The Classification of Style in Fine-Art Painting

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ABSTRACT

The computer science approaches to the classification of painting concentrate primarily on painter identification. While this goal is certainly worthy of pursuit, there are other valid tasks related to the classification of painting including the description and analysis of the relationships between different painting styles. This paper proposes a general approach to the classification of style that supports the following tasks: recognize painting styles, identify key relationships between styles, outline a basis for determining style proximity, and evaluate and visualize classification results.

The study reports the results of a review of features currently applied to this domain and supplements the review with commonly used features in image retrieval. In particular, the study considers several color features not applied to painting classification such as color autocorrelograms and dynamic spatial chromatic histograms. The survey of color features revealed that preserving frequency and spatial information of the color content of a painting did not improve classification accuracy. A palette description algorithm is proposed for describing the color content of paintings from an image's color map. The palette description algorithm performed well when compared to similar color features.

The features with the best performance were tested against a standard test database composed of images from the Web Museum[16]. Several supervised and unsupervised techniques were used for classification, visualization, and evaluation including k-Nearest Neighbor, Hierarchical Clustering, Self-Organizing Maps, and Multidimensional Scaling. Style description metrics are proposed as an evaluation technique for classification results. These metrics proved to be as reliable a basis for the evaluation of test results as comparable data quality measures.

1. INTRODUCTION

Researchers are marshalling advances in digital image processing, machine learning, and computer vision to solve problems of the attribution and interpretation of fine-art paintings[5,7,8,9,10,12,14,15,17,18,21,22]. The research to date focuses on painter identification (attribution) and authentication and therefore stresses high degrees of accuracy on small target datasets. As a result of this focus, the problem of the broad classification of style in painting receives relatively little attention[5]. In particular, the following questions of style classification in painting are as yet only partially addressed: Is it possible to classify paintings in general way? What features are most useful for painting classification? How are these features different from those used in image retrieval if at all? How are style classifications best visualized and evaluated? In answering these questions, this work endeavors to show that the style of fine-art paintings is generally classifiable with semantically-relevant features.

Previous approaches to style classification reveal five trends in the literature. First, the solutions proposed are often style-specific addressing only particular kinds of art or even the work of particular painters[7,10,12,15,18,21]. Second, the literature emphasizes texture features while minimizing the potential role of color features[5,14]. Third, the studies to date do not examine techniques for evaluating classification accuracy. Fourth, current research disregards the semantic relevance of the features studied[9]. Fifth, the projects currently undertaken forego a broad approach to style preferring small focused studies of particular painters or movements[18,21,22].

In contrast to previous approaches, this paper considers the components necessary to classify style in a general way with techniques that apply to a broad range of painting styles. Section 2 outlines the basis of formal approaches to painting style and discusses the formal elements considered in this paper: light, line, texture, and color. In Section 3, the feature survey addresses feature extraction, normalization, and comparison. A palette description algorithm is defined with some additional discussion of color features.. Section 4 reviews the classification methods for several supervised and unsupervised techniques including k-Nearest Neighbor (kNN), Hierarchical Clustering, Self-Organizing Maps (SOM), and Multidimensional Scaling (MDS). Section 5 organizes and summarizes the results of this paper and presents two approaches to the evaluation of classification results. Section 6 reiterates the conclusions of the study.

2. FORMAL APPROACHES TO STYLE

The formal approach to style presupposes that art is best understood in formal terms like line, color, and shape rather than content or iconography. For two reasons, the formal approach to style offers the best starting point for the computational classification of style in painting. First, the formal elements of a painting like line and color are precisely the qualities of images that computers can measure. Computer approaches based on iconography cannot be undertaken until computer techniques exist to recognize objects of interest in the art domain. That is to say, until object recognition algorithms can identify a woman holding a plate adorned with two eyes, a common iconographic representation of Saint Lucy, computer approaches to style based on content are not feasible. Second, many styles of painting, such as abstract expressionism, do not contain explicit identifiable content. Therefore, approaches to style based on content cannot address works of art whose content is largely and explicitly formal.

Art historians and critics use a nuanced vocabulary to discuss the formal characteristics of paintings[1,20]. The formal terms for describing a painting focus on how an artist painted the given subject in a particular context. Color, line, light, space, composition, depth, shape, and size are all examples of formal characteristics of a painting. The research presented in this paper aims to define the formal characteristics of a painting quantitatively in order to identify, classify, and analyze the formal elements inherent in a style. In particular, four formal elements are considered: light, line, texture, and color. The classification of style in painting therefore requires that features modeling these formal elements be extracted and analyzed to better understand particular artists and movements.

