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Original article

Predicting and grouping digitized paintings by style using unsupervised feature learning

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ABSTRACT

Objective. – To create n system to aid in the analysis of art history by classifying and grouping digitized paintings based on stylistic features automatically learned without prior knowledge.
Material and methods. – 6,776 digitized paintings from eight different artistic styles (Art Nouveau, Baroque, Expressionism, Impressionism, Realism, Romanticism, Renaissance, and Post-Impressionism) were utilized to classify (predict) and cluster (group) paintings according to style. The method of unsupervised feature learning with K-means (UFLK), inspired by deep learning, was utilized to extract features from the paintings. These features were then used in: a support vector machine algorithm to classify the style of new test paintings based on a training set of paintings having known style labels; and a spectral clustering algorithm to group the paintings into distinct style groups (anonymously, without employing any known style labels). Classification performance was determined by accuracy and *F*-score. Clustering performance was determined by: the ability to recover the original stylistic groupings (using a cost analysis of all possible combinations of eight group label assignments); *F*-score; and a reliability analysis. The latter analysis used two novel ways to determine the distribution of the null-hypothesis: a uniform distribution projected onto the principal components of the original data; and a randomized, weighted adjacency matrix. The ability to gain insights into art was tested by a semantic analysis of the clustering results. For this purpose, we represented the featural characteristics of each painting by an N-dimensional feature vector, and plotted the distance between vector endpoints (i.e., similarity between paintings). Then, we color-coded the endpoints with the assigned lowest-cost style labels. The scatter plot was visually inspected for separation of the paintings, where the amount of separation between color clusters provides semantic information on the interrelatedness between styles.
Results. – The UFLK-extracted features resembled the edges/lines/colors in the paintings. For feature-based classification of paintings, the macro-averaged *F*-score was 0.469. Classification accuracy and *F*-score were similar/higher compared to other classification methods using more complex feature learning models (e.g., convolutional neural networks, a supervised algorithm). The clustering via UFLK-extracted features yielded 8 unlabeled style groupings. In six of eight clusters, the most common true painting style matched the cluster style assigned by cost analysis. The clustering had an *F*-score of 0.212 (no comparison painting clustering method is available at this time). For the semantic analysis, the featural characteristics of Baroque and Art Nouveau were found to be similar, indicating a relationship between these styles.
Discussion/conclusion. – The UFLK method can extract features from digitised paintings. We were able to extract characteristics of art without any prior information about the nature of the features or the stylistic designation of the paintings. The methods herein may provide art researchers with the latest computational techniques for the documentation, interpretation, and forensics of art. The tools could assist the preservation of culturally sensitive works of art for future generations, and provide new insights into works of art and the artists who created them.

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1. Introduction

Artistic visual style is typically defined after the art has been created, and the style must be a significant break from other styles [1]. However, the definitions of such styles are unclear since styles may overlap, or a painter may have multiple styles, which causes difficulties in stylistic recognition [2]. Experience in observing art objects and the ability to focus on technique despite the subject matter are skills necessary to differentiate styles of various artists [3]. Furthermore, a concrete requirement for defining visual style does not exist, but some visual cues from paintings may be utilized, such as color palette, composition, scene, lighting, contours, and brush strokes [4].

Recently, computer vision has provided the opportunity to analyse paintings via advanced computational methods [5,6]. These computational methods could augment the knowledge and abilities of artists, scholars, and curators [7] in the same way microscopes aid biologists [8]. For this purpose, we present computational techniques based upon recent feature extraction algorithms for developing an automatic system of extracting the salient features of art. This is independent of any prior knowledge regarding the features and stylistic content of the art. Furthermore, we demonstrate methods to evaluate the grouping of paintings, which augment the analyses of art researchers. These methods were implemented on a large dataset of digitized paintings, which spanned various artistic movements. The methods presented in this study will allow researchers to use the latest computational techniques to preserve, document, and provide new insights into the stylistic development of different artists and their stylistic movements.

There have been many studies focusing on the utility of computational techniques to analyse works of art. For a detailed review of the types of computational methods and analyses performed, such as on the brushstrokes, *craquelure*, or composition, please refer to [8,9]. The number of studies which pertain to the classification of artistic style or art movements that involve large groups of paintings are minimal compared to the number of studies for specific works created by individual artists [1]. To identify painting styles, previous studies extracted a variety of features to enable characterization of digitized paintings. Zujovic et al. [10] classified the five art movements of Abstract Expressionism, Cubism, Impressionism, Pop Art, and Realism. The features employed were edge maps for gray level and histograms for color, which were obtained from the hue, saturation, and value space. Gunsel et al. [11] completed similar studies except they proposed that luminance and the corresponding color features of images were more suitable. Spehr et al. [12] utilized 200 features to cluster and classify paintings from eight styles. The major features in their study consisted of color distributions based upon pixel histograms and contextual and semantic features derived from template matching and face detection. Lombardi et al. [13] deployed the k-nearest neighbor classifier with features, which captured light, line, and color to classify paintings.

