The Classification of Style in Fine-Art Painting

by
Thomas Edward Lombardi

Submitted in partial fulfillment
of the requirements for the degree of
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in Computing

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We hereby certify that this dissertation, submitted by Thomas Lombardi, satisfies the dissertation requirements for the degree of *Doctor of Professional Studies in Computing* and has been approved.

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Abstract

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The computer science approaches to the classification of painting concentrate on problems of attribution. While this goal is certainly worthy of pursuit, there are other valid tasks related to the classification of painting including the identification of period styles, the description of styles, and the analysis of the relationship between different painting styles. This dissertation proposed and developed a general approach to the classification of style and achieved this goal using a semantically-relevant feature set. The resulting automated painting analysis system supports the following tasks: recognize painting styles, identify key relationships between styles, outline the basis for style proximity, and evaluate and visualize classification results.

The study initially conducted a review of the features currently applied to this domain and implemented these features, supplementing them with commonly used features in image retrieval applications. The study evaluated these features for classification accuracy, speed, storage space, and semantic relevance, and mapped the features considered to formal elements discussed in the domain, including light, line, texture, and color. In particular, the study successfully employed several color features not previously applied to painting classification, such as color autocorrelograms and dynamic spatial chromatic histograms. The dissertation proposed and developed a palette description feature for describing the color content of paintings. In tests, the palette description feature classified style as well as comparable color features.

The study evaluated the features against two databases of paintings using a variety of supervised and unsupervised classification techniques including k-nearest neighbor, hierarchical clustering, self-organizing maps, and multidimensional scaling. In summary, the dissertation proposed and developed a theoretical style center and variance as both an analytical tool and an evaluation technique for classification accuracy. A style description ratio based on the theoretical style center and variance served as a reliable basis for the evaluation of classification results.

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Finally, I dedicate this work to my wife, Ola, who has suffered and sacrificed in this our first year of marriage. My darling, my time spent studying numbers has led me to only one certain fact: there are not numbers of sufficient quantity or size to describe my love for you.

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Chapter 1

Introduction

1.1 Problem Description and Thesis

In the first decade of the Twenty-First Century, researchers are marshalling advances in digital image processing, machine learning, and computer vision to solve problems in the authentication and interpretation of fine-art paintings. The research to date focuses on painter identification and attribution and therefore stresses high degrees of accuracy on small target datasets. The focus on forensic applications obscures the problems of broad classification of style in painting. In particular, the following questions of style classification in painting are only partially addressed: Is it possible to classify style in paintings in a general way? What features are most useful for painting classification? How are these features different from those used in forensic applications or image retrieval applications? How are classifications of style best visualized and evaluated? How can these methods and approaches aid users in the classification of artistic style? In addressing these questions, this work endeavors to show that the style of fine-art paintings is generally classifiable with semantically-relevant features.

An example from the career of the infamous forger, Han van Meegeren, highlights the distinction between forensic and general style classification. In 1937, the renowned art historian Abraham Bredius referred to *Christ and the Disciples at Emmaeus* in glowing terms as “the masterpiece of Johannes Vermeer of Delft” [9]. The work, displayed in Figure 1, was in fact that of Han van Meegeren, the art dealer and master forger. Indeed, van Meegeren's work in Vermeer forgeries was legendary including a sale of his *Christ and the Adultress* to Hermann Göring.

Figure 1: Han van Meegeren, *Christ and the Disciples at Emmaeus*, 1937. Photo Credit: MyStudios [116].

The forensic approach to style classification seeks to address the traditional concerns of art dealers, auction houses, and critics by answering questions of authenticity or attribution. In this respect, forensic applications have two and only two relevant classes given any particular work of art: authentic and not authentic. Given the aims of such applications, the technical details include the need for high resolutions images, small, concentrated, and targeted databases, and the focus on accuracy above other design considerations such as speed or semantic relevance. Therefore, a forensic approach successfully applied to van Meegeren's work should identify that it is not an authentic Vermeer based on a close comparison of the questionable work with verifiably authentic works.

A general approach to the classification of fine-art paintings, on the other hand, addresses the concerns of art historians, students, and researchers by focusing on the stylistic relationships between paintings, artists, and periods. In this context, the problem of classification is no longer one of binary determination but rather the categorization of a work or group of work with respect to a larger body of artistic heritage. In addition to the classification of a particular work, a general approach to classifying style addresses the relationship of the categories themselves identifying and laying bare the intricate developments of styles. The goals of this approach suggest a rather different set of techniques and technical choices favoring larger datasets of smaller images and a different balance of application design considerations. A general approach to classifying paintings, therefore, should position van Meegeren's forgeries within the larger corpus of painting tradition only classifying the work as a Vermeer if in fact the work shares more of the stylistic elements of Vermeer's work than the style elements of any other artist considered.

An examination of the handling of faithful copies of well-known paintings outlines the primary difference between the forensic and general approaches to the classification of painting style. Suppose another artist forged a perfect copy of van Meegeren's, *Christ and the Disciples at Emmaeus*, in order to demonstrate van Meegeren's techniques. Suppose further that the copy was indistinguishable from the original even to the eye of an expert. A perfectly functioning forensic application still should classify the painting as inauthentic and yet a perfectly functioning general classification system should classify the painting as a van Meegeren because it shares more stylistic affinity with his work than that of any other.

1.2 Relevance and Contributions

A broadly defined approach to the classification of style in painting unites two currently disparate approaches to the computational study of painting: image indexing and retrieval and painting classification. Both approaches have similar requirements, methods, and techniques and yet there have been few attempts to draw on the literature from both fields to bear on the style classification problem. The forensic approach to classification encourages this because there is little need to consider retrieval metrics or design considerations with databases of 100 images or less. In this regard, the study repositions the style classification problem such that it has a relationship to the context of both image classification and image retrieval research.

Both classification and image retrieval research focus on feature extraction, normalization, and comparison techniques. The present study surveys and evaluates a broad range of color and texture features according to accuracy, efficiency, and semantic relevance. The study demonstrates an important property of color features in the domain of the classification of painting styles: preserving additional spatial and frequency information in color features does not necessarily improve style classification accuracy. This finding suggests that there is a greater relationship between painting style and the colors chosen by the artist than that between painting style and the arrangement of colors on the canvas.

This study maps features to semantically-relevant formal elements commonly employed to analyze paintings: light, line, texture, and color. Although this list of formal elements is in no way complete, these categories served as a point of departure in an attempt to unite the goals and techniques of two communities: computer scientists and art historians. The research presented in this dissertation organizes feature extraction techniques into categories more familiar to students of art in the hope that these techniques might gain more popular acceptance among researchers engaged in art history. Just as researchers frame computer science concepts and techniques in language familiar to art historians, researchers can also translate the language of art history and its methods into computer science techniques. The study proposes a palette description feature that captures the central tendency of a painter's use of color demonstrating that computer science techniques can express domain concepts specific to painting.

Researchers have analyzed the classification of artistic style in painting from a variety of perspectives. Several studies have used supervised techniques such as naïve Bayes [81], Support Vector Machines [161], and Neural Networks [60] to classify artistic style. These approaches focus on the classification of individual artists and the elements of style evident in the work. The unsupervised methods of classification presented in this paper offer several critical extensions to the literature on painting classification. Self-organizing maps, hierarchical clustering, and multidimensional scaling techniques [107] provide unique opportunities to evaluate and visualize the style classifications offered by the supervised techniques. The paper proposes theoretical style center and variance metrics to identify the cluster density of paintings given a set of feature measurements. These measurements allow researchers to identify relationships between period and individual styles with respect to the formal elements of those styles. The theoretical style center and variance provide the basis for a style description ratio that serves as an evaluation technique for classification results.

As a review of collegiate-level art history textbooks reveals, the classification of artistic style is anything but a simple a matter. There are many different ways to classify artistic style including those based on chronology, nationality, medium, school, and artistic movement. Experts often disagree about how to classify paintings or a painter's style. For example, H.W. Janson [70] categorizes the work of Giotto as Gothic; Frederick Hartt [58] labels the work of Giotto as Renaissance in style; and Stokstad discusses Giotto's paintings in the context of both periods [146]. Definitive answers to questions of classification are difficult to achieve because particular classifications often depend on the needs and aims of particular research projects. The extensions to previous work in style classification offer the opportunity to assess these subjective questions without sacrificing the subtlety or nuance prized by researchers in the humanities.

1.3 Scope

The scope of the dissertation follows from the concentration on general style classification. For example, the dissertation focuses exclusively on the classification of images in the JPEG format that are freely and commonly available on the internet [11, 56, 109, 110, 119, 127]. Although other formats are available such as TIFF, the JPEG format is the most commonly used in this research domain and the most readily available to researchers. The largest images are of 1600 x 1600 pixel resolution, a necessary upper limit for the analysis of databases with 500 images or more as those employed in this study. The study does not consider preprocessing techniques in its treatment of the images largely because the literature addresses it in a cursory way [60] and the efficiency overhead precludes working with datasets of this magnitude.

The semantic relevance criterion for feature evaluation deserves mention in this context. Semantically-relevant features are those representing the terms and ideas art historians use to discuss, analyze, compare, and classify paintings. Although no comprehensive list exists, several sources [3, 16, 88, 133] outline a reasonable number of terms including hue, saturation, value, contour line, contrast, and intensity. For a style classification system to be successful, the system must use the concepts familiar to users. Art historians and critics rarely, if ever, write their studies and analyses in terms of mathematical coefficients, equations, and matrices. In other words, the system must attempt to bridge the semantic gap [145] between the measurable features in the digital image of a painting and domain-relevant information commonly applied in analytical discussions of painting. The study concentrates on semantically-relevant features extracted from the two-dimensional digital representation of a painting. Conversely, the study neither addresses feature extraction techniques requiring special photography nor features requiring a third dimension for measurement [13, 111].

1.4 Outline

The dissertation is subdivided into the following sections. Chapter 2 presents the background material necessary for the study. This chapter presents critical art terms and domain knowledge with a discussion of style informed by art historical studies and more general domain resources. The computer science background discusses the relevant work in painting analysis, painting classification and image retrieval research. In the painting classification subsection, the study delineates works with forensic emphasis demonstrating how the techniques of this approach inform the goals of general style classification. Throughout the chapter, the text links the domain knowledge to the computer science context whenever possible. The evaluation of features gleaned from previous work forms the main thrust of Chapter 3. The chapter presents the palette description feature and its associated distance metric as well as techniques for feature normalization and comparison. In Chapter 4, the text describes the supervised and unsupervised classification techniques used to integrate, analyze, visualize, and interpret the features. The chapter discusses the role of self-organizing maps, hierarchical clustering, and multidimensional scaling techniques in the evaluation and understanding of style relationships. In this context, the chapter proposes the theoretical style center, variance, and the style description ratio as class quality descriptors. Although experimental results appear throughout the paper, Chapter 5 presents the results in their entirety. Chapter 6 summarizes the key findings of the research and offers some general statements concerning future research and possible applications.

Chapter 2

Background Material and Previous Work

2.1 Introduction

In 1933, the mathematician George David Birkhoff attempted to explain aesthetics in terms of mathematics. In his paper entitled, "Mathematics of Aesthetics" [6], he proposed nothing less than a formula for describing beauty. Birkhoff argued that aesthetic measure (M) is simply the ratio of order (O) to complexity (C):

$$M = O / C \ .$$

Although most critics do not find the work convincing, Birkhoff sets an important precedent for the computational study of artistic style in that he assumes that aesthetic qualities are measurable and formally definable.

In order to classify artistic style in painting, researchers must understand "style" in its art-historical and computer science contexts. On the one hand, the literature of art historians provides general definitions of style, descriptions of the formal elements of style, and a well-developed classification system for painting. In other words, formal approaches to style delineate measurable elements in painting. On the other hand, computer science researchers outline techniques and algorithms necessary for quantifying the formal elements of style in painting. The goal of this chapter is to outline previous attempts to map the techniques and algorithms of computer science to specific descriptions of the formal elements of style.

The chapter is divided into two sections addressing the art history background and the computer science background separately. The art historical section describes the formal approach to style and describes the formal elements considered in this study: light, line, texture, and color. The computer science section reviews previous approaches to painting including feature analysis, style classification, and image retrieval. The section reviews current research trends with respect to image preprocessing, feature extraction, feature comparison, and classification technique. The formal elements addressed in this study serve as an organizing principle for the features considered.

2.2 The Art-historical Background

2.2.1 Formal Approaches to Style

The formal approach to style [98, 138, 163, 164] presupposes that observers understand art in formal terms like line, color, and shape in addition to content or iconography [4]. 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.

A general definition of style is not particular to painting or art. In fact, other disciplines such as archeology have definitions of style with a different emphasis than that discussed in the context of art. Shapiro argues that "style is, above all, a system of forms with a quality and a meaningful expression through which the personality of the artist and the broad outlook of a group are visible" [138]. Moreover, Shapiro delineates three aspects of art considered in the description of style: form elements, form relationships, and qualities. In terms of painting, form elements comprise characteristics such as line, hue, and saturation while form relationships and qualities include common design elements like balance and proportion.

Art historians categorize styles in a number of overlapping ways [138, 164]. A period style refers to that collection of formal elements common to painting in a particular age [88]. Some historians of art, on the other hand, discuss national or regional styles based on geography [88]. Perhaps the most accessible category of style is a painter's personal style, that which distinguishes the work of an individual from the work of others. Meyer Shapiro summarizes the challenge these overlapping categories pose to researchers attempting to classify style in art: "The characteristics of styles vary continuously and resist systematic classification into perfectly distinct groups" [138]. Despite this challenge, researchers have made significant strides in the analysis of style in painting.

2.2.2 Formal Analysis and Style

Art historians and critics use a nuanced vocabulary to discuss the characteristics of paintings [3, 16, 133]. These characteristics often overlap in ways that defy classification. Nevertheless, for the purposes at hand, the descriptive terms related to paintings can be divided into three rough but useful categories: physical, subjective, and formal. The terms relating to physical characteristics of a painting describe its contextual aspects [87]. For example, the medium and date of the work, and the artist who painted it are all examples of terms that define the context of a painting rather than its subject. The subjective terms, on the other hand, describe the content of the painting [4]. These characteristics include the title and the subject matter itself, i.e. portrait, still life, landscape, etc. Finally, the formal terms used to describe a painting focus on how the artist painted the subject given a particular context. Color, line, light, space, composition, depth, shape, and size are all examples of formal characteristics of a painting. While sensitive to the interdependencies of these characteristics, the research proposed in this study aims to define the formal characteristics of a painting quantitatively in order to identify and classify the paintings according to their physical and subjective characteristics. For the sake of organizational simplicity, this study groups the formal elements of painting into the following categories: light, line, texture, and color [3, 70, 88, 133, 138, 146].

2.2.3 Light

The use of light in a painting relates closely to other formal elements including color and composition. The rendering of light, for example, can produce high or low regions of contrast depending on the goals of the artist. Subtle gradations of light contribute to the illusion of space in a painting by visually representing depth. *Chiaroscuro*, literally meaning light-dark, is a technique perfected in the Italian Renaissance where artists created dramatic effects by juxtaposing light and dark sections of a painting [16]. Leonardo Da Vinci also employed a related technique known as *sfumato* where painters depicted figures or objects as if enveloped by a smoky haze [16]. An artist's use of light and dark provides important insights into the meaning and method of their art and style.

2.2.4 Line

Lines provide several crucial functions in a painting including: compositional organization, shape formation, spatial organization, and to some extent texture. Several aspects of line are relevant for describing paintings including the outlines of shapes or contour lines, the thickness, the length, and the orientation of lines (horizontal, vertical, diagonal). The arrangement and orientation of the lines in a painting contribute to the illusion of depth or recession in space. For example, single point perspective relies on the observation that parallel lines appear to converge at a point in the distance, the vanishing point [46, 78]. Overlapping, foreshortening, hatching, and shading are techniques that use lines to create a sense of depth in drawing and painting.

2.2.5 Texture

Texture defines the quality of a surface in terms of its roughness or smoothness. Smooth, polished, rough, grainy, pitted, and oily are all terms referring to the texture of a painting. Art historians are careful to distinguish between perceived and actual texture [88]. The perceived texture of a painting relates to the illusionary roughness or smoothness rendered by the artist. The actual texture of a painting relates to the physical roughness or smoothness of the paint as applied to a surface. *Impasto*, for example, refers to paint applied thickly to a canvas or panel such that it rises above the painting's surface thereby creating rough actual texture [16]. A painting can often have a perceived texture that is quite distinct from its actual texture.

2.2.6 Color

Color provides perhaps the most immediately recognizable formal element in painting. Art historians discuss color with respect to three aspects: hue, saturation, and value. Hue describes the common sense notion of what we mean when we say 'color'. In other words, the hue gives a color its name. Red and blue are both examples of hues. The saturation or hue intensity defines the strength of the hue. A pale color has a low saturation; a vibrant color has a high saturation. The value of a color, also referred to as brightness or intensity, defines the lightness or darkness of a hue. For instance, adding white to a color forms a tint of that hue and makes the value higher and adding black to a color forms a shade of that hue and makes the value lower. Complementary colors are those opposite each other on the standard color wheel. Red and green, yellow and violet, and orange and blue are three pairs of complementary colors.

2.2.7 Discussion

The formal analysis of painting is the technical description of a work of art and its salient features [3]. Art historians conduct such analysis with a specific vocabulary, as do the practitioners of any profession. With respect to style, art historians take great pains to identify the nature of these formal characteristics as they relate to personal, regional, and period styles. The goal of computer science approaches to capturing style depends on the extraction and summarization of these formal qualities. A computational approach to painting assumes that researchers can describe and analyze such characteristics mathematically. In other words, computer scientists attempt to model the formal qualities of painting for the purpose of analysis, image retrieval, and classification. Table 1 summarizes and categorizes the formal elements discussed in this chapter. The next section addresses how previous researchers have approached the measurement and use of these formal elements.