3. FEATURE SURVEY

3.1 Database

The feature survey was conducted using the database described by Herik and Postma[5] comprising ten paintings each from the work of Cezanne, Monet, Pissarro, Seurat, Sisley, and Van Gogh. Table 1 describes the characteristics of this database. For each artist, the mean vertical resolution (pixels), mean horizontal resolution (pixels) and mean file size (bytes) are reported.

Table 1: Database Description

Artist	Vertical Res.	Horizontal Res.	Size
Cezanne	889	1031	156399
Monet	832	877	179350
Pissarro	699	845	157190
Seurat	810	946	241553
Sisley	870	977	199670
Van Gogh	810	958	201501
Overall	*818*	*939*	*189277*

3.2 Extraction

The feature survey conducted for this study included 11 features modeling light, 14 describing properties of line, 17 summarizing texture, and 15 color features. The features were extracted from each image in the database described above. The feature extraction process did not include any image preprocessing beyond that required for the feature. The images were not filtered, corrected for size, or corrected for orientation. The feature extraction process consisted solely of summarizing the relevant image content.

Figure 1 demonstrates the visualization for a spatial chromatic histogram (SCH), a color feature designed to capture the spatial arrangement of color in an image. The feature extraction process for this feature required the production of this transformation followed by the numerical summarization of the color content in the image. For the SCH, the feature extraction process results in a feature vector of 76 fields recording the baricenter, variance, and count of each color bin represented in the image. The full documentation of all features considered in this study is beyond the scope of this paper but can be reviewed in materials from the reference list[13].

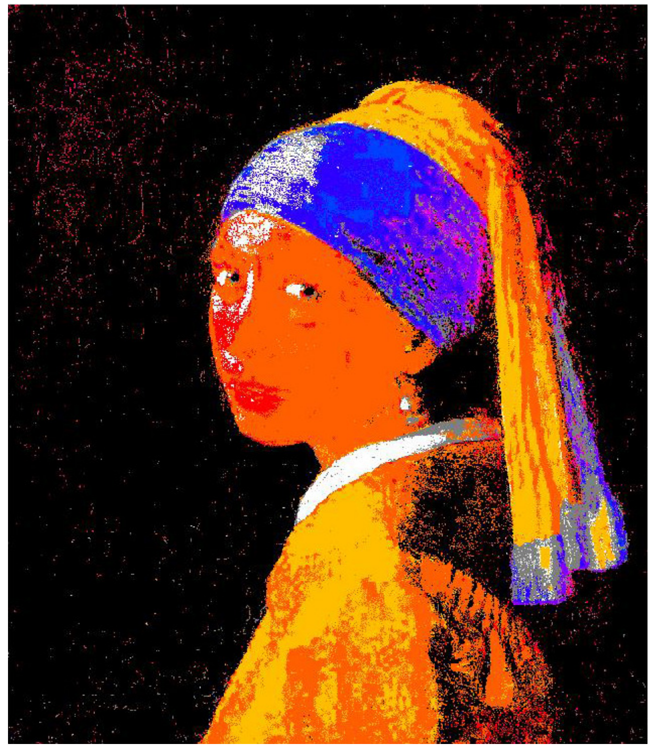


Figure 1: The Spatial Chromatic Histogram

3.3 Normalization

The raw numbers produced by the feature extraction process are more often than not scaled inconsistently. Unless otherwise corrected, these inconsistencies result in variances that provide *de facto* feature weights increasing the importance of some features and decreasing that of others. Moreover, many features require several levels of normalization. For example, features recording spatially-dependent properties of an image such as line length or the number of colors must be normalized by the total number of pixels in an image before the values are normalized with respect to other features. Normalization therefore ensures the internal consistency of features and prepares feature vectors for direct comparison. The feature vectors were normalized to values between 0 and 1 using the following technique[4]:

$$\frac{V(i) - \min(V)}{\max(V) - \min(V)},$$

where $V(i)$ represents individual values in the feature vector, $min(V)$ represents the minimum value in the feature vector, and $max(V)$ represents the maximum value in the feature vector.

3.4 Comparison

After the features were rescaled, the feature vectors were compared to identify the relative distance between two paintings. In most cases, the Euclidean distance metric serves as a decent approximation of the distance between two feature vectors. In cases where features record ordinal or modulo measurements however, the Euclidean distance metric is often ineffective[2,19]. For example, hue histograms record the angular measurement of hue values and their differences are best represented by distance metrics that can account for this. The palette description algorithm described below and its corresponding palette distance algorithm will serve as an example of a feature not well served by Euclidean distance metrics.

3.5 Palette Description Algorithm

An image can be broken down into two main parts: an image map and an image index. The image map records the set of colors required to display the image and the image index records the spatial arrangement of those colors in the image. In terms of a painting, the image map corresponds to a painter's palette while the image index corresponds to the canvas. It is often desirable to compare the entire color palette of one painting to that of another. The palette description algorithm summarizes the color content of an image map for HSV colors by defining the central tendency of the colors in the image.