Shamir et al. [14], developed and employed a feature extraction toolbox containing 4,027 image descriptors [15] to classify paintings from Impressionism, Expressionism, and Surrealism, but for only nine artists. Culjak et al. [16] employed features similar to Zujovic et al. [10] and Gunsel et al. [11], but for styles which were difficult to classify, such as Fauvism and Naïve art. Condorovici et al. [17] used features for six artistic styles of paintings, which considered lightness perception, shape extraction, color distribution, texture, and edge analysis. Nonetheless, all of the aforementioned feature-based studies of style used handcrafted features, i.e., they were created via specific mathematical models and definitions, such as Gabor filters and statistical measures, which were decided by the experimenter empirically, prior to classification or clustering. To overcome the limitation in which prior knowledge is necessary to create features for paintings, deep neural networks and other similar techniques may be utilized.

Deep learning methods, which are based on traditional neural network techniques, contain many layers of hidden units [18] in contrast to traditional neural networks. These deep layers allow deep learning (also known as deep neural networks) of many complex features, which subsequently allow learning of intricate relationships within the data [19]. Until recently, such deep learning models had limited implementations due to the lack of computational power and numerical techniques necessary for solving the numerous model parameters [20,21]. However, the learning ability of deep neural network techniques has overcome the need to design (handcraft) classification features, as shown in different domains such as image classification and speech recognition [21].

Karayev et al. [22] were the first to utilize a deep learning algorithm to classify painting styles. They previously utilized a very deep version of Convolutional Neural Networks (CNNs) [23], which are feed-forward networks specialized for images [24]. They trained their CNN on paintings from the WikiArt gallery (available at http://www.wikiart.org). Bar et al. [1] also utilized CNNs and the same dataset to classify painting style, but combined them with "Picture Codes" features [25] which are descriptive image features extracted and compressed into binarized representations. Saleh and Elgammel [26] utilized the same CNN model and dataset as in [1,22], but their model was a combination of semantic-based features and CNN features, and further employing a feature selection framework. Although Karayev et al. [22], Bar et al. [1], and Saleh and Elgammal [26] achieved satisfactory classification accuracy, they did not analyze the features extracted from CNNs. Instead, their sole focus was improving style classification accuracy.

Since CNNs are supervised feature-learning algorithms [27,28], they require ground-truth labels (e.g., the known artistic movement/style of each painting) during the training phase of the algorithm. This requirement for prior knowledge leads what is termed the "grouping problem of paintings" [29], in which a naïve person is unable to cluster paintings with similar styles without expert knowledge of the art field. The grouping problem is due to the naïve person's inability to provide the necessary prior style information during the training phase of deep neural networks such as CNNs [30]. In our work, we overcame this limitation of CNNs in feature learning and artistic style clustering and classification by using unsupervised feature learning.

Unsupervised feature learning is an umbrella term describing recently developed feature extraction methods, which do not employ labeled data during model training. Examples of unsupervised feature learning are the deep learning methods of Restricted Boltzmann Machine (RBM) neural networks and Autoencoders [30]. Specifically, a RBM neural network is composed of many stacked RBM units, with each unit composed of a "visible" input layer and a "hidden" feature-learning layer [18]. An Autoencoder is composed of successively smaller stacked RBM units, which reduce the dimensionality by extracting the most important features for a specific dataset. Autoencoders and other neural network-like algorithms can be considered as a nonlinear generalization of principal components analysis (PCA) [18]. The nonlinear aspect of neural networks refers to their ability to combine features in an intricate way, which cannot be performed by simple matrix multiplication.

A disadvantage of deep neural networks such as RBMs and Autoencoders is their complexity during the process of unsupervised feature learning. Recently, to reduce complexity, the traditional K-means clustering algorithm was utilized instead for the feature-learning part of the algorithm [31], which the authors applied to classifying photographs of objects. We implemented this procedure for feature extraction and style classification in paintings. In the study of [31], substitution of the K-means algorithm in place of RBMs and Autoencoders was found to greatly reduce