Table 1: Summary of Formal Elements in Painting

Formal Element	Category	Notes
Light	Light	Chiaroscuro, sfumato
Contrast	Light	Chiaroscuro demonstrates high contrast
Contour Line	Line	Lines demarking the shape of objects in a painting
Line Orientation	Line	Horizontal, vertical, diagonal
Line Measurement	Line	Length and width of lines
Shape	Line	Lines delineate important shapes in painting
Space	Line	Line and light often organize pictorial space, i.e. depth and perspective
Perceived Texture	Texture	The apparent texture formed by the illusion of the painting: rough/smooth
Actual Texture	Texture	The physical texture formed by brushstroke, i.e. impasto
Hue	Color	A color’s name: red, orange, yellow, green, blue, violet
Saturation	Color	The hue intensity: crimson has a higher saturation than pink.
Value	Color	Brightness of a hue: dark colors have low value

2.3 The Computer Science Background

2.3.1 Computer Science Approaches to Artistic Style

This study relies on the work of three distinct but related computer science approaches to artistic style: style analysis, style or artist classification, and image retrieval research. Style analysis focuses on identifying the characteristics or features necessary to understand a painter's particular technique often focusing on particular formal elements such as color. Style classification studies, on the other hand, concentrate on distinguishing the style of particular painters or groups of painters for the purpose of authentication or painter identification. Image retrieval research provides additional features, comparison algorithms, distance metrics, and retrieval techniques useful for digital image archives for painting.

Style analysis focuses on using computer techniques to gain a deeper understanding of art. The analytical study of painting has produced three applications germane to the present study: feature analysis, conservation, and hypothesis verification. Feature analysis seeks to study the key characteristics of a painting to learn the features crucial to its design [5, 61, 154, 155, 156, 157, 158, 159]. The conservational approach to painting facilitates the management, storage, preservation, and reconstruction of paintings in digital format. Many applications relate to this research including digital archiving of images, digital color restoration, and image reconstruction [33, 48, 54, 99, 102, 120]. Other researchers attempt to verify hypotheses that exist in the domain of art history [34, 35, 36, 37, 38, 39, 147, 148, 149, 150, 151]. These studies contribute important information concerning potential features for the present study.

In addition to feature specific studies, researchers have approached the classification of artistic style from a number of perspectives. The earliest attempts to address the problem focused on specifying formal grammars for particular artistic styles [82, 83, 84, 85, 86]. More recently, researchers have concentrated on the authentication of drawings and paintings [95, 107]. In addition to these forensic applications, researchers have conducted style identification studies to classify style by individual painter and artistic movement [60, 68, 81, 161, 162]. Forensic applications focus on two classes and a few high-resolution images, but style classification systems concentrate on larger numbers of classes and larger numbers of images with lower resolution. Researchers have pursued so many unique approaches to style classification that the literature is difficult to organize in a meaningful way. These approaches include local feature extraction [81], global feature extraction [60], segmentation [132, 161, 162], and brush stroke detection [72, 114, 129, 130].

The classification studies conducted to date have leveraged research in image retrieval. Image retrieval provides literature that directly and indirectly contributes to the analysis and classification of digital images of paintings. In particular, image retrieval research provides cutting edge features for describing images [22, 23, 25, 26, 27, 66, 67, 123, 124, 135, 141], distance measures necessary for comparing image features [19, 28, 131], and applications that bridge the semantic gap between extractable features and relevant domain knowledge [145]. The relevant contributions of research in image retrieval supplement the study of style classification in painting.

The focus on painter identification has resulted in five themes in the literature related to computational approaches to painting. First, the solutions proposed are style-specific addressing only particular kinds of art or even the work of particular painters. Second, the literature emphasizes texture features and minimizes the potential role of color features. Third, the studies to date do not examine techniques for evaluating classification accuracy. Fourth, current research disregards the semantic relevance of the features studied. Fifth, the projects currently undertaken forego a broad approach to style preferring small focused studies of particular painters or movements.

Style classification systems of all kinds undertake four major tasks regardless of the approach taken to the problem: preprocessing, features extraction, feature comparison, and classification technique. Preprocessing techniques prepare an image for feature extraction and include techniques such as size correction, orientation correction, and noise filtering. The feature extraction stage captures the light, line, texture, and color information contained in an image. After extracting the required features, the application must normalize and compare the features in a manner appropriate for the task. Finally, the system classifies the images according to its analysis of the extracted feature sets.

2.3.2 Image Preprocessing

Researchers have considered several approaches to image preprocessing in this domain. A common approach is to ignore the issues of preprocessing. Some studies [81] do not preprocess images before extracting features assuming that the cost of doing so is higher than the benefit, the images are correctly oriented, and the scale is not a critical factor in image analysis. In their survey of features, Herik and Postma [60] perform two preprocessing steps: image filtering and size correction. The researchers apply a Gaussian filter to all images in order to reduce the noise from the JPEG encoding process. Furthermore, the researchers adjust the size of each image so that their dataset corresponds consistently to the scale of the actual paintings. A middle approach to preprocessing handles filtering and other preprocessing tasks as part of the feature extraction process [68]. Although in most contexts preprocessing is desirable, the present study neither filters every image nor addresses size and scale correction because researchers have achieved excellent classification results without these preprocessing steps [81]. Table 2 summarizes the preprocessing techniques employed in the studies reviewed.

Table 2: Preprocessing Techniques

Study	Technique	Notes
Herik [60]	Gaussian filter	Implementation details are not available
Herik [60]	Size and scale correction	
Icoglu [68]	Median Filter	Filters grayscale images for some features

2.3.3 Light

A number of studies address light and dark in an attempt to analyze and classify artistic style. In their survey of features, Herik and Postma [60] use common statistical descriptors (mean, standard deviation, kurtosis, and skewness) to describe nine regions of the grayscale image of paintings. In particular, the mean intensity was an effective feature that, after training a neural network, correctly classified a test set of paintings with roughly 57% accuracy. In another study [68], researchers distinguished between the works of three artistic movements using features largely related to luminance or grayscale histograms including the percentage of dark colors, the number of peaks in the luminance histogram, the deviation from the mean intensity in nine segments of the image, and the skew of the grayscale distribution. Using these global features, the researchers classified the paintings with a Bayesian classifier, k nearest neighbor, and support vector machine. The system classified paintings into three classes with rates ranging from 78 to 95% accuracy. Kröner and Lattner [95] employed a number of measures related to light and dark pixels in their analysis of freehand drawings. Working strictly with black and white images, the researchers build a histogram of the ratio of black to white pixels in the image consisting of eight bins. The features comprise three values calculated from the histogram: the difference of the third and fourth bin, the quotient of the fifth and fourth bin, and the product of the first and fourth bin.

Table 3: Light Features

Study	Feature	Accuracy	Classes	Training Set	Testing Set
Artspy [2]	Intensity Mean	77.5-92.5%*	3	9	120
Herik [60]	Intensity Mean	57%	6	60	60
Herik [60]	Intensity Standard Deviation	43%	6	60	60
Herik [60]	Intensity Kurtosis	47%	6	60	60
Herik [60]	Intensity Skewness	52%	6	60	60
Icoglu [68]	Percent of Dark Pixels	78-95%*	3	27	107
Icoglu [68]	Luminance Peaks	78-95%*	3	27	107
Icoglu [68]	Deviation of Mean	78-95%*	3	27	107
Icoglu [68]	Skew	78-95%*	3	27	107
Kröner [95]	Histogram Bin Difference	87%*	2	16	25

Kröner [95]	Histogram Bin Quotient	87%*	2	16	25
Kröner [95]	Histogram Bin Product	87%*	2	16	25

* The accuracy represents these features taken together with other features in the study.

Table 3 summarizes the features used to measure light and dark in a painting. The present study implements and considers most of these features omitting only those from Kröner's study designed explicitly for the analysis of drawings.

2.3.4 Line

The computer recognition of line, shape, perspective, and depth is a rich area of research in computer science. The Cartesian coordinate system provides a convenient method to describe constructs like lines. Lines are rendered mathematically as linear equations in the form y=Ax+B. Researchers have devised many line and edge detection algorithms for both gray scale intensity and color images [7, 14, 15, 41]. After a system identifies lines and edges, it is possible to identify properties of the lines such as length and orientation. Furthermore, a collection of lines permits other forms of analysis: shape detection [73, 74], vanishing point detection [10, 112, 115, 117, 134, 153], and depth estimation [12]. The goal of vanishing point detection algorithms is to identify the point at which lines intersect. The identification of vanishing points is crucial to determining the role, if any, of perspective in painting [34, 35, 36, 37, 38]. In addition to these features, a number of approaches exist to measure depth in an image [34, 35, 36, 37, 38]. These features combine to yield a quantitative description of the use of line, shape, and space in a painting.

Joan and Russell Kirsch pioneered the application of line and shape to the study of artistic style. In a series of articles spanning a decade, these researchers adapted the techniques and insights of formal grammars to the problem of style definition [82, 83, 84, 85, 86]. The authors specified formal grammars for the paintings of Richard Diebenkorn's *Ocean Park* series and Joan Miró's *Constellation* series [83, 84]. The grammar specifying Diebenkorn's style specifies 42 transformation rules based primarily on linear composition. In contrast to the Diebenkorn grammar, the Miró grammar, based on identifiable shapes in the composition, referenced a dictionary of shapes derived from his body of work. The research, based largely on Curtis Carter's theoretical discussion of style, attempts to implement his "language-like" system for art in a formal grammar [17, 85]. Kirsch used the technique to specify a shape grammar for the prehistoric rock art of Barrier Canyon [86].

While Kirsch employed line in an attempt to construct style grammars, Criminisi and Stork used line to analyze perspective and depth estimation in painting. For example, Criminisi and Stork have assessed Hockney's theory [35, 36, 39, 62, 147, 148, 149, 150, 151] that Jan Van Eyck used optical aids in the making of his paintings. They extracted edge information from the chandelier in the *Portrait of Arnolfini and his Wife* in order to build a three-dimensional model and check it for symmetrical consistency [35, 36, 147, 148, 151]. They report that the three-dimensional reconstruction of the chandelier demonstrated inconsistencies not consistent with Hockney's theory. In other related studies [37, 38], researchers analyze the geometry of perspective paintings to explore the development of linear perspective in Renaissance painting. In particular, the study assesses the consistency of vanishing points, the rate of receding regular patterns, and the relative height of objects.

In a novel technique for the purpose of conservation, researchers have employed line measurement techniques designed to eliminate the cracks from the infrared images of paintings [54]. A network of cracks (*craquelé*) appears in paintings due to the aging process. These cracks often provide a texture to painting quite different from the brushwork inherent in the painter's style. The research team employed a technique called viscous morphological reconstruction to separate the cracks related to aging from the lines related to the brushwork of the artist. The technique relies on the fact that cracks are generally thinner and occur in predictable orientations consistent with the properties of wood panels.

The analytical and conservation work described above has analogues in painting authentication research. Several studies include line and linear characteristics in their attempts to classify and authenticate painting. Kröner and Lattner [95], for example, have used Kirsch masks to identify the orientation of strokes in freehand drawings. After determining the frequency of the direction of identifiable strokes, two higher order features are calculated: the product of the vertical and left diagonal edges and the product of the horizontal and right diagonal edges. In an attempt to distinguish paintings from photographs [40], another group calculated the ratio of intensity edges to the total number of edges in the image, the sum of intensity and color edges. Researchers working on the Artspy project [2] attempted to characterize an artist's style by calculating the number of edges detected using the Sobel edge detector. Researchers have also employed Gradient maps [68] to extract edge information and classifying style.

Table 4: Line Features

Study	Feature	Accuracy	Classes	Training Set	Testing Set
Artspy [2]	Number of Sobel edges*	77-92%	3	9	120
Criminisi [35-39]	Depth and Perspective	NA	NA	NA	NA
Cutzu [40]	Ratio of intensity edges to total edges*	72%	2	2000	10000
Hanbury [54]	Line measurement and orientation	NA	NA	NA	NA
Icoglu [68]	Gradient maps	78-95%	3	27	107
Kirsch [82]	Line and Shape Grammars	NA	NA	NA	NA
Kröner [95]	Line orientation*	87%	2	16	27

* The accuracy represents these features taken together with other features in the study.

Table 4 compiles the line features studied in the analysis of paintings. The present study considers most of the features discussed in these studies excepting those based on line and shape grammars, depth, and perspective. The present study does not consider these features because they apply only to specific styles of painting. On the other hand, this study incorporates some additional features related to the analysis of line. The block difference of inverse probabilities measures edges and valleys in an image [22, 23] and the study considers this feature in its evaluation.

2.3.5 Texture

Researchers have conducted more studies of texture and painting than any other type of feature. Despite this depth of concentration there is no real agreement concerning the definition of texture [60] as it applies to this domain. Researchers generally consider texture the most effective type of feature for the classification of artistic style because it more closely approximates brushwork than any other type of feature. The intense interest and lack of a precise definition of texture combine to create a loosely collected group of features aiming to characterize the same phenomena. At the most basic level, texture attempts to describe the relative roughness or smoothness of a surface.

The work of Richard Taylor, a physicist who studies the occurrence of fractals in nature, is an example of analytical research in texture analysis. In several works [154, 155, 156, 157, 158, 159], Taylor and his research team demonstrated that the controversial work of Jackson Pollock is fractal in nature, prompting Taylor to coin the term "fractal expressionism" to describe Pollock's style. Taylor argues that this characteristic alone may be sufficient to authenticate the works of Pollock [159]. In their survey of features, Herik and Postma [60] calculated the Hurst coefficient [122, 128], an estimate of fractal dimension, for each painting in nine sections of the image. The fractal measurement proved to be their most effective feature classifying the correct artist with 75% accuracy [60].

Gabor filters [40, 45, 50, 94, 96], like fractals, offer another option for describing the texture of artwork. Gabor filters transform grayscale images into coefficients rendering texture in multiple scales and orientations. By calculating the mean and standard deviation of the Gabor coefficients for four scales and four orientations, a research team [40] trained a neural network to distinguish between paintings and photographs with 79% accuracy.

The wavelet transformation, like the Gabor filter, allows texture analysis in multiple scales and orientations. Researchers from Dartmouth have designed an authentication technique that applies to prints, drawings, and paintings [107]. Their technique divides images into 64 sub images of 256 x 256 pixels so that each sub image can be decomposed into wavelet coefficients at five levels and three orientations. The resulting feature vector comprises the four statistical moments and error statistics based on these coefficients. The researchers applied this methodology to two aspects of authentication: verification of authenticity and the problem of many hands. In order to test the method's utility for authentication, eight known drawings of Pieter Bruegel and five acknowledged imitations were scanned at 2400 dpi yielding images of 3,894 x 2,592 pixels. When the researchers analyzed the distance matrix between the drawings with multidimensional scaling, the authentic works clustered tightly and the imitations were loosely scattered. The same methodology determined the number of hands that went into the production of Perugino's *Madonna with Child.* The researchers segmented the original 16,852 x 18,204 pixel image into six regions, one region for each face in the painting. Each segment was further subdivided into multiple 256 x 256 sub images for wavelet decomposition. The analysis suggested that four total hands, Perugino's and three from members of his workshop, painted the *Madonna with Child* confirming the conclusions of some art historians. The Artspy project [2] also used wavelet transformations calculating the Besov norm of the wavelet coefficients.

Researchers have surveyed a number of additional texture features to identify their ability to classify artistic style [60] including oriented spatial features, features derived from Fourier spectra, and the independent components in an image. Oriented spatial features measure the local spatially-oriented texture using Gaussian derivatives. The fast Fourier transform reveals spatially-oriented features when sampled at a fixed distance from the center of the transformation. Finally, independent components can characterize texture in digital images: the FastICA algorithm transforms two-dimensional vectors into components as independent from each other as possible.

Local texture features have also been a focus for approaches to painter identification. Keren designed a classification scheme based on local features derived from the discrete cosine transformation [81]. The feature extractions program divides the sample paintings into nine by nine blocks and calculates the discrete cosine transform coefficients for each block. From the feature set, the program constructs a table relating the probability that a particular painter exhibits a particular discrete cosine transform coefficient. The probability table provides the basis for a naïve Bayes classifier that classifies every pixel in an image and classifies a test painting by majority vote of the individual pixels. Using the technique, Keren accurately distinguished the work of five painters 86% of the time.

Researchers have studied the texture of paintings extensively in the context of conserving cultural heritage. Recently, a research team modeled the effects of applying surface treatments such as varnish with texture features [13]. The researchers measured the energy and entropy of the gray-level cooccurrence matrix generated for sample images. Both features proved to be sensitive to the varnishing process.

In most of the above studies, texture has referred to perceived texture rather than actual texture. Several studies model and measure actual texture as detected in brush strokes in order to classify paintings. One such study measures the brush stroke of oil paintings using three-dimensional range data [111]. The researchers converted the range images into gray scale Gaussian and mean curvature images. The study measures the characteristics of the brush stroke of three painters by extracting 35 local autocorrelation features from the curvature images. The method distinguished among the styles of particular artists using the linear discriminant analysis of the features. The study achieved 72.9% accuracy with a dataset consisting of three images per artist. Other studies have concentrated on modeling brush strokes for the purpose of painting and animation generation and painting tool identification [21, 71, 101].

Table 5: Texture Features

Study	Feature	Accuracy	Classes	Training Set	Testing Set
Artspy [2]	Wavelets: Besov Norm	NA	3	9	120
Cai [13]	GLCM: Entropy and Energy	NA	NA	NA	NA
Cutzu [40]	Gabor Filters	79%	2	2000	10000
Herik [60]	Fractals: Hurst	75%	6	60	60
Herik [60]	FFT240	65%	6	60	60
Herik [60]	FastICA	55%	6	60	60
Herik [60]	Oriented Spatial Features	45%	6	60	60
Keren [81]	Discrete Cosine Transformation	86%	5	Unknown	Unknown
Lyu [107]	Wavelets: Statistical Moments	NA	2	8	5
Masuda [111]	3D Range Data	72%	3	9	9
Taylor [154-159]	Fractals: Box counting	NA	NA	NA	NA

Table 5 inventories the texture features applied to this domain. This study considers most of the features except those deemed ineffective in previous studies such as the Besov Norm, FastICA, and oriented spatial features. On the other hand, this study excluded the features derived from the discrete cosine transformation despite their effectiveness because they have little identifiable semantic relevance. The features based on 3D range data were outside of the scope of this study because range data photographs require special photography that was unavailable at the time of the study. This study implements features based on the gray-level cooccurrence matrix, Gabor filters, wavelets, the fast Fourier transformation, and two types of fractal measurements, box counting and Hurst coefficient estimation. In addition to these features, researchers have proposed several other features measuring texture in the image retrieval literature [22, 23, 55, 64, 77, 80, 142]. This study considered block variation of local correlation coefficients and statistical moments of the gray-level cooccurrence matrix in the feature evaluation because these features are to date untested in this domain.