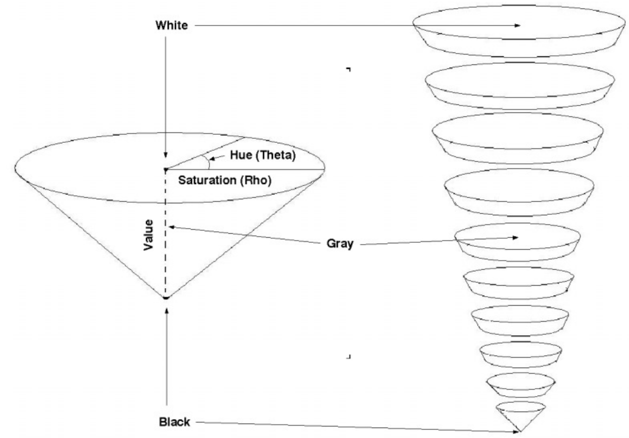


Figure 2: HSV Decomposition into Value Slices

Figure 2 demonstrates the first step of the palette description algorithm. The HSV cone is divided into equal value slices. For each value slice, the mean hue, saturation, and value was calculated. The distance between every color in the slice and the HS mean of that slice was calculated to determine the variance of the colors around the mean. Finally, the total number of colors in the slice was also calculated. Figure 3 displays the color distribution for a single slice from a palette description. The mean value is displayed at the top of the figure. The hue-saturation mean is represented by the labeled red crosshair in the center of the distribution of colors. The circle surrounding the hue-saturation mean represents the variance. These palette description statistics provide a basis for comparing the color content of images.

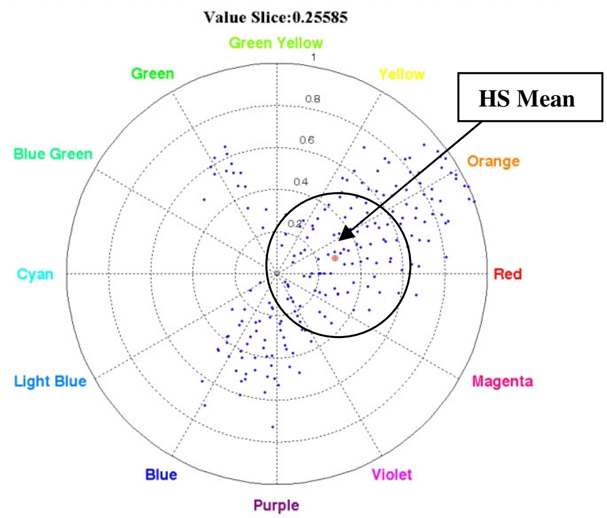


Figure 3: Value Slice

3.6 Palette Comparison Algorithm

The distance between two palette descriptions is simply the slice by slice difference of the two palettes. The palette comparison algorithm requires the following six steps to determine the difference between two palette descriptions. First, the difference between HS pairs was calculated with the law of cosines:

$$hsdist = \sqrt{sat_1^2 + sat_2^2 - 2sat_1 sat_2 \cos(hue_2 - hue_1)}$$

Second, the distance between values was calculated:

$$vdist = | val_1 - val_2 | .$$

Third, the distance between the variances was calculated:

$$vrdist = | vr_1 - vr_2 | .$$

Fourth, the difference between the color counts was computed:

$$countdist = | countdist_1 - countdist_2 | .$$

After finding the above differences for each slice, the fifth step computes the overall slice distance:

$$slicedist = \sqrt{hsdist^2 + vdist^2 + vrdist^2 + countdist^2}$$

Finally, the total palette distance is the sum of the slice distances normalized by the number of slices:

$$palettedist = \frac{\sum_{i=1}^{n} slicedist_i}{n} .$$

Table 2 presents the classification accuracy of the palette algorithms as described above with those of comparable color features. When tested with the kNN classifier, the palette description algorithm classified images at a rate similar to comparable color features with less required storage (measured in doubles). In fact, algorithms designed to preserve spatial and frequency information in the color channel were often less effective for classification than the palette description algorithm.

Table 2: Classification Results of Color Features

Feature	Storage	kNN1	kNN13
Palette Description 10	50	36.7	30.0
Autocorrelogram 16	64	10.0	20.0
Hue Histogram 100	100	26.7	16.7
Saturation Histogram 100	100	30.0	30.0
DSCH 16	112	20.0	23.3
RGB Histogram	768	33.3	23.3

4. STYLE CLASSIFICATION

Two general types of classifiers were used in this study: supervised and unsupervised. Supervised techniques require that data is divided into training and testing sets. The goal of supervised classifiers is to "teach" the machine to recognize test paintings based on prior knowledge gleaned from the training set. Many of the studies in this domain rely on this technique to produce classification results gauged by overall accuracy[5,7,22]. In this study, two types of supervised learning were used to evaluate features and groups of features: kNN and an Interactive approach.

