandt showed an increased penchant for strong lighting contrast as he aged, reaching a peak in Period 4, and dropped during his final productive Period 5 when paintings became mostly dark. We seek to verify this trend using our proposed LuCo metric.

TABLE II. Average luminance contrast scores of Rembrandt's paintings in different periods

Periods	Proposed	Gradient	[2]	[6]	[7]	[8]
Period 1	1.25	1.86	2.35	1.86	2.07	1.24
Period 2	1.39	2.42	2.66	2.43	2.40	1.39
Period 3	1.75	2.43	2.69	2.43	2.45	1.63
Period 4	1.91	2.52	2.69	2.52	2.47	1.72
Period 5	1.81	2.53	2.63	2.52	2.51	1.75

We collected 7 images for each period and calculated the average LuCo scores, and also average values by the competing gradient-based method [2] and saliency-based method [2], [6], [7], [8]. The results are shown in Table II. From the table, we see that only our method reflects the trend described previously.

It is also well known that Rembrandt painted many self-portraits over his career, which are representative works at these periods. We collected all available high-resolution self-portraits for experiments. The LuCo trend for these self-portraits is shown in Fig. 7, which also fits the described trend.

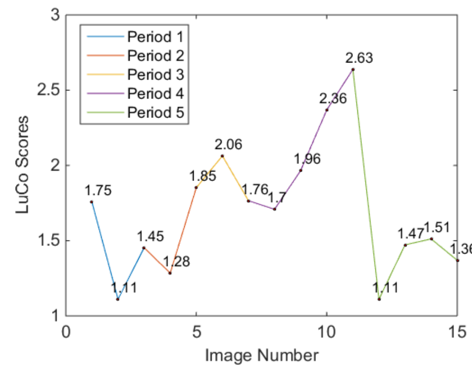


Fig. 7. LuCo scores for Rembrandt's self-portraits

For more intuitive illustrations, we show some example paintings in Fig. 8. We observe that Rembrandt used more lighting contrast as he aged until Period 4, and then his painting became mostly dark in Period 5. Our LuCo scores below also reflect this trend.

VI. Conclusion

Grand masters have accentuated light and shadows in a scene to portray objects and figures more prominently in paintings—a style popularized in Renaissance called Chiaroscuro. In this paper, we propose the first computational model named LuCo to capture and quantify this effect, introducing a measure of lighting surprise. The Bayesian surprise value is first calculated based on a set of local observations of luminance patches. Precision matrices of a GMRF model for the prior and posterior distributions are estimated via sparse graph learning. Finally, a histogram of the acquired surprise map is constructed, and the computed skewness parameter of the histogram is deemed the LuCo score. A large LuCo score thus means that luminance surprises are either very big or very small in a painting, reflecting the artist's intention to accentuate lighting contrast. Experimental results verify the effectiveness of our LuCo metric when compared to a gradient-based method and saliency-based methods. In particular, our computed LuCo scores reflect different usages of lighting contrast in Chiaroscuro and Impressionism paintings, and capture the luminance contrast changes throughout Rembrandt's life. Such measures as LuCo open possibilities towards preservation of artistic intentions during media delivery.

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(a) LuCo=1.53 (b) LuCo=1.38 (c) LuCo=1.89 (d) LuCo=1.57 (e) LuCo=1.57 (f) LuCo=1.42

Fig. 5. Comparison of LuCo scores with Chiaroscuro paintings. (a) *Boy with a Basket of Fruit* by Caravaggio (1593), LuCo=1.53; (b) *The Matchmaker* by Gerard van Honthorst (1625), LuCo=1.38; (c) *Self-Portrait* by Georges de La Tour (1645), LuCo=1.89; (d) *The Milkmaid* by Johannes Vermeer (1657), LuCo=1.57; (e) *The Hunter's Gift* by Gabriel Metsu (1658), LuCo=1.57; (f) *Self-Portrait at an Easel Painting an Old Woman* by Aert de Gelder (1685), LuCo=1.42.

(a) LuCo=0.26 (b) LuCo=0.76 (c) LuCo=0.51 (d) LuCo=1.01 (e) LuCo=0.75 (f) LuCo=0.48

Fig. 6. Comparison of LuCo scores with Impressionism paintings. (a) *Bridge at Villeneuve la Garenne* by Alfred Sisley (1872), LuCo=0.26; (b) *In a Cafe* by Edgar Degas (1873), LuCo=0.76; (c) *The Starry Night* by Vincent van Gogh (1889), LuCo=0.51; (d) *Graystaks* by Claude Monet (1891), LuCo=1.01; (e) *The Child's Bath* by Mary Cassatt (1893), LuCo=0.75; (f) *Hay Harvest at ragny* by Camille Pissarro (1901), LuCo=0.48.

(a) LuCo=1.13 (b) LuCo=1.19 (c) LuCo=1.29 (d) LuCo=1.71 (e) LuCo=1.78 (f) LuCo=2.50 (g) LuCo=1.82

Fig. 8. The comparison of LuCo scores with Rembrandt paintings from different periods. (a) *The Raising of Lazarus* (1630, Period 1), LuCo=1.13; (b) *The Destruction of Jerusalem* (1630, Period 1), LuCo=1.19; (c) *Self-Portrait* (1634, Period 2), LuCo=1.29; (d) *A Polish Nobleman* (1637, Period 3), LuCo=1.71; (e) *Saskia van Uylenburgh* (1643, Period 4), LuCo=1.78; (f) *Jan Six* (1654, Period 4), LuCo=2.50; (g) *Titus* (1660, Period 5), LuCo=1.82.

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