2.3.6 Color

The science of color easily requires a full-length textbook for a complete treatment but some foundational concepts are worth reviewing in this context [51, 52, 75, 165]. The spectrum of colors, as experienced by humans, represents the range of wavelengths from 400 nm (bluish purple) to 700 nm (red). The International Commission on Illumination [24] defines standards for measuring the wavelengths of light in the ultraviolet, visible, and infrared spectrums. These wavelength measurements are useful for scientific enquiry but can be rather awkward for other applications. In response to this, color models facilitate and standardize the notation and specification of color. Different color models serve different purposes and therefore emphasize different aspects of color to suit a particular application. Table 6 lists common color models along with common applications associated with each model.

Table 6: Common Color Models

Color Model	Common Application
RGB (Red, Green, Blue)	Computer Monitor and Human Eye
CMY (Cyan, Magenta, Yellow)	Professional Printing Applications
NTSC (Luminance, Hue, Saturation)	United States Color Television
YCbCr	Digital Video
HSV (Hue, Saturation, Value)	Color Picker Applications
HSI (Hue, Saturation, Intensity)	Image Processing
HSL (Hue, Saturation, Lightness)	Image Processing
CIE L*a*b	Perceptually-Uniform Color space

In essence, color models provide mathematical notations for describing colors. For example, the RGB color model specifies color in the form of a 24-bit RGB triplet with each color encoded in eight bits. The color red is expressed with the following RGB triplet (255, 0, 0) indicating that the red channel is at its maximum value and its green and blue channels are at minimum values. Simple arithmetic demonstrates that the RGB model can express 16,777,216 colors proving adequate for most applications of computer graphics. For many applications however, the RGB model is rather clumsy because it departs from the human experience of color. The HSV, HSI, and HSL models, on the other hand, correspond much more closely to the human experience of color as well as the critical language used to describe color. The color models outlined above therefore provide the mathematical notation necessary to encode the color characteristics of a painting as color features for analysis.

Despite all that is known about color, there have been few treatments of the role of color in painting analysis and style classification. The most ambitious attempt to analyze the color used by an artist is a digital analysis of Van Gogh's use of complementary colors [5]. The research team studied 617 digitized images of Van Gogh's oil-on-canvas paintings to verify the critical claim that Van Gogh used complementary colors to emphasize contours of objects. The researchers converted the RGB images into an opponent-color representation similar to CIE L*a*b or YCbCr where one channel carries the grayscale luminance component and the color components are represented as two channels expressing the complements yellow and blue and green and red. The color channels are then convolved with Gabor filters in four orientations and four scales. By calculating the total energy averaged over all orientations and scales and summing these values for both color channels, the system produces an opponency value for each image. The overall result of the study confirms the assumptions of art historians that Van Gogh increasingly relied on complementary colors as he matured as an artist.

The work on painting conservation sometimes relies on color for its aims [33, 48, 120, 140]. For instance, Michail Pappas and Ioannis Pitas have studied digital color restoration of old paintings [120]. The authors note that paintings degrade chemically over time requiring experts to touch up or clean the original work in order to preserve its appearance. Traditional approaches to cleaning include a trial and error approach where conservationists apply chemical cleaning solutions to small inconspicuous areas of the work to test for safety and effect. The testing method can often damage the paintings in the process. The authors offer their digital painting restoration method as a safe and effective alternative to the traditional method of testing. The researchers simulate the restoration process by extracting the original color information from the painting and then applying filters to the painting to demonstrate how different chemical cleaners might alter the painting's appearance. In another study [48], researchers used color to differentiate cracks from brushwork in paintings.

A number of classification studies that consider color rely on color histograms [152]. Herik and Postma [60] employed RGB, HSI, and hue histograms of 256 bins per channel in their survey of features. Although their findings conclude that RGB histograms outperformed HSI and Hue histograms, color features in general were not as effective as other texture features considered: fractals, FFT240, and intensity mean. Other researchers used a 20-bin saturation histogram to calculate the ratio of the most saturated pixels to the least saturated pixels in their attempt to distinguish photographs from paintings [40].

In another approach based on segmented images, researchers attribute works based on the color profiles of skin patches extracted from paintings [161, 162]. After a series of normalization procedures, features were extracted from the segmented skin patches using the RGB, HSV, HSI, HSL, and CIE L*a*b color channels. The researchers used the features to classify the paintings with support vector machines. Using a weighted voting system based on the four best channel classifiers, the study correctly classified test samples of four artists with 85% accuracy.

Researchers devised three additional color features to distinguish paintings from photographs [40]. The spatial variation of color was measured by normalizing the R, G, and B channels of the image by the image intensity and calculating the oriented plane that best fit a 5 x 5 neighborhood around a pixel. If the orientation is non-zero for two of the channels, the color changes qualitatively. The sum of each group of normals was then averaged over the entire image. The algorithm also calculated the total number of unique colors used in an image. Finally, the paper analyzed the distribution of pixels in RGBXY space. In this technique, the researchers converted the MxNx3 image cube into a two-dimensional matrix of MxN rows and five columns representing the R, G, and B values positioned at X and Y coordinates. The researchers computed the features by calculating the 5 x 5 covariance matrix of the RGBXY space and the singular values of the covariance matrix.

Table 7: Color Features

Study	Feature	Accuracy	Classes	Training Set	Testing Set
Berezhnoy [5]	Opponency Values	NA	NA	617	617
Cutzu [40]	Saturation Ratio	62%	2	2000	10000
Cutzu [40]	Spatial Color Variation	64%	2	2000	10000
Cutzu [40]	Number of Colors	62%	2	2000	10000
Cutzu [40]	RGBXY	81%	2	2000	10000
Herik [60]	RGB Histogram	57%	6	60	60
Herik [60]	HSI Histogram	46%	6	60	60
Herik [60]	Hue Histogram	35%	6	60	60

Widjaja [161]	RGB Skin Profiles	68%	4	40	40
Widjaja [161]	HSV Skin Profiles	77%	4	40	40
Widjaja [161]	HSI Skin Profiles	77%	4	40	40
Widjaja [161]	HLS Skin Profiles	82%	4	40	40
Widjaja [161]	CIE L*a*b Skin Profiles	80%	4	40	40

Table 7 summarizes the approaches to measuring color in this domain. This study did not consider those color features designed for style-specific purposes. For example, the study excluded all of Widjaja's features [161] because they specifically address paintings of a particular subject, i.e. people. The only color features from Table 7 implemented in this study were the number of colors, RGBXY, RGB histograms, and HSV histograms.

With respect to color analysis, painting classification techniques have relied largely on the image histogram, which preserves color frequency information but ignores the spatial distribution of colors. This study supplements these features with several features commonly used in image retrieval applications: color coherence vectors [124], spatial chromatic histograms [25, 26, 27] and color correlograms [20, 66, 67, 97]. These techniques have been included in the feature survey to test the role of spatial color information in style classification. In addition to these features, this paper proposes a palette description feature to capture the central tendency of the colors in a painting.

2.3.7 Composite Feature Techniques

In addition to the analysis of individual features, researchers have analyzed broader compositional structures using a number of features simultaneously. For example, a number of studies [60, 68] segmented paintings into nine blocks dividing paintings into a three by three series of segments. The program extracts the features from each segment in order to compare each corresponding segment independently. Segmentation schemes such as this preserve balance and symmetry information in an image. In a few studies, researchers have concerned themselves with the organization and relationship of features in order to extract compositional structure from a group of paintings.

Researchers have studied the relationship between digital images of paintings and photographs. Cutzu, Hammoud, and Leykin have designed a technique to estimate the photorealism of images and thereby they distinguish between paintings and photographs [40]. The researchers specify a number of features that adequately distinguish paintings from photographs including the ratio of color edges to intensity edges, the spatial variation of colors, the number of unique colors, pixel saturation, pixel distribution in RGBXY space, and texture features based on Gabor wavelets. Using a database comprising 6000 images of paintings and 6000 digital photographs, a neural network trained on extracted features from these images correctly distinguished paintings from photographs with accuracy above 90%.

Other research teams have concentrated on the role of segmented images in style classification. In a series of studies, Sablatnig, Kammerer, and Zolda, have classified 600 portrait miniatures of the Austrian royal family with a structural analysis based on brush strokes, color, and facial recognition techniques [72, 129, 130, 132]. The classification system devised by this team analyzes the color of the depicted face, facial extraction, region of interest segmentation, shape classification, stroke detection, and stroke classification. The system comprises a hierarchical classification system with ever more detailed classification as the data moves from color to stroke classification. The researchers designed particular artist-models to work in conjunction with the classification system. The artist-models are mathematical descriptions of the facial features rendered in the image.

Table 8: Composite Feature Approaches

Study	Feature	Accuracy	Classes	Training Set	Testing Set
Cutzu [40]	Photorealism	90%	2	2000	10000
Herik [60]	9 block segmentation	43-57%	6	60	60
Icoglu [68]	9 block segmentation	80-94%	3	27	107
Sablatnig [130]	Feature Hierarchy	NA	NA	600	600

Table 8 reviews the composite feature approaches to painting classification. Although the present study reviews many of the individual features used in the composite feature studies, this study does not consider the composite feature approaches as such. For example, researchers designed the feature hierarchy [130] to treat portrait miniatures specifically. A feature hierarchy for portrait miniatures cannot address many of the paintings considered in this study such as landscape or abstract paintings. The study incorporated the nine-block segmentation technique for the implementation of specific features where appropriate.

2.3.8 Feature Comparison

After the feature extraction stage, a classification system compares the feature vectors for particular images to each other in order to return relevant images in response to user queries and to classify images effectively. Different features are best suited to certain types of distance metrics [28, 131, 139]. For example, the well-known Euclidean distance metric serves rather well for individual features. For features such as hue histograms, however, Euclidean distance measures can be ineffective or even inaccurate. Image retrieval researchers have devised improved distance metrics for comparing these types of features. For example, researchers have treated histogram distance measures [19] and HSV color comparison measures [25]. The classification of style in painting should address the role of distance metrics because several classification techniques such as k-nearest neighbor rely on accurate distance measures to classify instances and define class boundaries.

Table 9: Feature Comparison Techniques

Study	Comparison Technique	Notes
Artspy [2]	Euclidean Distance	For RGB color distance
Lyu [107]	Hausdorff Distance	

Table 9 presents the feature comparison techniques discussed in previous studies of painting analysis and classification. This study used the Euclidean distance for most comparisons. Many color features require special distance metrics for accurate comparison including HSV histograms, color coherence vectors, and spatial chromatic histograms. In addition to these distance metrics, this paper proposes a palette distance metric associated with the palette description feature.

2.3.9 Classification of Style in Painting

After a system extracts, normalizes, and compares the features, an algorithm classifies the images in terms of style. Table 10 presents the range of techniques used to classify paintings in the literature. Most of the techniques applied are supervised learning techniques and in all cases, the number of classes considered is quite small with six as the maximum number of classes considered. The supervised techniques have three weaknesses with respect to a general approach to the classification of style. First, as the number of classes increases the accuracy will degrade significantly. Second, supervised learning techniques produce conclusive classifications rather than visualizations of the complex relationships between styles. Third, the number of features required to separate a large number of classes often exceeds the capabilities of supervised techniques. Therefore, unsupervised techniques such as multidimensional scaling may prove to be more useful for general style classification because these techniques present complex data in visually meaningful ways while confronting the curse of dimensionality.

Table 10: Classification Studies

Study	Classifiers	Accuracy	No. of Classes	Training Set	Testing Set
Cutzu [40]	Neural Networks	90%	2	2000	10000
Herik [60]	Neural Networks	85%	6	60	60
Icoglu [68]	Naïve Bayes, k-Nearest Neighbor, Support Vector Machines	80-94%	3	27	107
Keren [81]	Naïve Bayes	86%	5	Unknown	Unknown
Kröner [95]	Naïve Bayes	87%	2	16	25
Lyu [107]	Multidimensional Scaling	NA	2	8	5
Masuda [111]	Linear Discriminant Analysis	100%	3	9	9
Sablatnig [130]	Interactive	NA	NA	600	600
Widjaja [161]	Support Vector Machines	85%	4	40	40

This study considers two supervised and three unsupervised classification techniques. The study used the supervised techniques, k-nearest neighbor and an interactive approach, for the feature survey. In addition to the supervised techniques, the survey reviewed three unsupervised techniques: multidimensional scaling, self-organizing maps, and hierarchical clustering. In previous studies, researchers used multidimensional scaling to authenticate paintings and drawings [107]. In this study, multidimensional scaling provided a basis for visualizing the stylistic relationships among paintings and a method for comparing styles. Self-organizing maps [93] produce visual representations of complex data in two dimensions. Hierarchical or agglomerative clustering also provides a hierarchy of classes demonstrating the relationship of relevant classes to each other [43]. Although these techniques do not necessarily produce definite answers in terms of classification, they make effective analytical tools by showing class relationships

2.4 Conclusion

Despite the broad array of approaches taken to style classification, several identifiable trends exist. First, most studies of style identification in painting are of a highly limited scope. Some studies focus only on particular types of paintings such as portraits and others consider only certain types of features like those captured from brushstroke analysis or fractals. For example, classification systems based on color analysis of skin tone regardless of how effectively they perform do not apply to abstract art. Second, most studies consider the problem of style classification narrowly, constructing style-specific models used to describe the features of particular artists, movements, or works. Although this is a valid approach for many problems, it is difficult to apply to a general classification system because it requires building a new model for each new artist, movement, region, and period under consideration including those that do not yet exist. Third, most previous studies measure and emphasize classification accuracy neglecting other measurements necessary for applications such as speed or storage requirements. Many of these applications require special photography for feature extraction thus complicating the analysis of large datasets. Fourth, many of the studies depart seriously from features that have any real connection to visible characteristics in the paintings. Many authors were careful to note that the quality of the result occurred despite the fact that the feature set did not address typical properties analyzed by experts in manual authentication [95]. Other reviewers of these studies argued that the features analyzed were not necessarily visible [29] raising questions about the relationship between classification accuracy and style characterization. In short, in many cases high classification accuracy does not necessarily reflect accurate style description. Fifth, most of the classification applications address painter authentication and identification rather than style classification. That is to say, the approaches were more interested in demonstrating accurate classifications rather than presenting relationships between styles and movements. Finally, most approaches rely heavily on texture features overlooking the role color plays in style.

In order to build a general classification system for style identification, the system must conform to four specifications. First, the system cannot be based on content- or style-specific models. The general style classification system aims to provide a basis for classifying paintings of any content or style and, by definition, content- and style-specific models cannot address all paintings. For example, a classification system based on color features extracted from segmented skin patches applies only to portraiture. Second, the system cannot be based solely on features with little domain relevance. Forensic systems concentrate on classification accuracy, but general systems focus on style relationships. The general system represents style relationships in a manner accessible to domain experts by using concepts and methods familiar to them. Third, the system must not simplify the complicated relationships between styles. The relationships among artistic styles are often complicated and multifaceted. The general system facilitates the study of these complex relationships rather than simplifying or ignoring them. Fourth, the system must not identify the basis for style relationships on a sparse feature set. In many cases, forensic applications do not require multiple types of features to achieve high accuracy classifications. On the other hand, general systems preserve style for its own sake and therefore require a broad range of features to capture the many aspects of style found in paintings.

The chapters that follow explore the basis for such a general classification system of style. Chapter 3 summarizes the results of a feature survey addressing each of the four feature categories: light, line, texture, and color. Chapter 4 reviews a survey of classification techniques identifying the benefits and drawbacks of different techniques for general style classification systems.

Chapter 3

Digital Image Analysis of Fine-art Painting

3.1 Introduction

In order to build a general classification system for style in painting, it is essential to identify the most discriminating features available. Although one research team has conducted a survey of features [60], many features remain untested in this domain. Therefore, a feature survey including both features previously used in the domain and those of compelling interest to the domain were tested and classified for accuracy, performance, information quality, and semantic relevance. The feature survey demonstrates a preference for texture features that often overlooks color features commonly used in other domains such as color coherence vectors, spatial chromatic histograms, and color correlograms. An analysis of these advanced color features suggests that preserving additional frequency and spatial information in the color channels of an image does not necessarily improve classification accuracy. In light of this evidence, this chapter proposes a palette description feature and a palette comparison technique specifically designed for style classification. The chapter rounds out the discussion of features by considering the role of normalization and feature selection.

3.2 Features

The survey constituting this chapter has two goals: describe the features considered and evaluate those features that are most appropriate for style classification systems of painting. The survey details the features used most frequently in the domain of style classification supplementing these with features not tested in this domain. The feature descriptions include references to the implementations evaluated, feature visualizations, mathematical descriptions, and implementation details where appropriate. Figure 2 will serve as a running test image to demonstrate the transformations and feature visualizations to follow.

Figure 2: Jan Vermeer, *Girl with a Pearl Earring*, 1665. Photo Credit: Scala/Art Resource, NY [1].

This study evaluated features according to the following criteria: classification accuracy, performance, information quality, and semantic relevance. Classification accuracy measured the success of classification with a k-nearest neighbor classifier and an interactive classification technique described more fully in Chapter 4. The study measured performance in feature extraction time and the number of doubles required to store the feature. The information quality measurements considered each feature as a signal with a quantifiable degree of disorder (entropy) and degree of independence (mutual information) compared to other features. The semantic relevance of a feature describes the proximity of a feature to its analogue in formal art-historical terms. For example, many color features exhibit a high semantic relevance in that hue, saturation, and value metrics closely correspond to the language used in the description of color in a painting. Chapter 5 provides the complete results of the evaluation with more detailed explanations of the criteria. The survey organized the material according to the formal elements considered in this study: light, line, texture, and color.

3.2.1 Light

Features rendering aspects of light are both efficient and effective classifiers of artistic style. These features are generally extracted from grayscale images. Furthermore, features based on light are effective because the use of lighting characterizes many styles of painting such as Baroque. One of the simplest techniques to gauge the use of light is the intensity mean. Grayscale images can easily be summarized by taking the arithmetic mean of the intensity. For example, the arithmetic mean of the grayscale image of the *Girl with a Pearl Earring* is 57.2 or 0.2245 if normalized. The feature by itself has proven effective in several studies [60, 68].

A similar feature calculates the standard deviation of the mean intensity [68]. This feature divides an image into nine segments of equal size. The feature results from the sum of the differences between the intensity of each segment and the global image intensity normalized by the total number of pixels. According to the author [68], the feature discerns styles even if lighting or resolution conditions differ. The mean deviation for the test image is 0.00002178. The same researchers [68] also posited an additional feature, intensity skew, designed to resist extreme changes in brightness. The feature divides the difference between each pixel value and the mean intensity value for the image by the standard deviation of the intensity value for the image.