While the supervised learning techniques are appropriate for many applications, they suffer from a few drawbacks. First, as the number of classes increases, the classification accuracy degrades significantly. Second, they are not particularly well-suited to analysis and visualization. For applications requiring analysis and visualization capabilities, unsupervised learning techniques offer the following advantages. First, these algorithms operate on an entire dataset eliminating the need to divide the data into training and testing sets. Second, the algorithms are designed to show the relationships between the classes allowing for a detailed analysis of the relationships between styles in painting. In this study, three unsupervised learning techniques were used: agglomerative hierarchical clustering, SOM, and MDS.

4.1 Supervised Learning

4.1.1 k-Nearest Neighbor

The kNN algorithm is a well-known supervised classification technique[3]. In this algorithm a test instance is classified by assuming the label of the most frequently occurring neighbor of k training samples. The k closest training samples are examined and the label with the most votes is assigned to the test sample. The critical decision in the implementation of the kNN algorithm is choosing or finding the best window size or k. The k values chosen for this study were 1 and 13. The bulk of the feature testing relied on kNN classification.

4.1.2 Interactive

The kNN testing described above was repeated using an application-oriented classification scheme. The interactive technique is a modified version of kNN where the ten closest images are returned as one might expect an Image Retrieval system to behave. Figure 4 displays a sample application designed to use the interactive classification technique. The interactive technique was developed to gauge how various classifiers and features would perform in an application setting.

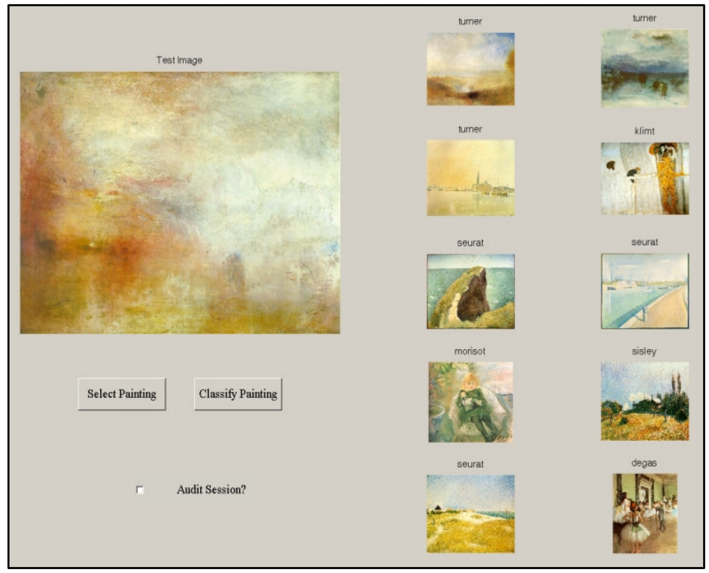


Figure 4: Interactive Classification

4.2 Unsupervised Learning

4.2.1 Agglomerative Hierarchical Clustering

Hierarchical clustering provides information concerning clusters and subclusters found in data. In contrast to flat descriptions of data where clusters are primarily disjoint, hierarchical clusters identify multiple levels of structure in data convenient for classification systems like those used in biological taxonomy[3,4]. The technique as applied to artistic style provides detailed information concerning the relative proximity of styles. As with many clustering techniques, hierarchical classification offers a natural visualization, the dendrogram. Figure 5 depicts a style dendrogram of the Impressionist and Post-Impressionist painters in the test database. The dendrogram shows three subclusters grouping Cezanne with Van Gogh, Monet with Pissarro, and Seurat with Sisley.

The algorithm that generated this dendrogram was the agglomerative or bottom up hierarchical clustering technique based on the complete-linkage algorithm[3,4]. The complete-linkage algorithm determines cluster distance by measuring the most distant nodes in two clusters. Formally, the complete-linkage algorithm is defined as:

$$d\max(D_i, D_j) = \max \| x - x' \|,$$

Where D_i and D_j are clusters and x and x' are nodes in clusters D_i and D_j respectively.

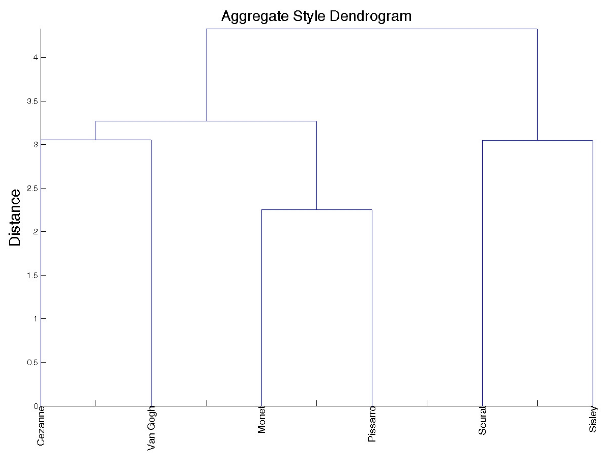


Figure 5: Style Dendrogram

4.2.2 Self-Organizing Maps

While agglomerative clustering provides opportunities for organizing styles in a hierarchical way, other approaches offer a greater range of analytical capabilities. Self-Organizing Maps[3,11] transform all points in the feature space to points in a target space that preserves the relative distances and proximities between instances as much as possible. The appeal of SOM derives from its advanced visualization capabilities and analytical techniques. Figure 6 displays a basic SOM for the Impressionist and Post-Impressionist database.

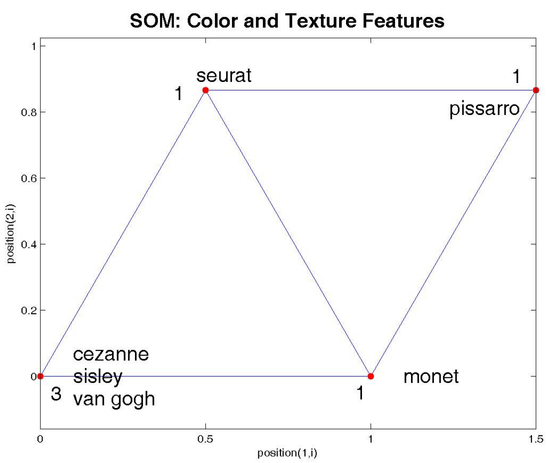


Figure 6: Basic SOM

In addition to the basic SOM, advanced SOM techniques permit the identification of cluster boundaries, the analysis of individual features, and the evaluation of SOM quality with error measurements. The SOM is a type of neural network that trains itself on an entire dataset to "learn" the structures inherent in the data. The user specifies a topology, number of training epochs, neighborhood distances, and neighborhood weighting functions determining the specific techniques used for fitting the data to the SOM. The training process involves mapping instances to the closest node in the map and identifying the best matching unit (BMU) for each instance. After the SOM has been trained to these specifications, the user must decide how to label the map nodes. Labels can represent instance names, class names or other designations that seem appropriate. Finally, the trained SOM is represented with the U-matrix visualization which displays the average distance between map nodes (codebook vectors). Figure 7 shows a U-matrix for a SOM with hexagonal topology using the Gaussian weighting function and trained for 5000 epochs. The labels on the U-matrix represent the most frequent class member assigned to that node. The U-matrix represents the distances as calculated with all features. It is possible to construct a U-matrix that considers only specific features as well. The U-matrix denotes cluster boundaries with dark patches such as that in the upper left-hand corner of Figure 7.

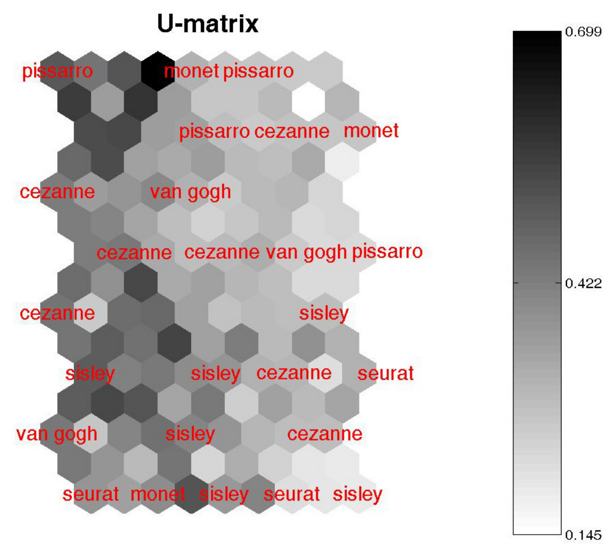


Figure 7: U-matrix Representation of SOM

In addition to the advanced visualization techniques, SOM provides a standard way to gauge the degree to which a map is actually organized. The average unit of disorder (AUD) or quantization error measures the average distance between an instance in the dataset and its best matching unit: the higher the AUD the less organized the map. The AUD can be plotted against the training epoch to estimate the quality of the SOM at various points of the training cycle. Figure 8 displays two graphs measuring the SOM quality. The top graph displays the AUD plotted against the training epoch. The bottom graph displays the first and second principal components of the best matching units plotted against the feature vectors to present graphically the AUD.