In addition to estimating intensity, other features related to light are worth measuring as well. First, the percentage of dark pixels in an image is a valuable feature [68]. Researchers define this feature as the number of dark pixels, those below 65 in a 0-255 grayscale image, divided by the total number of pixels in the image. Second, the number of local and global maxima also estimates the use of light in an image. A feature extraction program identified the local and global maxima in an image by finding the peaks in a luminance histogram [68]. Figure 3 shows the grayscale histogram for the test image. For example, bin number two represents a global maximum; bins six and ten represent local maxima. The total number of luminance peaks in this histogram therefore is three.

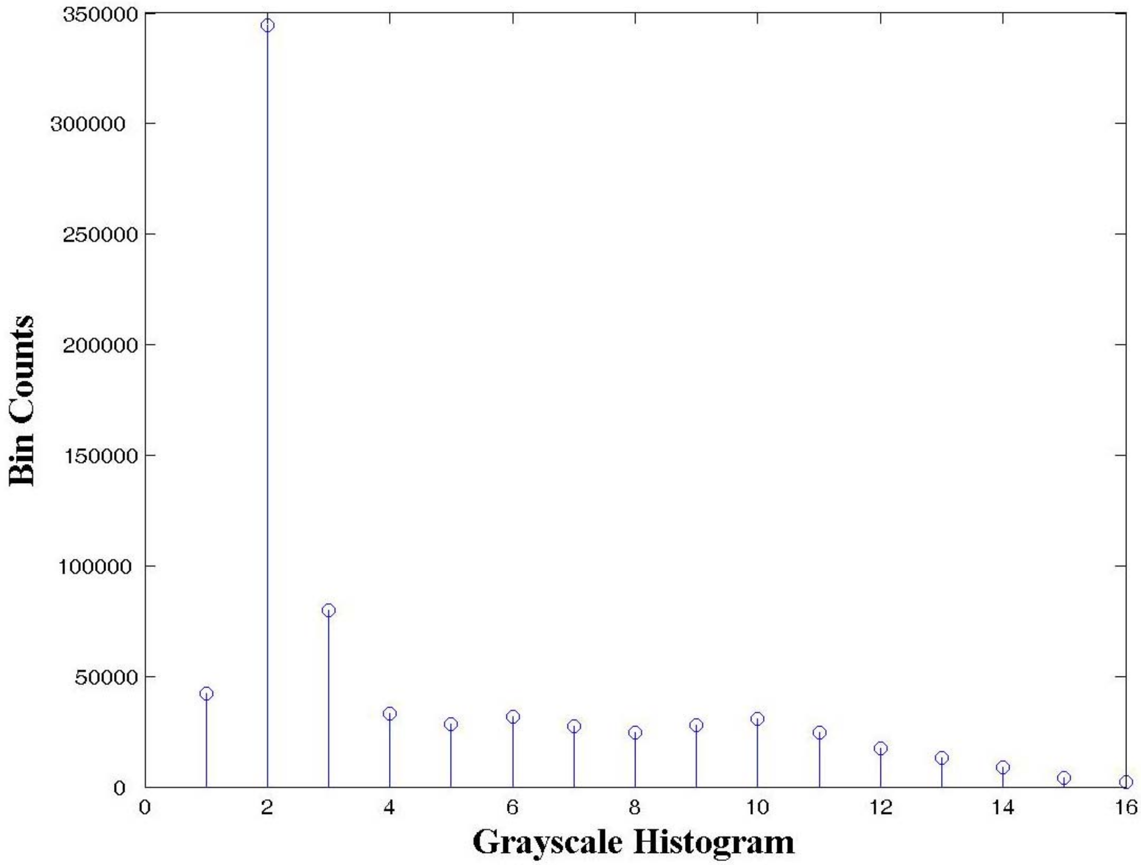


Figure 3: Grayscale Histogram Peaks

Finally, the feature survey considered a number of other statistical features for the sake of comparison including a 256-bin intensity histogram; the mean, variance, skewness, and kurtosis of the image intensity; and the distribution of intensity values in space (IXY) based on the RGBXY feature described in Section 3.2.4. The full results of the light survey found in Chapter 5 demonstrate some clear trends of note. The mean deviation of intensity outperformed both the segmented mean and the global mean on both test databases. Moreover, the mean deviation proved to be resistant to noise and highly independent with respect to other light features.

3.2.2 Line

Line and edge detection algorithms are among the most mature of feature extraction methods. There is a great deal of literature addressing edge detection [7, 14, 15, 41]. Researchers have applied several of these approaches to the domain of art history. The Artspy team [2] for example applied the Sobel edge detector and simply counted the number of lines found. Figure 4 demonstrates the output from the Sobel edge detection algorithm. This study does not address the Sobel edge detection technique because many of the edges identified appear arbitrary with little apparent connection to style.

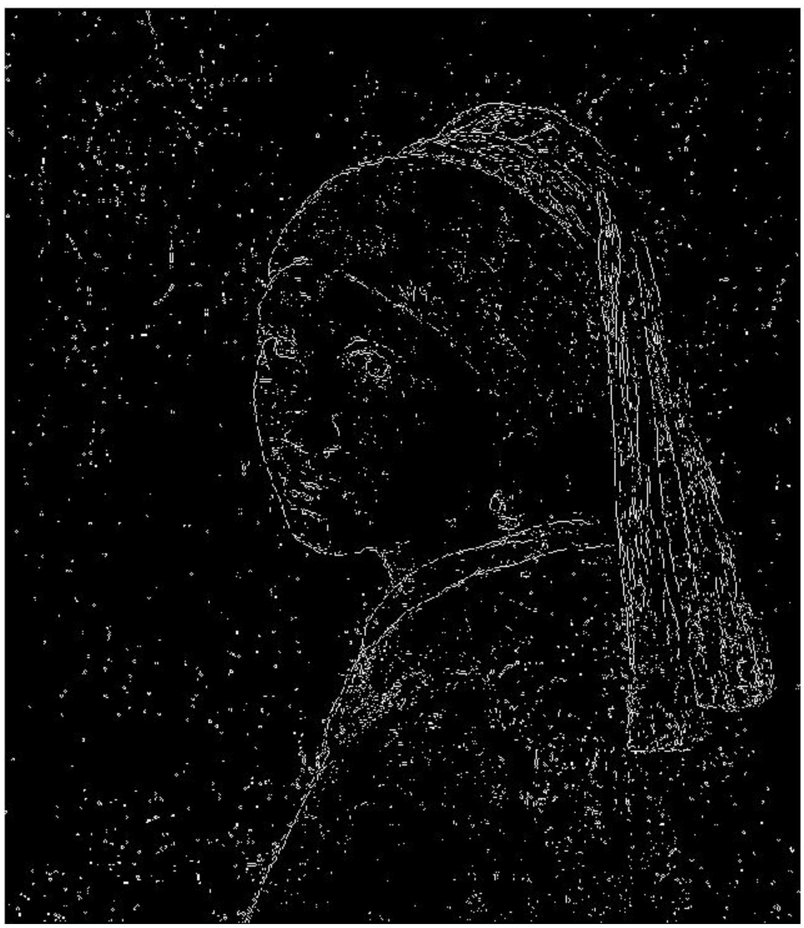


Figure 4: Sobel Edges

Researchers have devised other edge-based features to classify different types of lines. In an analysis of the distinguishing characteristics between paintings and photographs [40], researchers drew a distinction between pure intensity edges and those edges related to color. The technique uses the Canny edge detector to identify all edges in a grayscale image. The Canny edge detector extracts the edges resulting from color differences in the red, green, and blue channels of the RGB image. With this technique, the researchers separated color-dependent edges from pure intensity edges. The authors of the study use the ratio of pure intensity edges to total edges as a feature. Figure 5 shows the Canny edge image before removing color dependent edges and after. The feature extraction technique removed the strong lines around the neck and headscarf, caused by strong color contrasts.

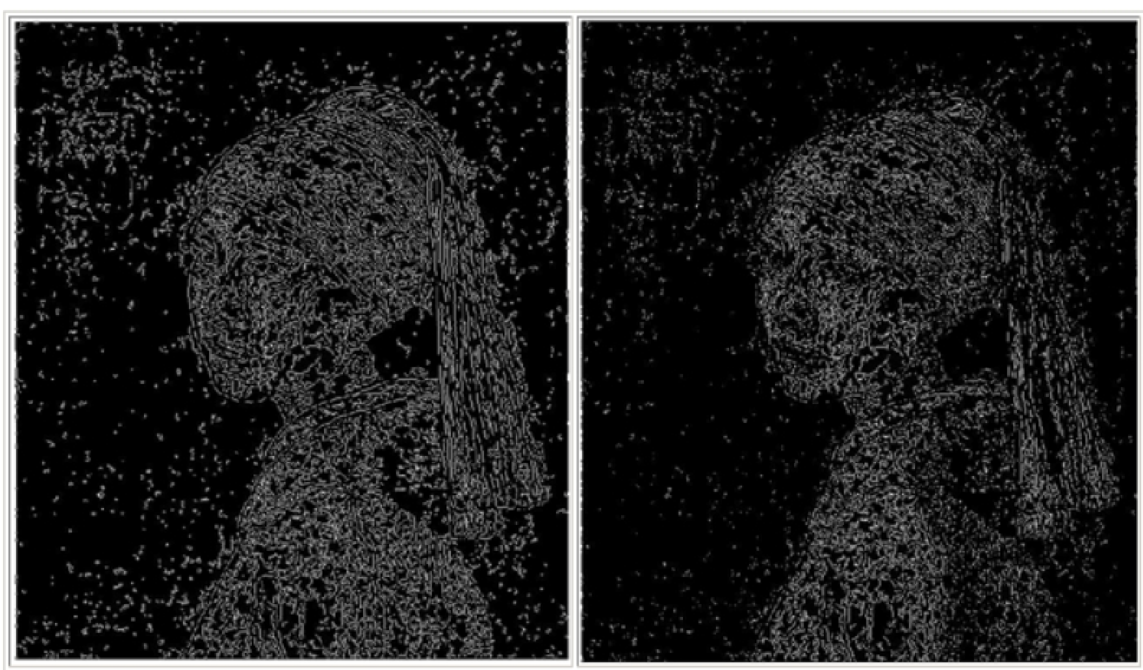


Figure 5: Total Edges and Pure Intensity Edges

The present survey configured the Canny edge detector to extract contour lines from images such as those represented in Figure 6. The technique calculated the number of lines, the mean and the standard deviation of the major and minor axes, the area, and the eccentricity, and an eight-bin line orientation histogram. The contour edge measurements were important features because they captured knowledge of style in a manner similar to that found in art-historical literature [95]. In particular, analysis of style in drawing sometimes uses quantitative measurement to characterize an artist's use of line [125].

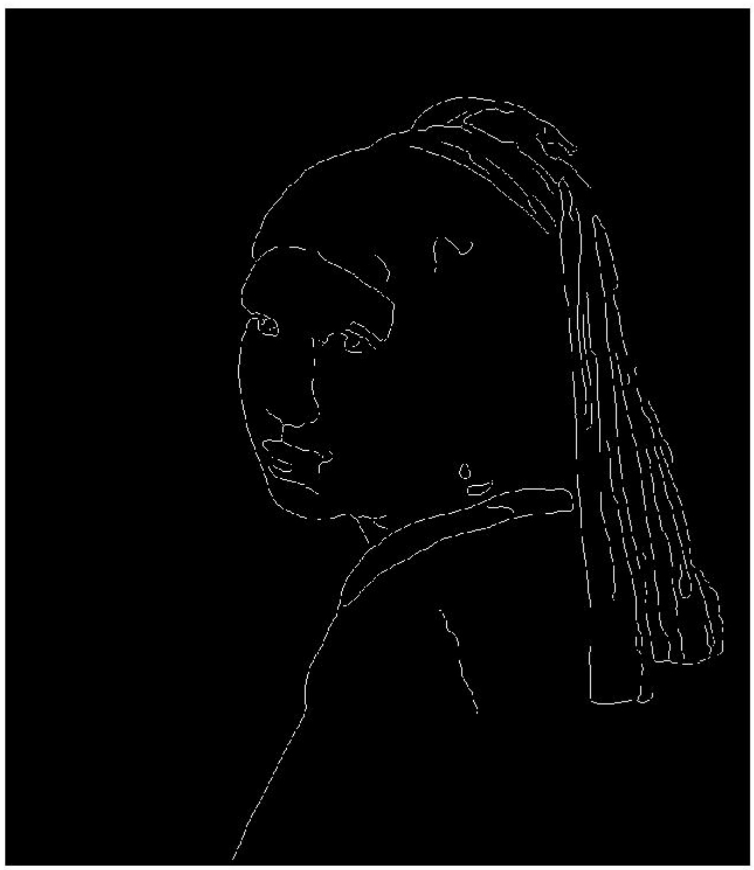


Figure 6: Canny Edge Detection

Gradient maps measure the rate of change in intensities across an image. The coefficients of a gradient map provide summarization of the intensity lines in an image. In one study [68], researchers used an aggregated value of the gradient coefficients for the distinction of styles. After filtering the grayscale image with a two-pass median filter, the program calculated the gradient for the intensity image and constructed the gradient map by calculating the following equation,

$$\sum_{i=1}^{r} \sum_{j=1}^{c} \sqrt{f(i,j)^2 x + f(i,j)^2 y} \, ,$$

where r is the number of rows, c is the number of columns in the image and *f(i,j)x* and *f(i,j)y* are the gradients of the pixels in x and y directions. Finally, the aggregate of the gradient coefficients is normalized by the total number of pixels in the image. Figure 7 shows the visualization of a gradient map for the test image.

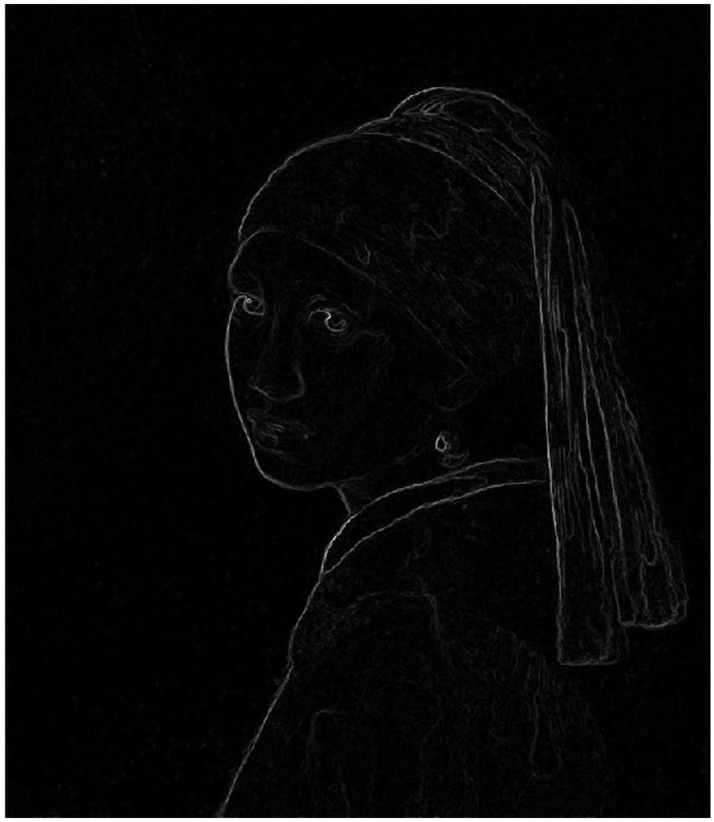


Figure 7: Gradient Map

Another technique proven effective for edge analysis is the block difference of inverse probabilities [22, 23]. Researchers define the block difference of inverse probabilities of an image as the difference between the count of pixels in a block and the ratio of the sum of the pixel intensities in the block to the maximum intensity in that block. Formally, the block difference of inverse probabilities equals,

$$M^2 - \frac{\sum_{(i,j)\in B} I(i,j)}{\max_{(i,j)\in B} I(i,j)},$$

where *I(i,j)* is the intensity of a pixel in the image and *B* represents a block of size *M x M*. Figure 8 displays the visualization for the block difference of inverse probabilities image using a 2 x 2 block. This study extracted the first and second statistical moments as features from the block difference of inverse probabilities coefficients. Researchers have applied the block difference of inverse probabilities to other transformations including wavelet decompositions for which they have proven effective for image retrieval applications [22].

Figure 8: Block Difference of Inverse Probabilities Visualization

The classification results related to line measurements demonstrated that features with high semantic content in this domain could classify with the same accuracy as those with less semantic relevance. For example, the mean length of the major axis of the contour lines proved to classify style as well as comparable block difference of inverse probabilities descriptors. Therefore, semantically-relevant features can provide an important supplement to more traditional approaches to image processing in this domain.

3.2.3 Texture

By far the most commonly used features for style classification are those based on texture. The emphasis on texture features relies on the assumption that such features capture the qualities of brushwork [60, 101]. Carr and Leonard aptly describe the importance of brushwork to the analysis of style: "Because it is, in essence, a direct reflection of the pressure and movement of the artist's hand across the surface of the painting, brushwork is one of the most intimate links that we, as viewers, have with the artist's mind at work" [16].

Although the importance of brushwork to style analysis is clear, the relationship between texture and brushwork is much less so. First, many researchers discuss the lack of a precise definition of texture [55, 64]. Moreover, texture as defined in computer science terms is not necessarily equivalent to texture in art-historical terms. Second, computer science approaches to texture analysis in this domain do not distinguish between actual texture and perceived texture. The actual texture of a painting is the three-dimensional height of the paint on the canvas corresponding most closely to brushwork [13, 21, 111]. The perceived texture of a painting is the two-dimensional illusion of texture conveyed by the skill of the artist. In most cases, the texture features used for research in this domain capture some undetermined blend of both types of texture. Third, many researchers do not distinguish between textures intended by the artist and those that are due to the aging process such as cracks and other types of damage

[48, 54]. Despite this lack of precision, texture features have proven effective in this domain in a number of studies [60, 107]. This survey considers the following texture features based on wavelet transformations, Gabor transformations, discrete cosine transformations, fast Fourier transformations, fractals, gray level cooccurrence matrices, and block variation of local correlation coefficients.

The wavelet transformation has received a great deal of attention in image processing and image retrieval research because of its elegant and powerful method for summarizing texture information in images. A team of researchers has successfully applied the wavelet transformation and features derived from it to the authentication of paintings and drawings of Pieter Bruegel the Elder and Piero della Francesca [107]. Features extracted from the wavelet transformation have proven effective at identifying artistic style. The power of wavelet transformation lies in its ability to summarize images in multiple resolutions and orientations. Researchers have claimed that wavelet characteristics provide detailed information concerning texture and brushstroke.