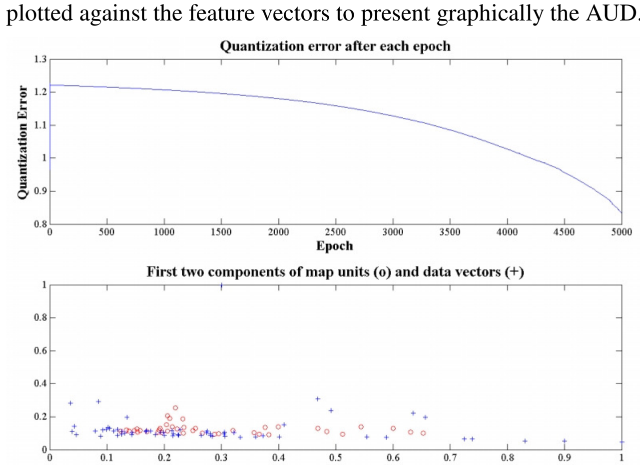


Figure 8: Graphs of the Average Unit of Disorder

4.2.3 *Multidimensional Scaling*

While SOM provides broad analytical powers for analyzing features and clusters of paintings, it often obscures the arrangement of sample paintings within clusters. There are often cases when the paintings themselves and their relationships to each other are the central focus of study. In these cases, multidimensional scaling (MDS)[3,4] techniques serve rather well. MDS is a data reduction technique that projects data with high dimensionality onto a Euclidean space preserving the original distances of the data points in a space that is easier to visualize. Figure 9 shows an MDS analysis of ten paintings by Cezanne. Each circle in the plot represents a painting. By averaging the values of the samples it is possible to construct a theoretical style center that represents the central stylistic tendency of the paintings considered. The average sum of the distances between each sample and the stylistic center provides and estimate of stylistic variance.

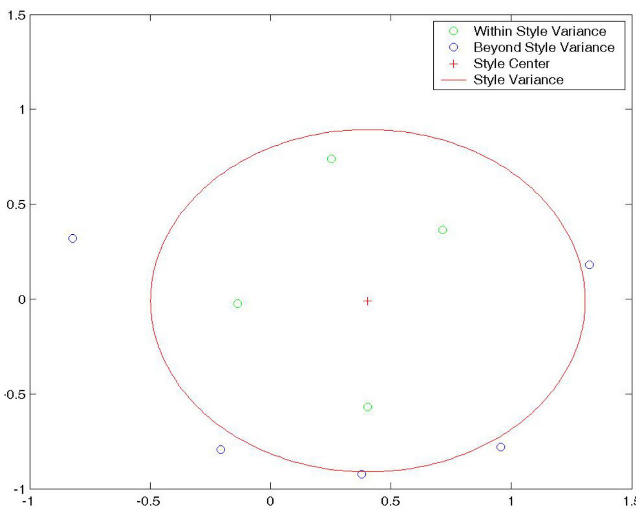


Figure 9: MDS Analysis of Paintings by Cezanne

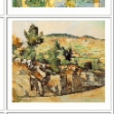
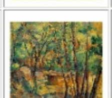
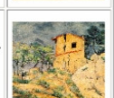
Painting Information	Painting Image	Painting Information	Painting Image
1 Painting: house-and-farm-at-jas-de-bouffan.jpg Distance from Style Center: 0.4839		2 Painting: jas-de-buffan-the-pool.jpg Distance from Style Center: 0.54223	
3 Painting: gardanne.jpg Distance from Style Center: 0.55894		4 Painting: mountains-in-provence.jpg Distance from Style Center: 0.76327	
5 Painting: well-millstone-and-cistern-under-trees.jpg Distance from Style Center: 0.91376		6 Painting: the-house-and-the-cracked-walls.jpg Distance from Style Center: 0.94038	
7 Painting: study-landscape-at-auvers.jpg Distance from Style Center: 0.94884		8 Painting: house-and-trees.jpg Distance from Style Center: 0.99438	
9 Painting: houses-along-the-road.jpg Distance from Style Center: 1.2689		10 Painting: gardanne-brooklyn.jpg Distance from Style Center: 1.6073	

Figure 10: Paintings Ordered By Distance to Stylistic Center

The style center and style variance can be used for additional analysis and visualization including providing lists of paintings ordered by proximity to the style center. Figure 10 organizes images by proximity to the style center. Just as MDS can spatially arrange and analyze data for a single artist, so can it arrange and analyze data for a group of artists. Figure 11 displays the MDS analysis for the entire test database. The MDS analysis in Figure 11 displays both the global style center and the global style variance with a yellow cross and ellipse. The distance between an artist's style center and the global style center offers further analytical capability. An identifiable cluster of Cezanne's work is labeled and sits at a considerable distance from the global style center. The theoretical style centers and variances are critical components to the evaluation of classification results.