Figure 9 shows the grayscale visualization of the sub band coefficients from a wavelet transformation for the *Girl with a Pearl Earring* at two scales and three orientations using the Haar filter. The wavelet transformation produces four groups of coefficients: the low pass (A), the horizontal (H), the vertical (V), and the diagonal (D). The low pass sub band is the rescaled image seen in the upper left corner of Figure 9. The horizontal sub band as shown in the upper right of Figure 9 reveals the horizontally-oriented features. The diagonal (lower right) and vertical (lower left) sub bands expose features in their respective orientations. Researchers have extracted a number of features from the sub bands of this transformation including Besov norms [2], statistical moments [107], fractal dimension [142], and additional transformations of the coefficients [22]. The implementation surveyed in this study used the Haar filter at three scales [51, 52] and extracted the mean and variance of the coefficients of the horizontal, vertical, and diagonal sub bands.

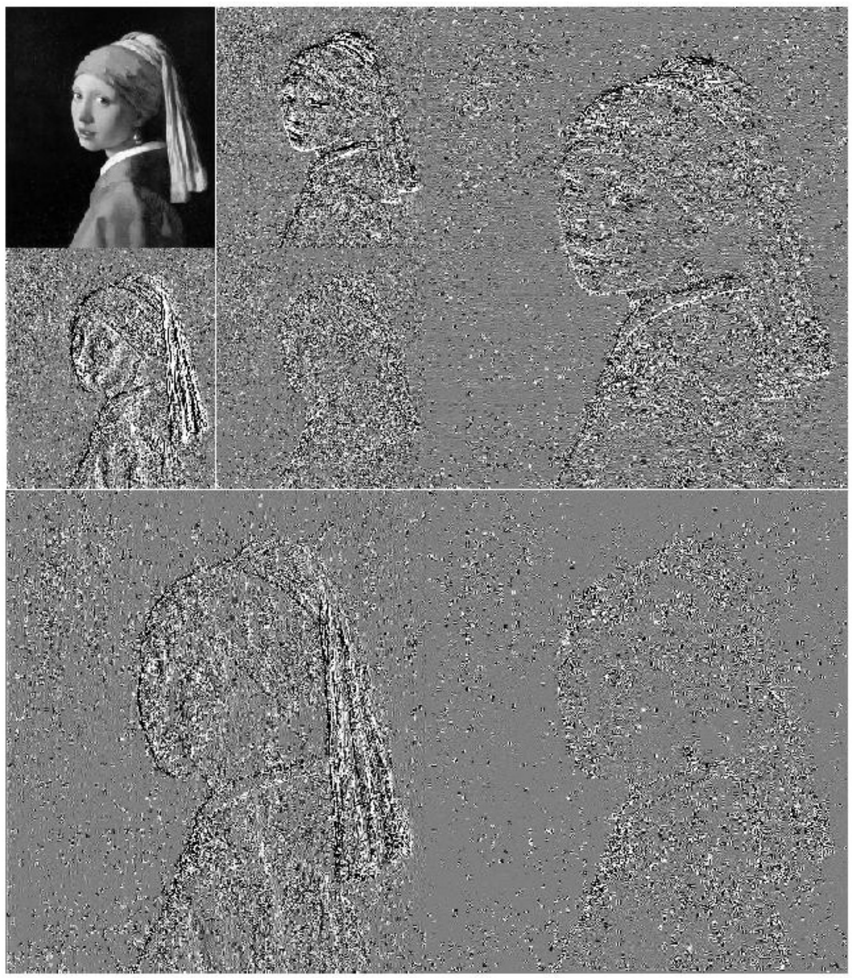


Figure 9: Wavelet Transformation

Gabor filters [50, 94, 96] provide another useful transformation revealing the texture of images. Figure 10 displays a Gabor transformation at four scales and in four orientations, vertical, horizontal, and the two diagonals. Like the wavelet transformation, Gabor transformations offer a number of options for feature extraction including statistical moments [40] and fractal dimensions. Although Gabor filters have been used for texture analysis extensively [45, 96], they have not been applied to the classification of artistic style. The implementation used in this survey was Kovesi's Gabor transformation [94]. The mean and variance of the coefficients were extracted from four scales and four orientations as specified in Cutzu [40].

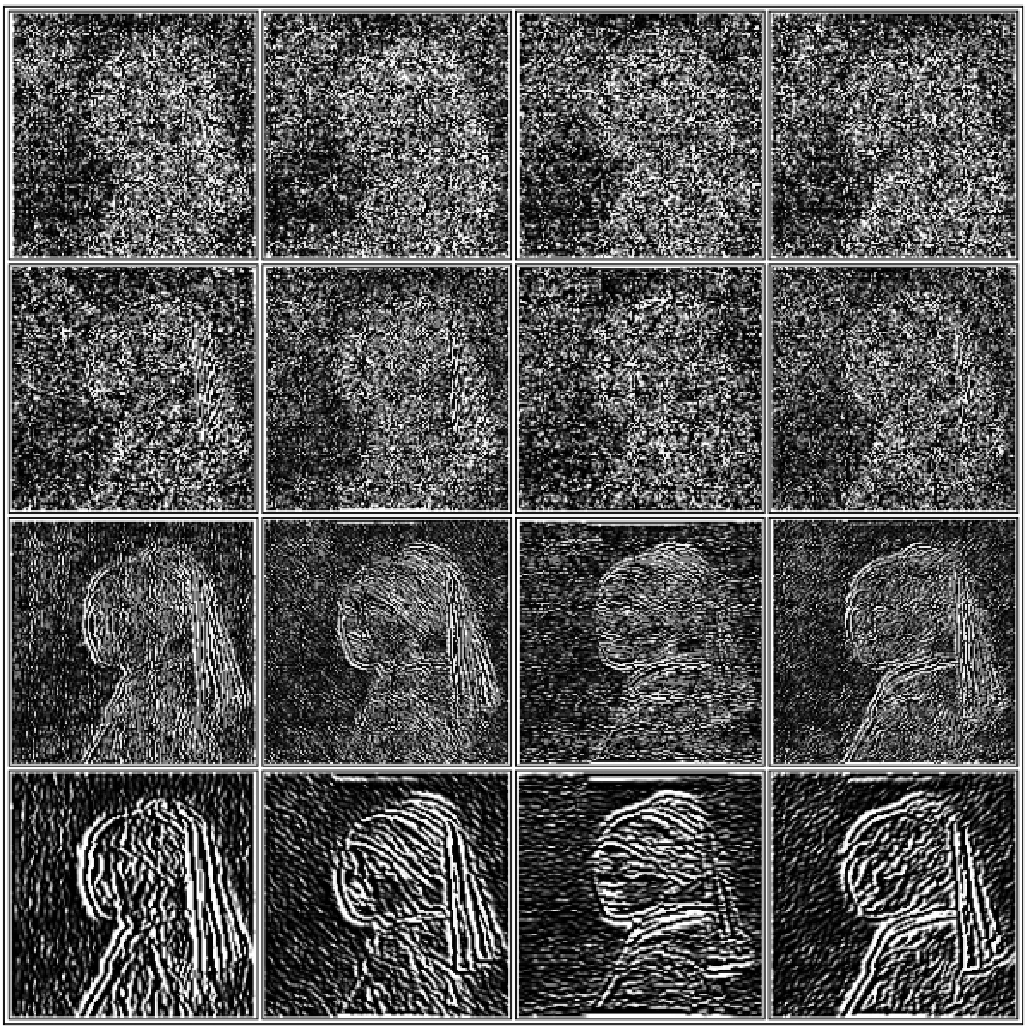


Figure 10: Gabor Transformation

The discrete cosine transformation provides another option for studying image texture. Keren has used the coefficients of the discrete cosine transformation to classify artistic style [81]. In Keren's implementation, the system subdivides each image of a painting into nine by nine blocks and calculates the absolute values of the discrete cosine transformation coefficients for each block. A histogram of the coefficients serves as the basis for classification with a naïve Bayes classifier. Figure 11 demonstrates a visualization of the discrete cosine transformation coefficients for an entire image. Although researchers have produced quality results with this feature, the study does not consider the feature because it lacks a clear connection to domain knowledge. Discrete cosine transformation coefficients serve as an example of a feature with little semantic relevance in the art-historical domain.

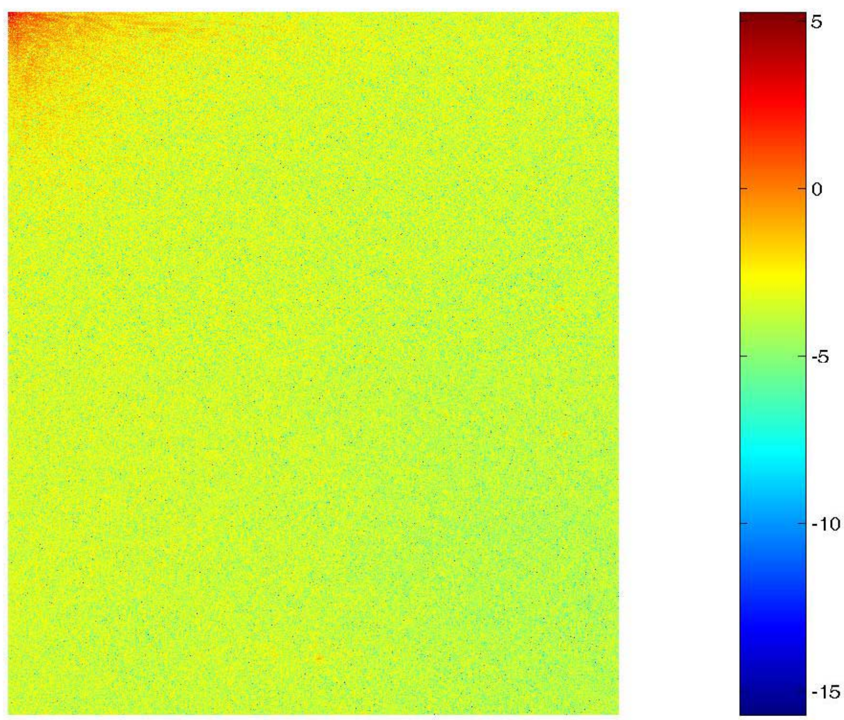


Figure 11: Visualization of the Discrete Cosine Transformation

The fast Fourier transformation, like the discrete cosine transformation, captures texture information in an image [60]. Herik and Postma obtained 50 features from evenly sampling the fast Fourier transformation 240 pixels from the center of the image. The center of the fast Fourier transformation image corresponds to a spatial frequency of zero or the mean intensity. Moving 240 pixels from the center of the image shows the spatial frequency at the orientation perpendicular to a given angle. The bright lines in the fast Fourier transformation image correspond to the strong lines found in the image. For example, the strong line running through the center of the image represents the horizontal grid sampling inherent in the JPEG format. The implementation reproduced in this study is that proposed by Herik and Postma [60] modified to measure values at a fixed distance of 100 pixels from the center.

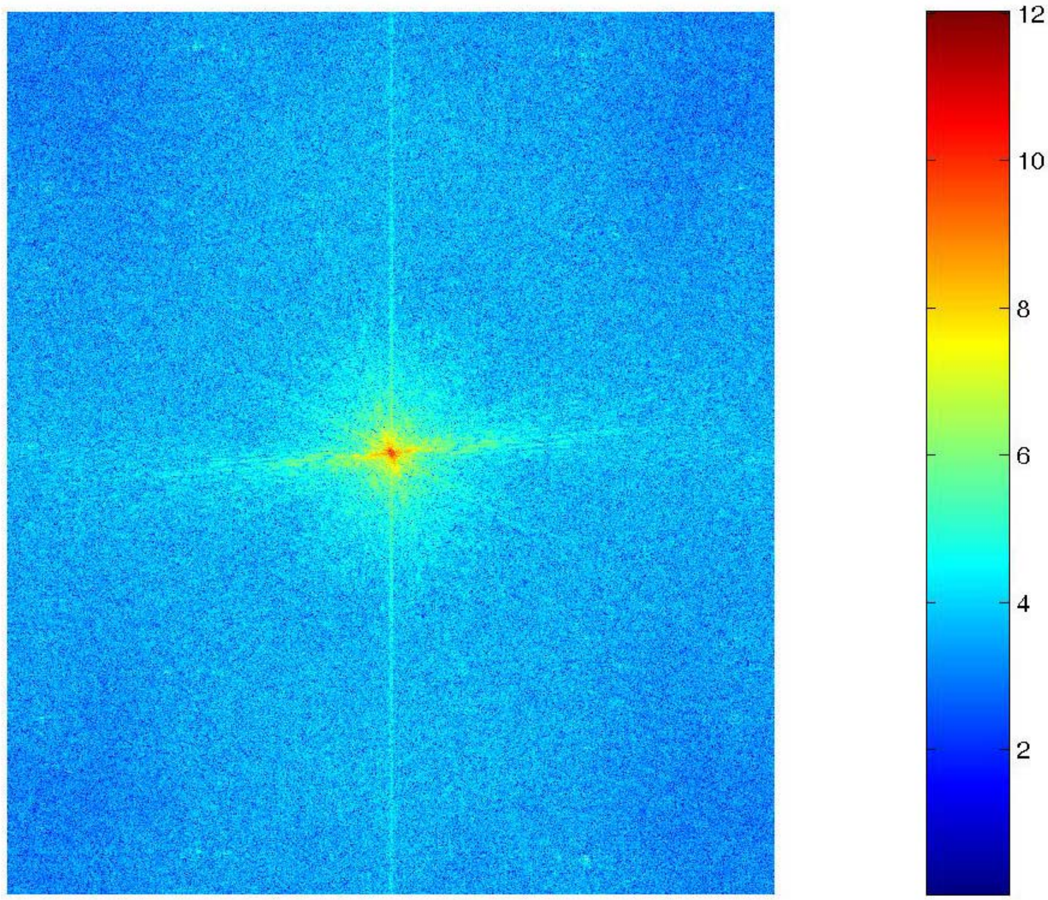


Figure 12: Fast Fourier Transform

Fractals have become an important feature for measuring the self-similar structures in the texture of an image. There are several approaches to measuring the fractal dimension in an image. The box counting method [154, 155, 156, 157, 158, 159] is a common technique used to measure fractal dimension. Formally, the box counting method is defined as,

$$D = \frac{\log N}{\log(1/h)},$$

where D is the fractal dimension, N is the number of boxes not empty, and h is the size of the boxes used. The Hurst coefficient [60, 122, 128] approximates the fractal dimension by plotting the log of the given scales or distances against the log of the average value in that scale. In early assessments of the Hurst coefficient technique as implemented by Herik and Postma [60], the efficiency was outside of the bounds possible for this study requiring over an hour to calculate the Hurst coefficient for one image.

Using wavelet decomposition [142] however, researchers calculate the Hurst coefficient by means of the average wavelet coefficient. The wavelet decomposition provides coefficients at multiple levels providing the scaling mechanism required. The log of the arithmetic mean of the absolute values of the wavelet coefficients provides the other component required to calculate the Hurst coefficient. The algorithm evaluated in this study considered the fractal dimensions of the horizontal, vertical, and diagonal coefficients separately. Figure 13 displays the calculation of the Hurst coefficient for the horizontal coefficients of a seven level wavelet decomposition using the Haar filter. The slope of the fitted line (d) holds the following relationship to (H) the Hurst coefficient,

$$d = \frac{1}{2} + H .$$

In this example, the slope of the fitted line is 2.3326 and the Hurst coefficient is 1.8326.

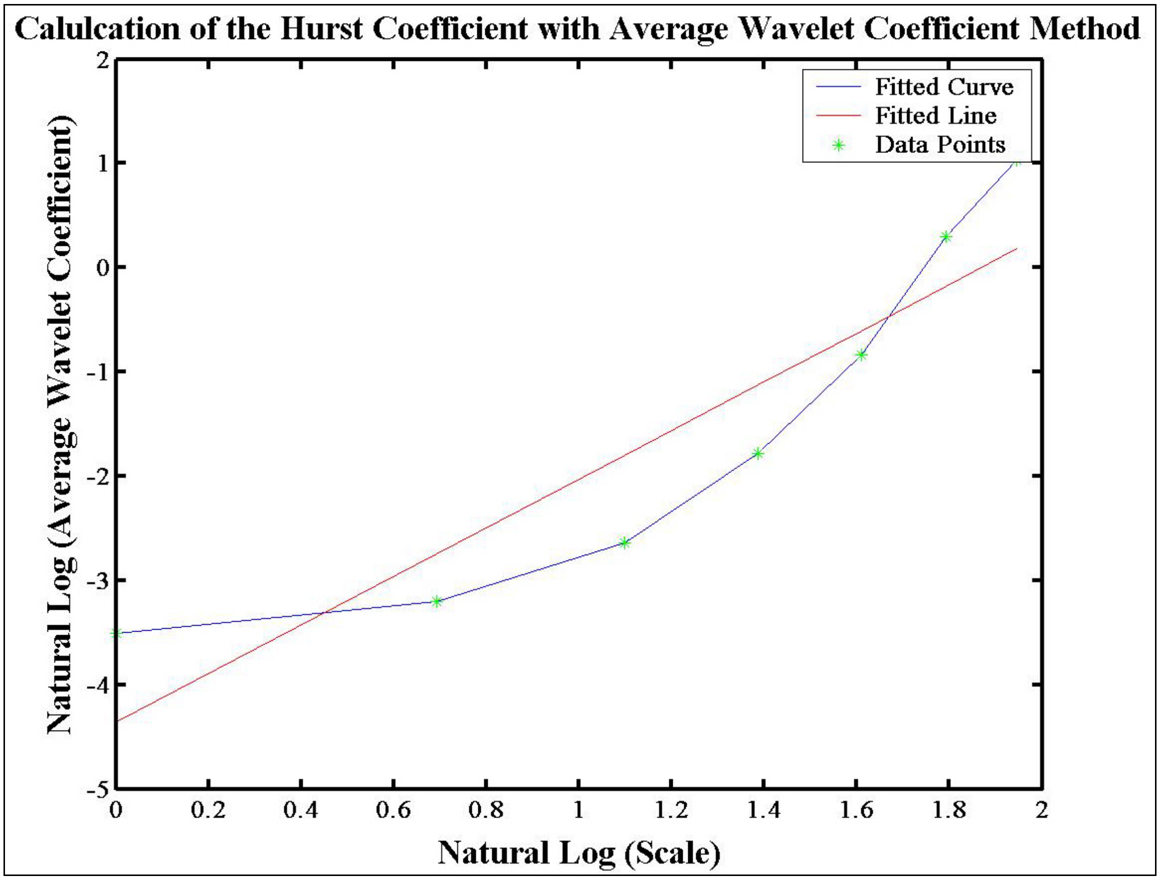


Figure 13: Hurst Coefficient

The gray level cooccurrence matrix [13, 55] provides second order statistical information concerning the texture of an image. The gray level cooccurrence matrix calculates the joint probability of intensity *a* and *b* for two pixels at a fixed distance and orientation. The resulting cooccurrence matrix of 256 x 256 provides detailed information concerning the spatial relationship of intensities given a distance and orientation. This study analyzed four gray level cooccurrence matrices for each image corresponding to four orientations, -45 degree, 0 degree, 45 degree, and 90 degree at a distance of one. The study extracted eight statistical features from each gray level cooccurrence matrix including contrast, correlation, energy, entropy, homogeneity, inertia, inverse difference moment, and maximum probability [55].