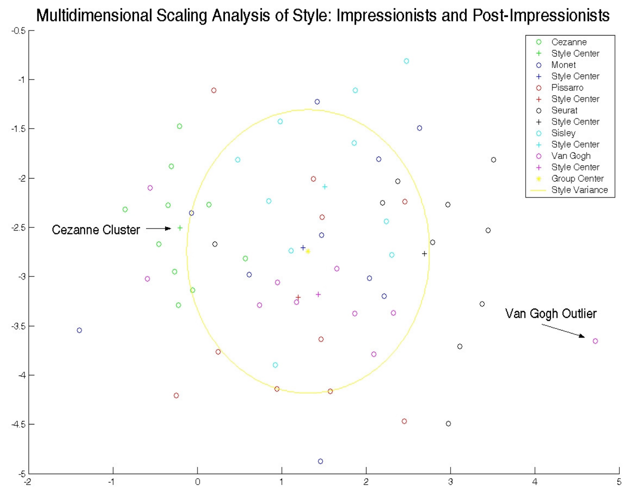


Figure 11:MDS Analysis of Style

5. RESULTS AND EVALUATION

Classification results often vary to high degrees: the same set of features often classifies one artist particularly well and another rather poorly. There are many possible explanations of this phenomena of which two are considered in this study: variance of data quality and variance of class quality. Data quality regards the relative properties of the image file itself in particular its resolution. Are paintings with higher resolution easier to classify? Class quality relates to the relative cohesion of a class. For example, perhaps Cezanne is easier to classify because his style variance is relatively small compared to other artists. Are classes with lower style variance easier to classify?

5.1 Data Quality

The nature of the data is a likely factor in classification accuracy. Several studies focus on a few high quality images to achieve high levels of accuracy in classification tasks. It is intuitive to assume therefore that data quality has a proportional relationship to classification accuracy: as the data quality increases the classification accuracy increases as well. The principal measurements of data quality in this context are average image resolution measured in pixels, average file size measured in bytes, and the ratio of bytes to pixels. Table 3 shows the data quality measurements and the accuracy of results for the test database.

Table 3: Data Quality Measurements

Artist	Pixels	Bytes	B/P	kNN13
Cezanne	916,559	156399	0.1706	100
Monet	729,664	179350	0.2458	20
Pissarro	590,655	157190	0.2661	0
Seurat	766,260	241553	0.3152	60
Sisley	849,990	199670	0.2349	20
Van Gogh	775,980	201501	0.2623	0

The average number of pixels proved to be the best indicator of classification accuracy. Figure 12 plots the relationship between the average number of pixels in an image class against the accuracy of classification for that class. The graph shows a strong relationship between these two variables.

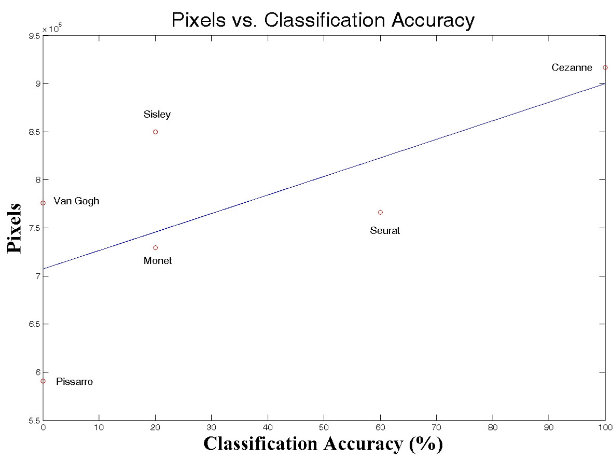


Figure 12: Pixels vs. Classification Accuracy

5.2 Class Quality

Another method of gauging classification accuracy involves measurements of class quality. In previous sections, this study outlined a technique for describing useful properties of a class including style variance and the distance between a class style center and the global style center. In this section, these metrics are employed as predictors of classification accuracy. The style variance and the distance between the class centers and the global center provide a useful way to evaluate classification accuracy. The style description ratio is the ratio of the class center from the global style center divided by the class variance. Formally, the style description ratio is:

$$S = \frac{\sqrt{(cc - gc)^2}}{cv},$$

where S is the style description ratio, cc and gc are the class style center and global style center, and cv is the class variance. As the style description ratio increases, theoretically, the accuracy of classification should increase as well. The rationale for this metric is based on two assumptions about class quality: classes whose central tendency is far from the global style center should be easier to classify than classes closer to the global center and classes whose variance is small should be easier to classify than classes with larger variances. Table 4 shows the class quality measurements and the classification results for the test database.