The block variation of local correlation coefficients [22, 23] is a measure of smoothness and coarseness in an image. Figure 14 shows the visualization of the block variation of local correlation coefficients for a median filtered version of the test image.

Figure 14: Block Variance of Local Correlation Coefficients

Light areas denote relative roughness, and dark areas signify relative smoothness. As in other transformations, the implementation extracted statistical moments (mean and variance) from these coefficients and compared them to those of other images.

Overall, the study found the statistical moments derived from the wavelet decomposition and the fractal measurements to be the most effective texture features. In terms of the speed of execution, the wavelet transformation was clearly the most efficient, but the box counting method for measuring the fractal dimension was the most efficient in terms of storage space. The features based on the fast Fourier transformation implemented in this study did not reproduce the accurate results reported by Herik and Postma [60]. The study did not implement the size-correction preprocessing step undertaken in the original study and this difference offers the best explanation for the variance in the results.

3.2.4 Color

Color features provide vital information concerning style in painting. For example, the pigments available to an artist depended on the availability of materials and the technology to process those materials [49, 63]. In addition to a painter's historical context, an individual's style partially depends on that artist's approach to the use of color. In contrast to the plethora of texture features applied to painting classification, researchers have tested relatively few color approaches. A general approach to the classification of style should benefit from the use of more robust color features. The color features surveyed in this section include palette scope, histograms, color coherence vectors, RGBXY, spatial chromatic histograms, color correlograms, and a palette description feature.

The palette scope describes the number of colors used in an image. Researchers have shown that this feature effectively distinguishes between paintings and photographs [40]. The palette scope (U) of an image is formally defined as:

$$U = C / P ,$$

where C is the total number of unique colors measured in RGB or HSV triples and P is the total number of pixels in an image. There are multiple ways to obtain the palette scope from an image. For example, one can calculate the palette scope simply by counting each unique RGB or HSV triplet as a unique color. In this case, the number of colors can be extremely large possibly the number of pixels in the image. A more useful way to arrive at the palette scope is to cluster the colors into meaningful groups with algorithms such as minimum variance quantization. Table 11 summarizes the values obtained by applying various methods to the *Girl with a Pearl Earring* in Figure 2. Despite the success of this feature in other applications [40], this survey did not consider the number of colors because it failed to distinguish between artists reliably in preliminary tests.

Table 11: Palette Scope Measurements

Palette Scope Method	Value	Value Normalized by Size
Unique Triples: All color spaces	110148	0.148799
Minimum Variance Quantization: RGB	3607	0.004872
MVQ: HSI	5259	0.007104
MVQ: CIE L*a*b	173	0.000233

MVQ: RGB (no duplicates)	3576	0.004830
MVQ: HSI (no duplicates)	5125	0.006923
MVQ: CIE L*a*b (no duplicates)	172	0.000232

The palette scope describes the number of colors used to create a painting but it does not describe the actual color content or the frequency with which those colors appear on the canvas. Histograms [106, 121, 141, 152] supply frequency information for the use of color in an image. There are several relevant types of histograms for the study of painting in digital formats: dynamic histograms, static histograms, and static histograms applied to a color map. A dynamic histogram organizes the colors in an image into color bins natural to that image. For example, Figure 15 represents the dynamic histogram

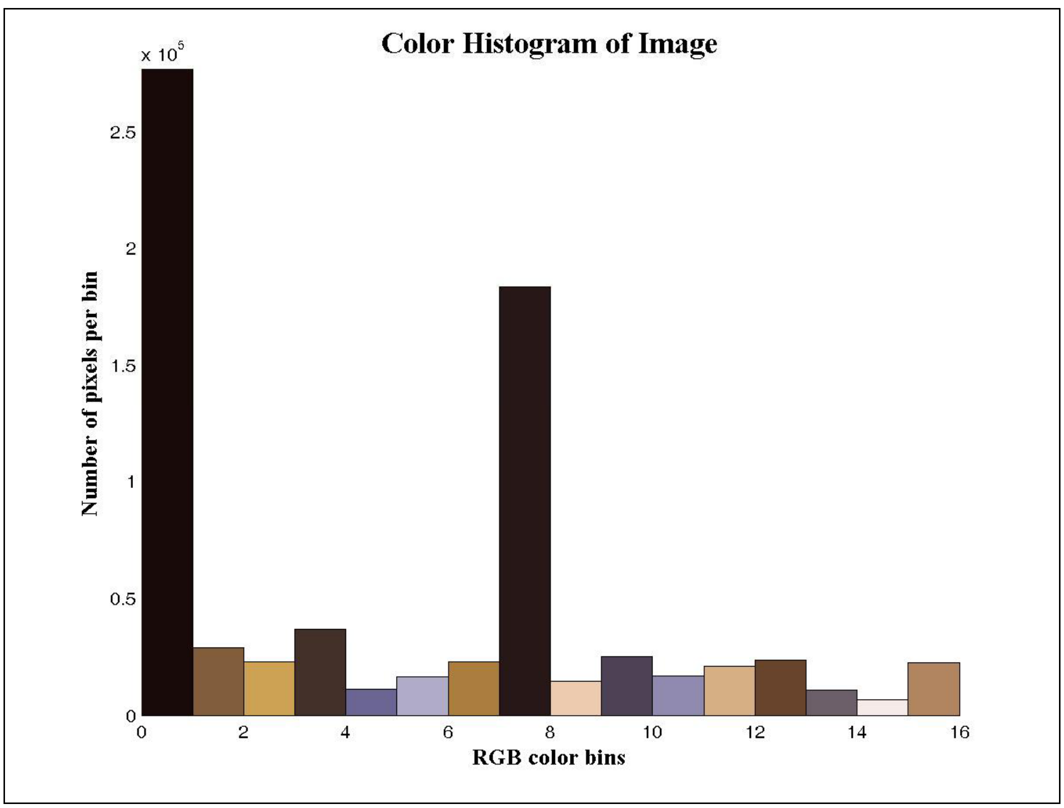


Figure 15: Dynamic Histogram

of the *Girl with a Pearl Earring*. The color map was obtained using a minimum variance quantization of the RGB image into 16 bins. The colors in the histogram are easily identifiable in the image and therefore are satisfying aesthetically. Unfortunately, this type of histogram does not provide an easy way to compare images because no two images will produce the same 16 colors. Comparing histograms of this type is like comparing apples and oranges unless systems measure the difference between the bins in addition to the number of pixels in the bins.

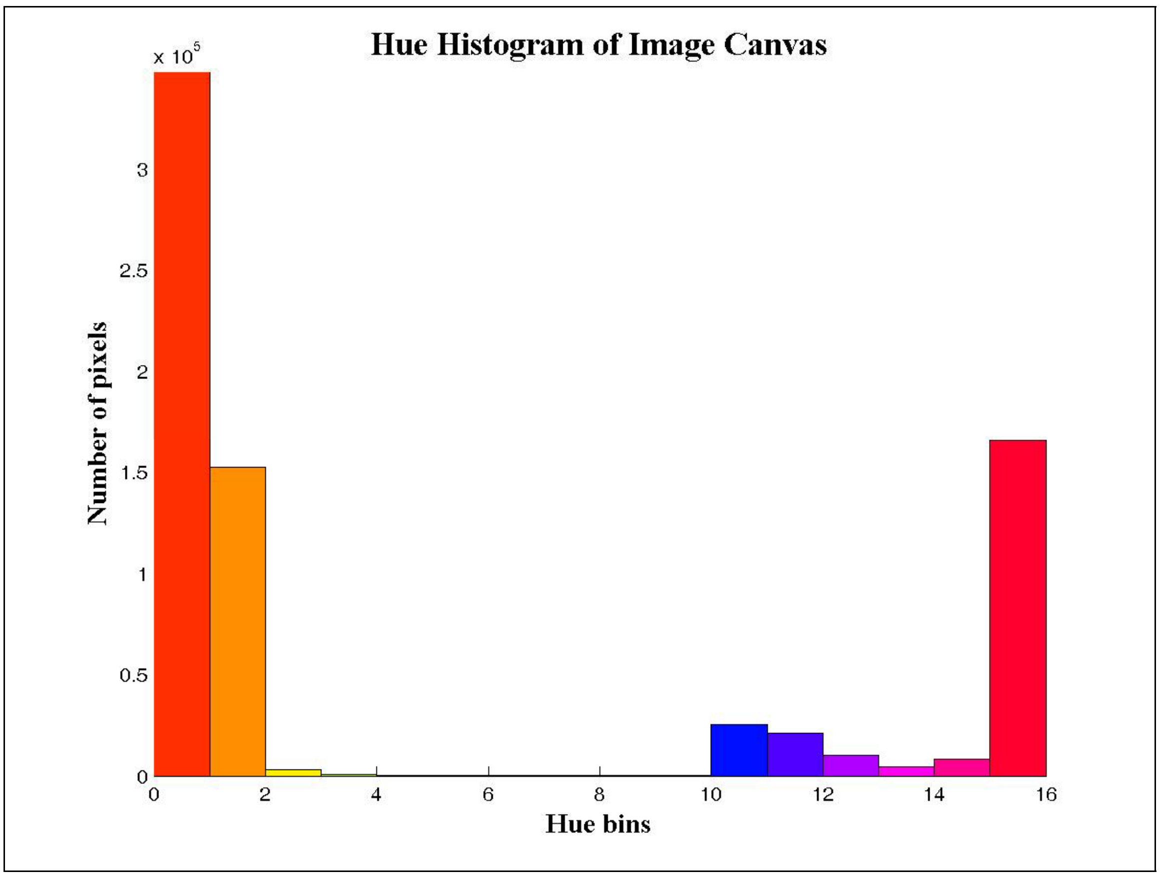


Figure 16: Static Hue Histogram

Static color histograms, on the other hand, analyze each channel separately in equally spaced bins. For example, the hue, saturation, and value channels can each be binned separately and compared faithfully to the histograms of other images. Figure 16 shows the static hue histogram of the *Girl with a Pearl Earring*. Although this histogram bears less direct resemblance to the image than does the image histogram, it serves as a more convenient basis for comparing two images.

In addition to dynamic and static histograms of an image, a static histogram of an image color map provides still more information about the color content in an image. Where the image canvas histogram places every pixel in a bin, the static histogram of a color map places every entry of the color map in a bin disregarding the frequency of the application of those colors. In essence, the static map or palette histogram provides insight into the dominant colors used by an artist.

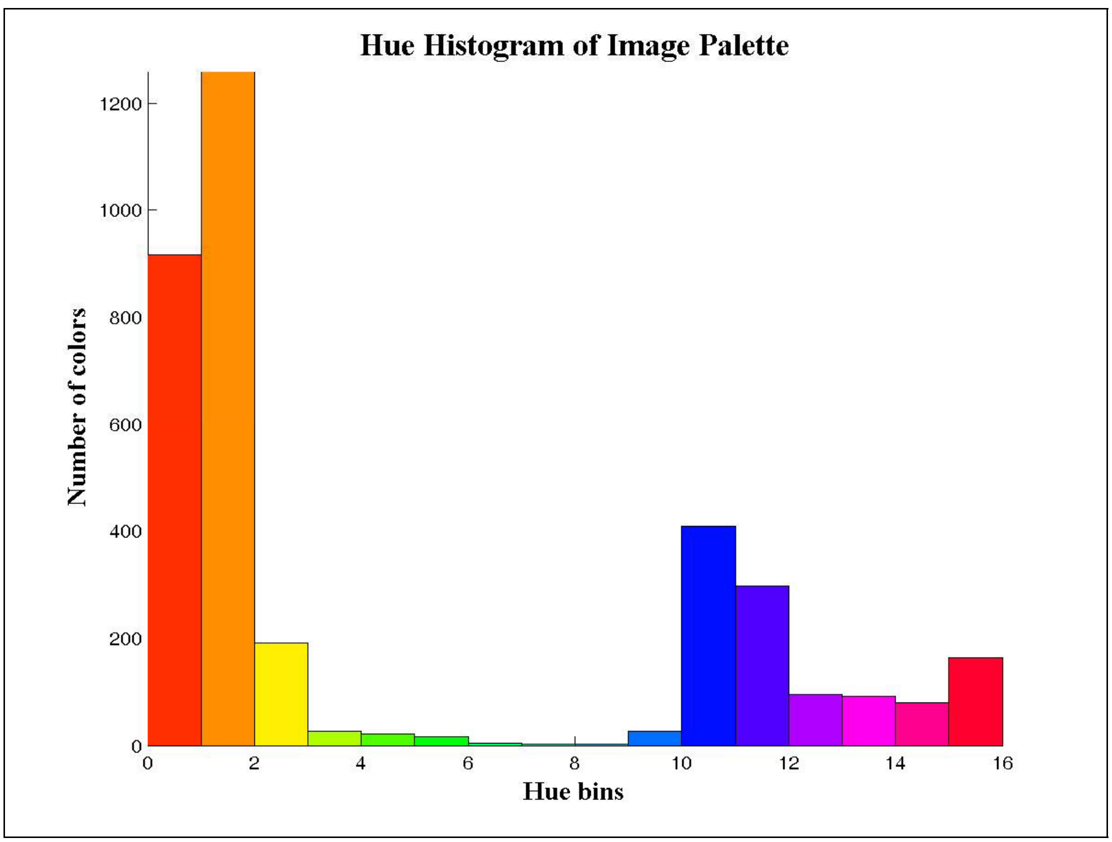


Figure 17: Hue Histogram of Image Palette.

Figure 17 demonstrates a static hue histogram for the image palette of the *Girl with a Pearl Earring*. Comparing Figures 16 and 17 reveals that the static histograms applied to the image index and color map for the same painting can be quite different. The survey included several types of histogram including static histograms applied to image indexes and color maps and dynamic histograms applied to image indexes in the HSV color space.

Histograms have proven to be powerful descriptors of color properties in an image. Image descriptions based on this technique, however, suffer from a lack of spatial information often resulting in dissimilar images having similar histograms. Color coherence vectors [124] preserve some spatial characteristics of image colors by distinguishing large blocks of coherent color from smaller blocks of incoherent color. Color coherence vectors classify image pixels into two categories: coherent pixels are those placed in a region of similarly-colored pixels numbering above a threshold, incoherent pixels are those placed in regions less homogenously colored. Figure 18 shows a visual representation of the coherent pixels and the incoherent pixels derived from one color bin of a static histogram. The implementation used in this example classified color regions of more than 5,694 pixels (total image pixels divided by 130) as coherent. The image on the left-hand side represents coherent pixels, and the image on the right represents incoherent pixels. This study considered color coherence vectors to supplement the approaches based on histograms.

Figure 18: Coherent and Incoherent Pixels

As useful as the palette scope and frequency descriptions of color are, they neglect a rather important aspect of painting: the spatial distribution of color. It is possible to characterize the spatial distribution of color in the RGBXY space [40]. First, the MxNx3 cube of the original image is reduced to a matrix of MxN rows, one row for each pixel in the image, and 5 columns, one for the Red, Green, and Blue channels and the X and Y coordinates. Second, the 5x5 covariance matrix is calculated for the new RGBXY matrix. The five singular values summarized the covariance matrix associated with the image. Paintings with larger palette scopes and larger variations in spatial color distribution will have larger singular values [40].

Table 12: Covariance Matrix of RGBXY Matrix.

	R	G	B	X	Y
R	4527	3966.6	3130.3	3308.5	-5.3274
G	3966.6	3572	2967.3	3101	-3.326
B	3130.3	2967.3	2936.9	2799.1	-2.8788
X	3308.5	3101	2799.1	70994	0
Y	-5.3274	-3.326	-2.8788	0	53600

Table 12 displays the covariance matrix of RGBXY space for the *Girl with a Pearl Earring*. The singular values derived from the covariance matrix are 71460, 53600, 10037, 513.2, 20.117. The singular values provide directly comparable values with those obtained from other images. In many applications, hue-based color transformations such as HSI perform better than transformations in RGB space. This study constructed an HSIXY feature for comparison with RGBXY. The implementation considered in this study derives the HSIXY feature in exactly the same manner as RGBXY except that the original MxNx3 image cube is transformed into HSI color space before processing.

The RGBXY feature provides a compact summarization of the spatial distribution of color in an image but it does not provide detailed spatial information about specific colors. Image retrieval researchers have defined the spatial chromatic histogram [25, 26, 27, 105, 135] for this purpose. Like ordinary histograms, spatial chromatic histograms can use static or dynamic bins. Figure 19 shows the 19 bin static spatial chromatic histogram for the *Girl with a Pearl Earring*. The spatial chromatic histogram consists of the following fields for each color: number of pixels in the color bin, the color baricenter in XY space, and the standard distance deviation of the distribution of the color.

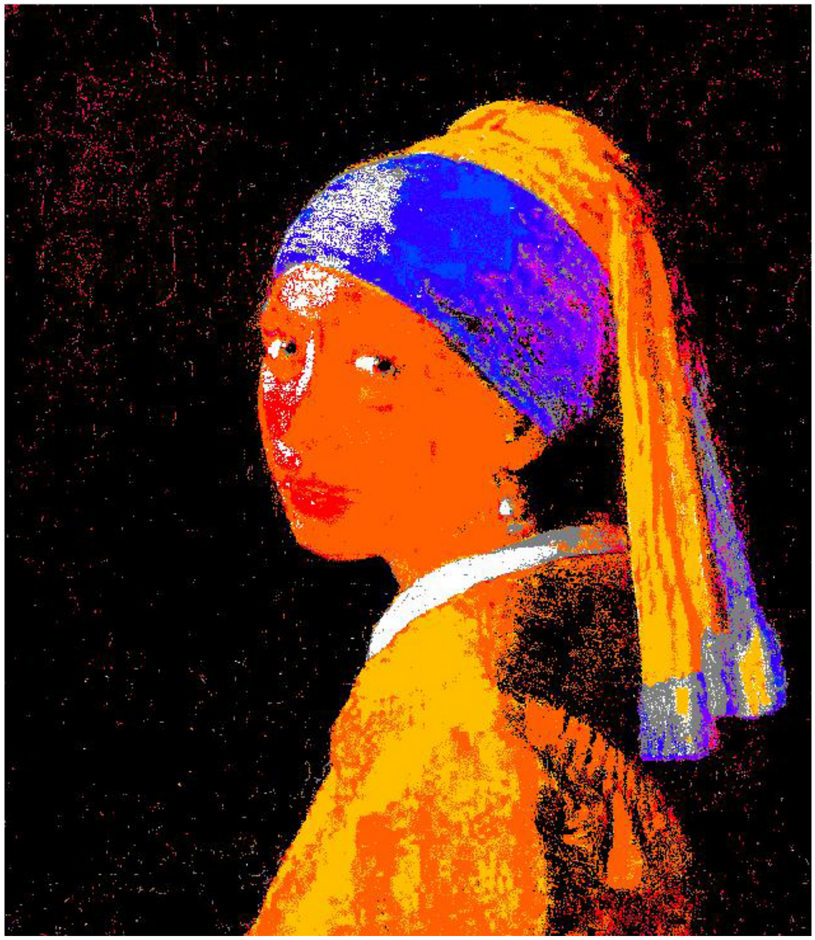


Figure 19: Spatial Chromatic Histogram

An ordinary static histogram provided the number of pixels per bin. The color baricenter defines the central point of the distribution of a color. The standard distance deviation characterizes the dispersion of the pixels around the mean. Figure 20 shows the visualization of one color entry from the spatial chromatic histogram of the *Girl with the Pearl Earring*. The center of the circle is the baricenter of the color; the radius of the circle represents the standard distance deviation around the baricenter. Figure 21 aligns multiple entries from the spatial chromatic histogram. The spatial chromatic histogram has proven effective in image retrieval applications. This study included this feature to test if capturing additional spatial information improves style classification. In particular, the study implements a variant called dynamic spatial chromatic histogram [26] designed to improve performance and accuracy.

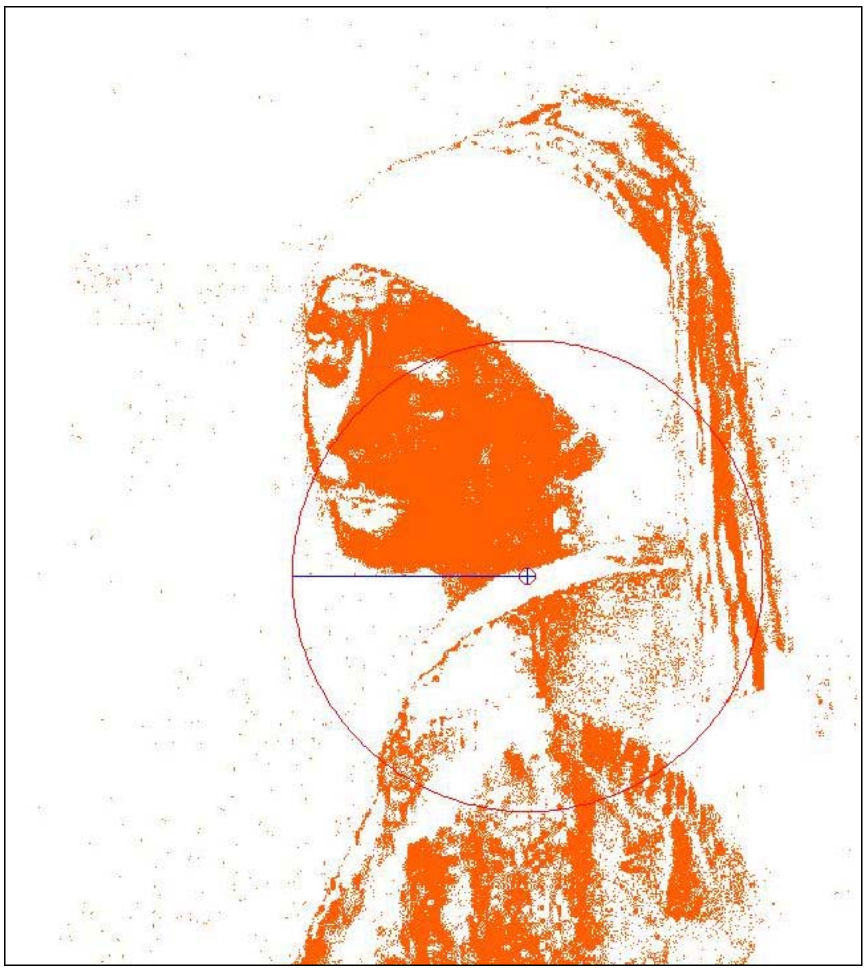


Figure 20: Spatial Chromatic Histogram Baricenter and Radius

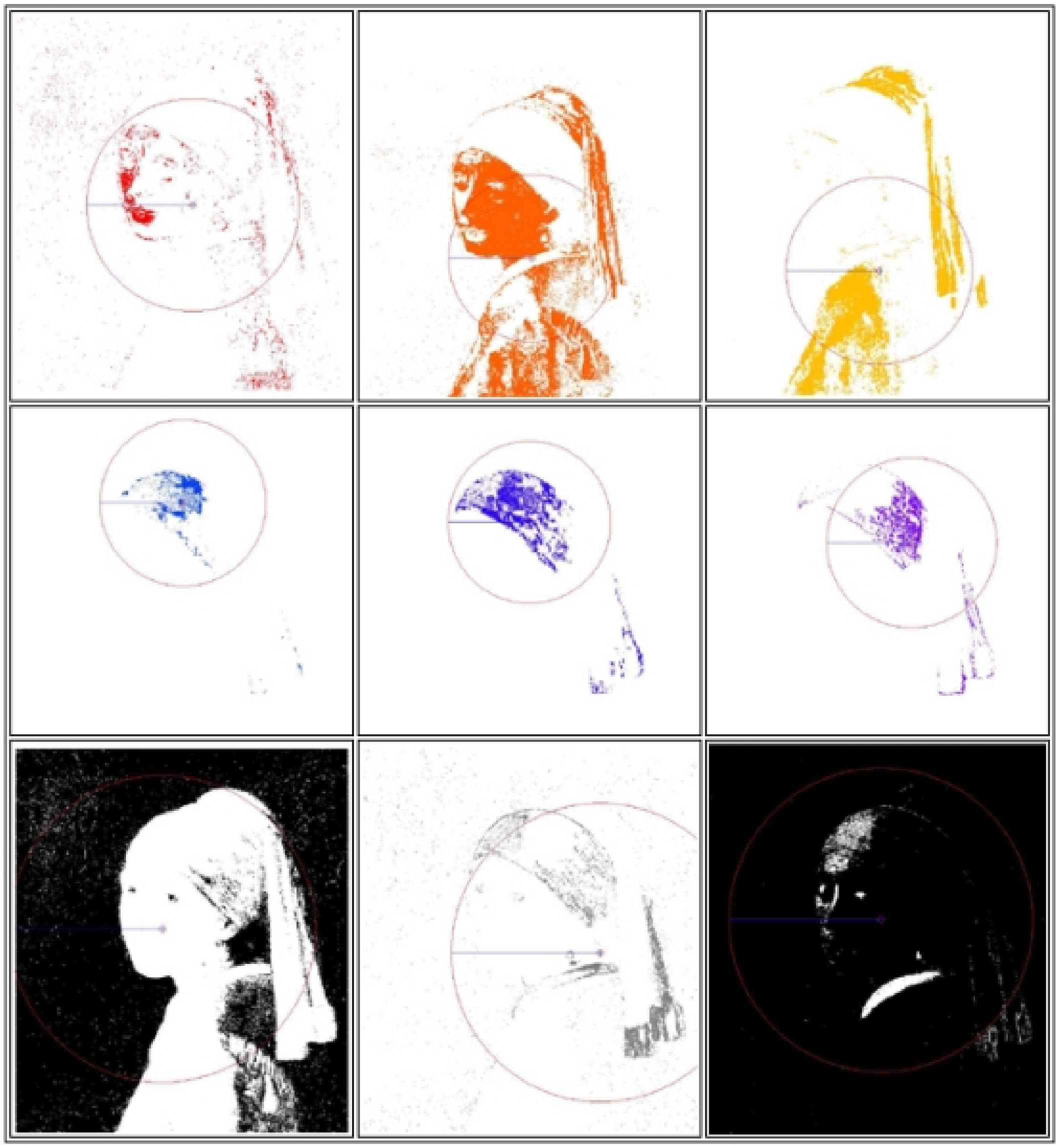


Figure 21: Spatial Chromatic Histogram Details

While the spatial chromatic histogram characterizes the global arrangement of color in space, correlograms [20, 66, 67, 97] describe the global distribution of the local correlation of colors in space. The color correlogram of an image relates the probability that color 1 lies a certain distance from color 2 resulting in (c*c)d rows in the correlogram table. For example, Table 13 shows the correlogram for an image represented in three colors, red, green, and blue, and measuring a distance of one pixel in four directions. In this sample correlogram, each color has a 25% chance of being placed adjacent to a pixel of the same color. The color correlogram provides additional detail concerning the local distribution of colors in an image.

Table 13: Color Correlogram

Color 1	Color 2	Distance	Probability
Red	Red	1	.25
Red	Green	1	.50
Red	Blue	1	.25
Green	Red	1	.25
Green	Green	1	.25
Green	Blue	1	.50
Blue	Red	1	.50
Blue	Green	1	.25
Blue	Blue	1	.25

Color correlograms can often be expensive to compute with large numbers of colors or with many distance measures. In these cases, it is often useful to construct autocorrelograms that only consider the distance between a color and itself resulting in c(d) rows in the correlogram table. Table 14 shows the autocorrelogram corresponding to the correlogram in Table 13. This study considered the autocorrelogram to gauge the importance of local color arrangement on style classification. The feature considered in this study measured local color variations at distances of one, three, five, and seven pixels.

Table 14: Color Autocorrelogram

Color 1	Color 2	Distance	Probability
Red	Red	1	.25
Green	Green	1	.25
Blue	Blue	1	.25

The color feature survey conducted in this study revealed that preserving more frequency and spatial information in the color channel does not necessarily improve classification accuracy. Although not conclusive, the result suggests that the spatial and frequency distribution of color channels characterizes the subject or content of the painting rather than providing significant information concerning style. Features from image retrieval applications are designed with precisely that goal in mind: improving the description of image content. This study proposed a palette description feature that captures the central tendency of color information in an image.

A digital 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 and 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 feature summarizes the color content of an image map for HSV colors by defining the central tendency of the colors in the image.

The palette description feature presented in this study breaks a color map into discrete value slices as depicted in Figure 22. For each value slice, the mean hue, saturation, and value were calculated. The mean values were computed by finding the RGB means and converting the RGB means to HSV values. The feature calculated the distance between every color in the slice and the HS mean of that slice to determine the variance of the colors around the mean. The total number of colors in the slice was also calculated.

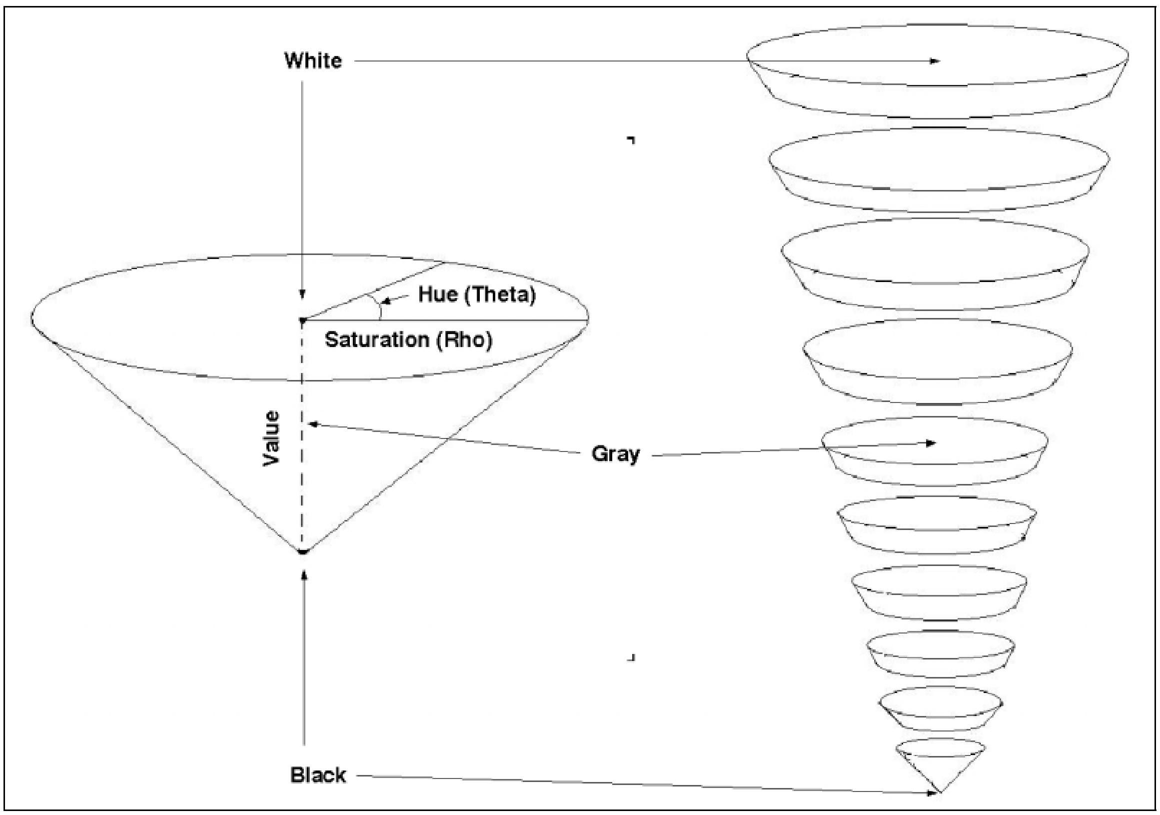


Figure 22: HSV Cone Decomposition into Value Slices

Figure 23 demonstrates the color distributions for a slice taken from the test image. Figure 23 depicts the value mean at the top of the figure. The red crosshair represented the hue and saturation means and the blue dots represent the scatter of colors in the value slice. The hue, saturation, and value means as well as the variance and number of colors are recorded for each slice of the HSV cone. The resulting palette description results in a robust feature for style classification.

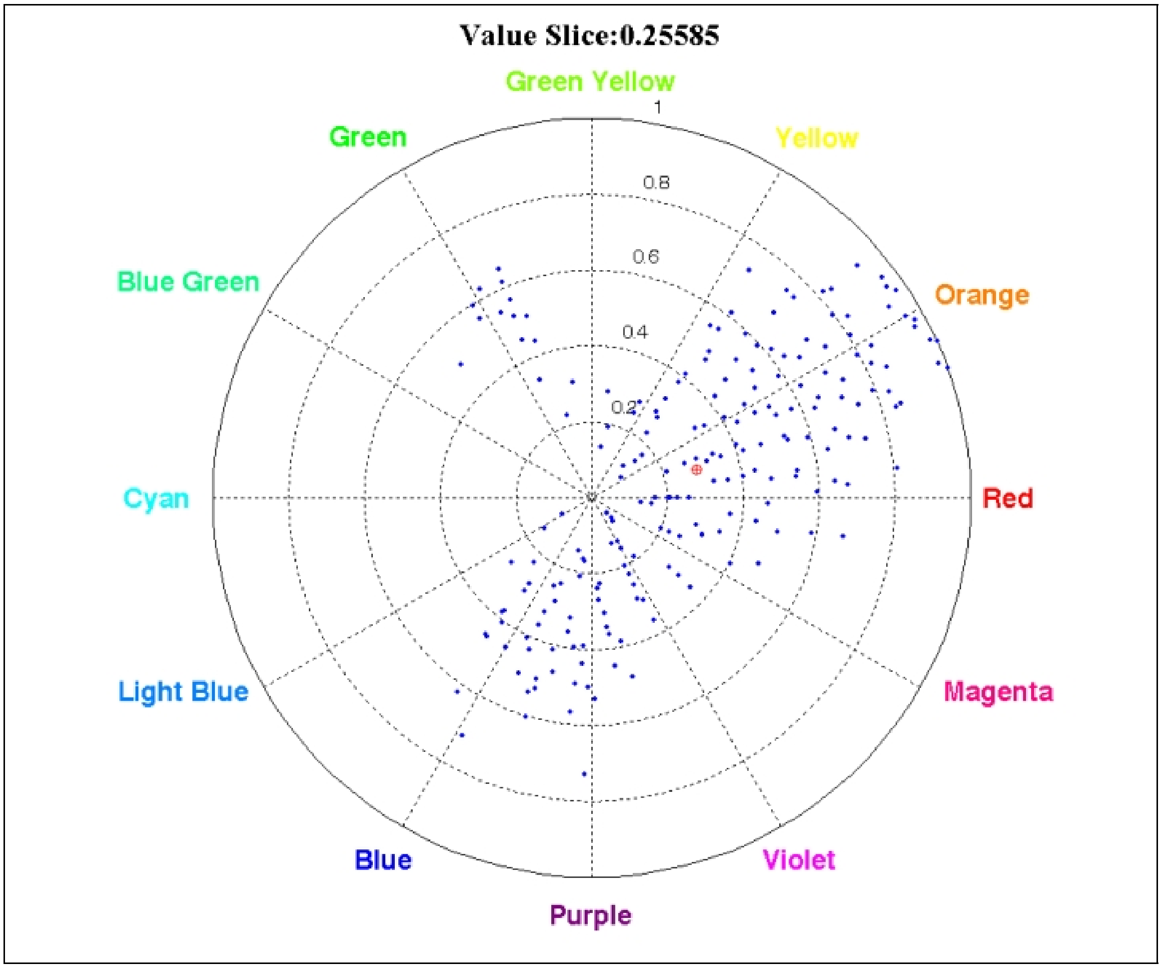


Figure 23: Value Slice of HSV Cone

The palette description can be extracted from any HSV image map in the following manner:

1. Sort the HSV color map by the value channel in descending order;

2. Cut the map into 10 uniformly-divided value slices;

3. For each of the 10 slices repeat steps 4 through 9:

4. Convert the HSV values in the slice into RGB values;

5. Find the Red, Green, and Blue means of the RGB values;

6. Convert the Red, Green, and Blue means to Hue, Saturation, and Value means;

7. Use the law of cosines to calculate the distances between each color in the slice and the Hue and Saturation means;

8. Find the variance of the color distribution by calculating the mean of the distances found in step 7;

9. Count the number of colors in the slice and normalize this value by the number of colors in the entire map.

The color features surveyed in this section reveal that preserving additional frequency and spatial information in the color channels does not necessarily improve classification accuracy. For example, the HSV static histogram of the color map outperformed the HSV static histogram of the image index in classification tasks suggesting that style in painting is more closely linked to a painter's palette than the arrangement of colors on the canvas. In a similar way, the HSV palette description feature performed as well as the features designed to capture the spatial arrangement of colors including HSIXY, color coherence vectors, dynamic spatial chromatic histograms, and color autocorrelograms. Although these results are not conclusive, they suggest that characterizing style is sufficiently different from characterizing image content to justify the development of features particularly suited to style classification.