Table 4: Class Quality Measurements

Artist	CV	CC-GC	S	kNN13
Cezanne	2.1265	1.5351	0.7219	100
Monet	3.5799	0.0712	0.0198	20
Pissarro	3.1643	0.4832	0.1527	0
Seurat	2.743	1.3812	0.5035	60
Sisley	3.2783	0.6856	0.2091	20
Van Gogh	3.9409	0.4548	0.1154	0

Figure 13 plots the style description ratio of the test data against the classification accuracy. The style description ratio provides the best explanation of the classification accuracy thus far with only one serious outlier in the data (Monet). Although not conclusive, the style description ratio is at least as effective as the pixel measurement in explaining the classification results presented.

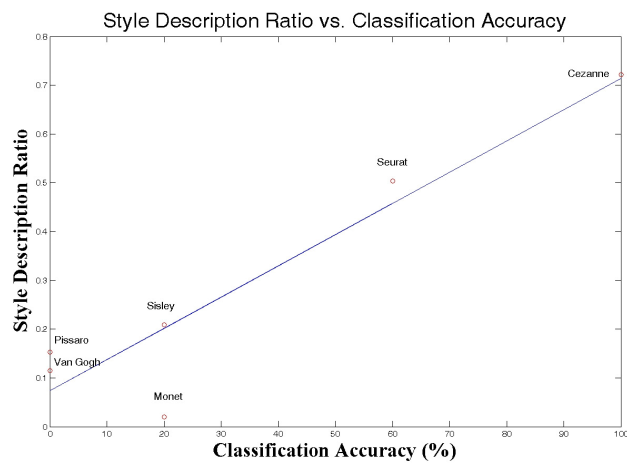


Figure 13: Style Description Ratio vs. Classification Accuracy

The evaluation technique discussed above has an important implication that deserves mention. In the test case examined in this paper, the classes considered are fairly straight-forward and difficult to dispute: most people identify the artist of a work to be a relevant, useful, and reliable category for discussing artwork. There are other categories, however, that are more tenuous and contentious such as those based on movement, school, geography, or time period. For example, it is common for early fourteenth-century Tuscan paintings to be categorized as early Renaissance works by some historians and late Medieval works by others. The evaluation technique outlined above provides a basis for gauging the quality of these classifications by defining a class variance and distance to the global style center. It allows a researcher to identify the formal properties that delineate a particular class from other related classes if such properties exist and are measurable. In other words, the evaluation technique provides a method of testing the formal properties of art-historical categories and of comparing the formal properties of these categories. The unsupervised classification techniques discussed can offer additional insight into class relationships by arranging the data in taxonomic formats. Consider the dendrogram of the aggregate test data in Figure 14. The graph bears out many of the same relationships found in the MDS analysis in Figure 11. For example, in both Figures Monet's style center is closest to the global style center and Cezanne and Seurat are a significant distance from it. In short, it may be possible to build a taxonomic system for the formal aspects of artistic style.

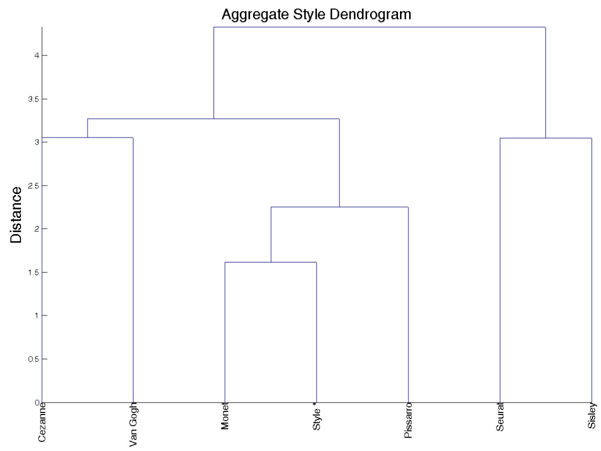


Figure 14:Style Dendrogram with Global Style Center

6. CONCLUSION

Despite the current trend toward building style-specific models for painting classification, test results demonstrate that broader style-independent approaches to classification are possible. It has been shown that preserving additional spatial and frequency color information does not necessarily improve classification accuracy. A palette description algorithm was proposed and demonstrated to perform as well as similar color description techniques with less storage overhead. Several machine learning techniques were explored for their capacity to analyze, classify, and visualize style relationships including kNN, Hierarchical Clustering, SOM, and MDS. Theoretical style centers and variances were proposed as descriptions of class style and global style characteristics. These style descriptors were combined to construct a style description ratio that proved useful for evaluating classification results.

7. REFERENCES

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