3.3 Feature Normalization and Comparison

After extracting the desired features, the proper evaluation of those features requires that features are directly comparable. In order to compare features reliably, those features must be rescaled or normalized to a consistent scale and then the standardized features must be compared in a manner appropriate to the nature of the feature. In many cases, features can be compared in a number of ways and therefore both normalization and comparison techniques are crucial for understanding style classification.

3.3.1 Feature 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 such as line length and palette scope must be normalized by the total number of pixels in an image before normalizing the values with respect to other features. Normalization therefore serves two important functions in feature comparison in that the techniques ensure that features are internally consistent and features are directly comparable.

Table 15: Feature Values before Normalization

No. of Colors	Intensity Mean	Intensity Skew	No. of Lines	Line Orientation
3607	65.2	-0.76	304	-45
1054	155.4	0.34	237	0
2365	109.3	-0.18	127	45

Table 15 displays feature values prior to the normalization process. The number of colors is at least an order of magnitude larger than any other feature considered. If the features are not normalized, the number of color values will overshadow the differences in other features. For the sake of example, assume that rows 1 through 3 are features extracted from images of 500 x 500, 300 x 300, and 400 x 400 pixels respectively. The first step is to ensure that the values in each feature column are internally consistent. In particular, the number of colors and the number of lines depend on the size of the image. That is to say, larger images are statistically more likely to have more colors and more lines due to higher resolutions. Therefore, these features must be normalized by the total number of pixels in the image. Table 16 displays the same feature values after the features have been normalized for internal consistency.

Table 16: Feature Values adjusted for Image Size

No. of Colors	Intensity Mean	Intensity Skew	No. of Lines	Line Orientation
0.014428	65.2	-0.76	0.001216	-45
0.011711	155.4	0.34	0.002633	0
0.014781	109.3	-0.18	0.000793	45

After adjusting the values for image size where necessary, the features must be rescaled to facilitate comparison. In this study, two normalization techniques are used. The first technique normalizes features to values between negative one and one based on the maximum absolute value of the feature values. Formally, the normalized features are defined as:

$$\frac{V(i)}{\max(|V|)}$$

where $V(i)$ represents each element in the feature vector and $max(|V|)$ represents the maximum absolute value in the feature vector. Table 17 demonstrates the sample features normalized using this technique. The technique preserves the sign (+/-) of each value, which introduces an inconsistency between feature vectors with mixed signs and those with all positive or all negative values. Feature vectors with mixed signs therefore can have twice the range of feature vectors consisting of values with only one sign.

Table 17: Features Normalized by Maximum Absolute Value

No. of Colors	Intensity Mean	Intensity Skew	No. of Lines	Line Orientation
0.97	0.41	-1.0	0.46	-1.0
0.79	1.0	0.44	1.0	0.0
1.0	0.70	-0.23	0.30	1.0

The second normalization technique [44] standardizes all values in a feature vector to values between zero and one. Although the technique does not preserve the sign of the values, the standardized values guarantee range consistency. Formally, the normalization technique is defined as

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

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. Table 18 shows the test features normalized with this technique.

Table 18: Features Normalized by Max and Min Values

No. of Colors	Intensity Mean	Intensity Skew	No. of Lines	Line Orientation
0.88	0.0	0.0	0.22	0.0
0.0	1.0	1.0	1.0	0.5
1.0	0.48	0.52	0.0	1.0

3.3.2 Feature Comparison

After scaling the features appropriately, the feature vectors must be compared to determine the relative nearness of two images. The literature includes a number of distance metrics including City Block, Euclidean, Minkowski, and Mahalanobis [44, 131]. Unless otherwise stated, the study used the Euclidean distance metric because of its ease of implementation and its general utility. Although other distance measures may increase classification accuracy, the detailed analysis of distance measures is beyond the scope of this study.

There are special cases where the Euclidean distance is not only an inappropriate distance metric but an inaccurate one as well. Researchers have shown that the Euclidean distance metric is inaccurate when comparing ordinal histograms like saturation histograms and modulo histograms such as those representing hue [19]. Researchers have devised accurate methods of comparing histograms to account for the specific properties of ordinal and modulo data.

The hue histograms discussed above introduce another important distance measure: the distance between two HSV values. The Euclidean distance between two HSV values is inappropriate because it leads to inconsistencies due to the circular nature of the hue measurement. For example, when comparing hue values of 0.9 and 0.1, the desired difference is 0.2 but the Euclidean distance returns 0.8. Another approach to comparing HSV values uses the polar coordinate system to calculate the difference. The method for HSV difference consists of the following steps: convert the hue values to radians, use the hue and saturation pairs to calculate the distance between the points using the law of cosines, and finally calculate the Euclidean distance of the hue/saturation distance and the value distance. Figure 24 demonstrates several examples of the hue saturation distance measure. The hue measurement is the angular measure of the circle (*theta*), and the saturation is the distance from the center (*rho*). For example, the distance between cyan (0.5, 1.0, 1.0) and red (0.0, 1.0, 1.0) is 2.0.

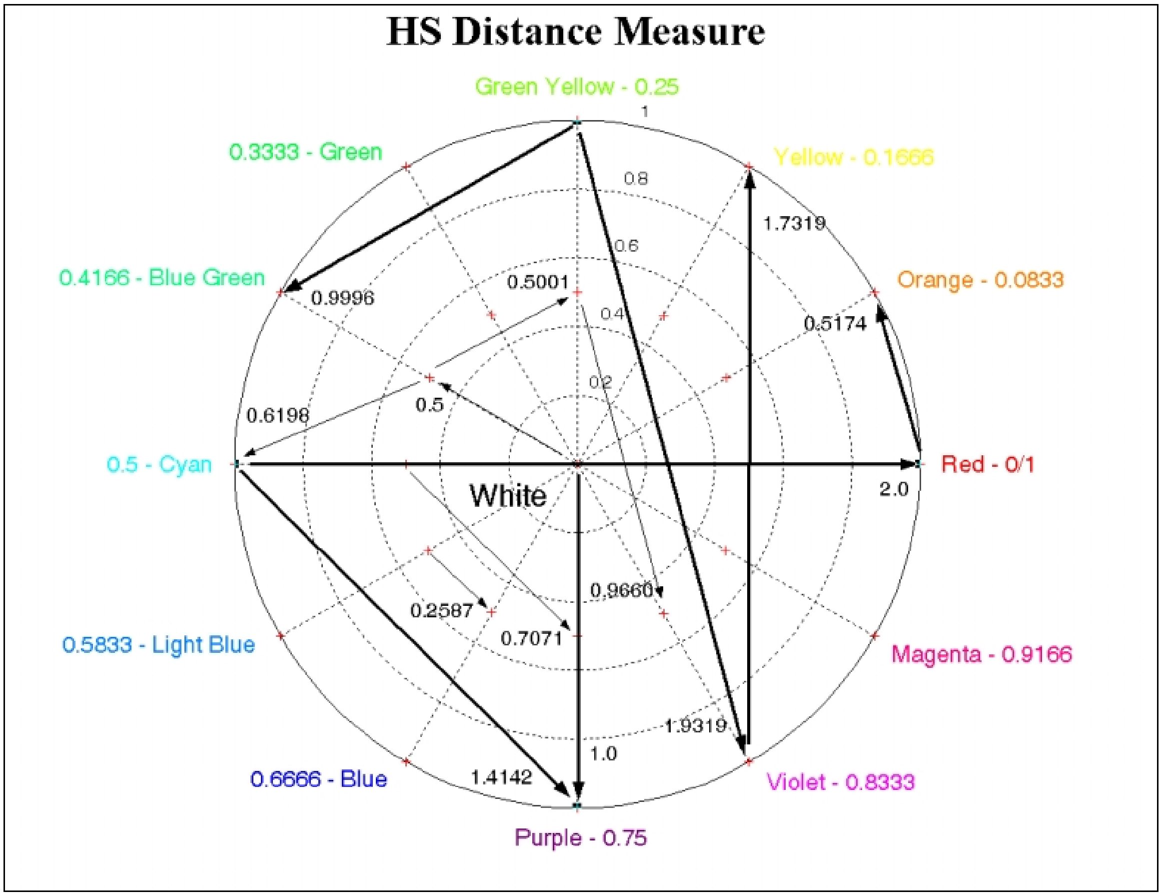


Figure 24: Hue-Saturation Distance Measure

In order to compare cyan and red, the following calculations are required. First, convert the hue channel of cyan (0.5, 1.0, 1.0) and red (0.0, 1.0, 1.0) to radians:

$$hrad = \frac{hue * 360}{180 * \pi}$$

resulting in cyan (3.14, 1.0, 1.0) and red (0.0, 1.0, 1.0). Second, the hue and saturation values are used to calculate the distance between points with the law of cosines:

$$hsdist = \sqrt{sat_1^2 + sat_2^2 - 2sat_1sat_2\cos(hue_2 - hue_1)}\ .$$

Figure 24 represents the distance between cyan and red with a black line. Third, the absolute value of the distance between the value channels was calculated:

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

Finally, the Euclidean distance of the *hsdist* and *vdist* components was calculated to find the distance between the two colors:

$$hsvdist = \sqrt{hsdist^2 + vdist^2} .$$

The overall distance between cyan and red is 2.0 because the value channel of both colors is 1.0 resulting in a *vdist* of 0.

The HSV distance metric discussed above was a fundamental component of the palette comparison technique associated with the palette description feature. It is often desirable to compare the entire palette of an image to that of another image. The distance between two palette descriptions is the slice-by-slice difference of the two palettes. The palette comparison method 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:

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

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 computed 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:

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

3.4 Feature Selection and Weighting

This study combined the features in order to compare them to similar features. The potential feature space is expansive and therefore requires a technique for winnowing the feature set when combining large numbers of features. The present study used three techniques to isolate desirable features from those that are not. First, the feature set should be semantically relevant: the features should translate to some concept in the domain. Second, the feature set should aim to reduce noise. Third, the feature set should reduce redundancy as much as possible. The feature selection and weighting algorithms were based on these three criteria.

Semantic relevance is the most difficult of the criteria to define. The concept has two major components: features must preserve visual properties of the image and the features must relate to the image and be identifiable as such. Features based on the discrete cosine transformation do not preserve the spatial arrangement of an image. Although these features have proven useful for painting classification tasks, it is rather difficult to envision how these coefficients relate to artistic style and its formal elements. Feature sets do not necessarily relate to specific images but rather relate to local features decoupled from their images of origin. The study rated features with one of three subjective labels: low, medium, or high relevance. Most of the features surveyed were of medium and high semantic relevance but the study considered some low relevance features for the sake of comparison.

Choosing semantically relevant features was largely a subjective and manual enterprise. The removal of noise and redundancy from the feature set relied on standard techniques from signal processing. Entropy measures the degree of disorder in a signal [43, 44]. The higher the entropy the more a signal appears as noise. The study considered each feature as a channel with a measurable degree of disorder. The features were assigned weights according to their relative entropies: the feature with the lowest entropy receives the greatest weight. The affect of this technique was to discount the importance of those features least likely to provide discriminating data.

After filtering the feature set for noisy features, the program checked the features for redundancy. It is possible for example, that two features provide the same type of discriminating power such as the standard deviation and the variance. This redundancy provides a *de facto* weighting for these features that may hurt the overall performance of classification. Therefore, the features were tested for mutual information [43] against other features in the dataset. Those features sharing the most information with others received lower weights than those that were relatively independent from other features.

It is important to say that other approaches to feature selection and weighting were possible. Heuristic approaches such as those offered by genetic algorithms or simulated annealing might serve to find the best balance of features. Other approaches include techniques based on principal component analysis and independent component analysis. Although these techniques may be considered in the future, the techniques based on information theory were effective in many applications and provided a decent basis for weighting and selecting features. The result of the feature selection and weighting component is a feature set that is semantically relevant and therefore suitable for a wide range of applications relevant to the domain, distant from noise, and largely free of redundancy.

3.5 Conclusion

The feature review presented in this study evaluated features based on performance, classification accuracy, information theory, and semantic relevance. The review revealed a preference for texture features that tended to downplay the potential role of color features. When examining additional color features, the survey demonstrated that preserving frequency and spatial information in the color channels does not necessarily improve classification accuracy. The proposed palette description feature and its accompanying palette comparison method proved to be as effective as similar color features with significantly less storage overhead. The feature survey was a necessary pre-study for the material related to analysis and evaluation in Chapter 4. The features discussed in this chapter served as the raw material for the analytical and machine intelligence techniques discussed in the next chapter.

Chapter 4

Classification, Visualization, and Evaluation of Artistic Style

4.1 Introduction

The feature study of Chapter 3 supplies the necessary raw data for the advanced analysis techniques of this chapter: classification, visualization, and evaluation. Researchers have treated the classification of artistic style as outlined in Chapter 2. The goal of the present discussion is to outline classification techniques with broad applicability: k-nearest neighbor and an interactive approach. Despite the appeal of applications that focus on classification, visualization techniques often provide additional analytical capabilities for researchers interested in the structure of data. This chapter explores three useful approaches to visualizing artistic style: hierarchical clustering, self-organizing maps, and multidimensional scaling. The evaluation of results concerns all researchers and the chapter concludes with a discussion of how to interpret the classifications and visualizations obtained.

4.2 Classification

4.2.1 k-nearest neighbor

The k-nearest neighbor algorithm is a well-known supervised classification technique [43]. The algorithm classifies test instances by assuming the label of the most frequently occurring neighbor of k training samples. After examining the k closest training samples, the test sample received the label with the most votes. The distance between samples is calculated by some vector distance measure such as the Euclidean distance. The critical decision in the implementation of the k nearest neighbor algorithm is choosing or finding the best window size (k). The standard technique for this type of optimization is ten-fold or leave-one-out cross validation [43]. Although this technique achieves high degrees of accuracy in studies, the broad range of testing conducted in this study precludes its use in this context. Instead the tests were conducted with preset k values (1, 5, 13, 54) appropriate for the given class size.

Using the k-nearest neighbor algorithm described above, the study conducted a number of tests against the test databases discussed in Chapter 5. First, the study evaluated each feature independently to gauge its ability to classify style. Second, the study tested the features from each of the four feature classes discussed in Chapter 3 as a group using the following weighting techniques: unweighted, entropy-weighted, independence-weighted, and both entropy- and independence-weighted. Third, the study combined and tested the overall best of breed features from each group together using the feature selection techniques described previously. In addition to the percent correct and semantic relevance, the noise and independence characteristics of the test sets determined the best features.

4.2.2 Interactive

The k-nearest neighbor testing described above was repeated using an application-oriented classification scheme. The interactive technique was a modified version of k-nearest neighbor where the query result comprised the ten closest images as one might expect an image indexing and retrieval system to behave. If the query returned at least one image from the appropriate class, the application classified the result as a success. The interactive technique was developed to support an early prototype of a simple fine-art painting classification system. Figure 25 displays the result of a query using the interactive technique. The interactive approach to classification offers two methods of gauging

Figure 25: Interactive Query Result

which artist painted a test image. First, a user could deduce the correct artist by noting the number of paintings returned per painter. The more paintings returned in a query by a particular artist the greater the probability that that artist is the painter of the test image. Second, the system arranged the paintings in rank order with the closest painting in the upper left position and the farthest painting in the lower right. In the example in Figure

25, a user would deduce correctly that Turner painted the test image because the result set includes three of his paintings holding ranks one, two, and six in the result set.

Table 19: Supervised Learning Test Summary

Test	Classification Method	Weighting Method	K Window Sizes
Individual Feature Tests	k-nearest neighbor	unweighted	1,5,13,54
Individual Feature Tests	Interactive	unweighted	10
Feature Class Tests	k-nearest neighbor	unweighted,entropy,mutual information, entropy and mutual information	1,13
Integrated Feature Tests	k-nearest neighbor	unweighted, entropy mean	1,8,13,21

Table 19 summarizes the supervised learning tests run for the feature evaluations and integrated feature tests. Chapter 5 lists the full results for the supervised learning tests.

4.3 Visualization

4.3.1 Unsupervised Learning

The k-nearest neighbor and interactive techniques described above are examples of supervised learning techniques [43]. Supervised learning techniques require the division of datasets into training, testing, and validation sets. These techniques as applied to painting classification produce accurate classification results similar to the forensic systems discussed in Chapter 2. Although the approach is useful and effective for smaller targeted datasets, the approach does not easily scale to larger databases comprising a greater number of styles. Moreover, often researchers do not desire classification but rather information concerning the relationships of styles to other styles.

Unsupervised learning approaches and clustering techniques provide a different basis for classifying artistic style. First, unsupervised techniques do not require the separation of datasets into training, testing, and validation subsets. Second, clustering techniques often relate to visualization methods appropriate to presenting the arrangement of complex data. The visualization techniques offered by clustering approaches provide a convenient basis for analyzing style and the relationships between styles in ways not possible with supervised techniques geared toward classification. Third, most unsupervised techniques are also dimension reduction techniques suiting themselves to working with larger datasets. Unsupervised learning techniques are important for a general approach to style classification because they provide mechanisms for analyzing and visualizing the complex relationships that exist among painting styles.

4.3.2 Hierarchical Clustering

Hierarchical clustering provides information concerning clusters and sub clusters 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 [43, 44, 137]. 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 26 depicts a style dendrogram of Impressionist and Post-Impressionist painters.

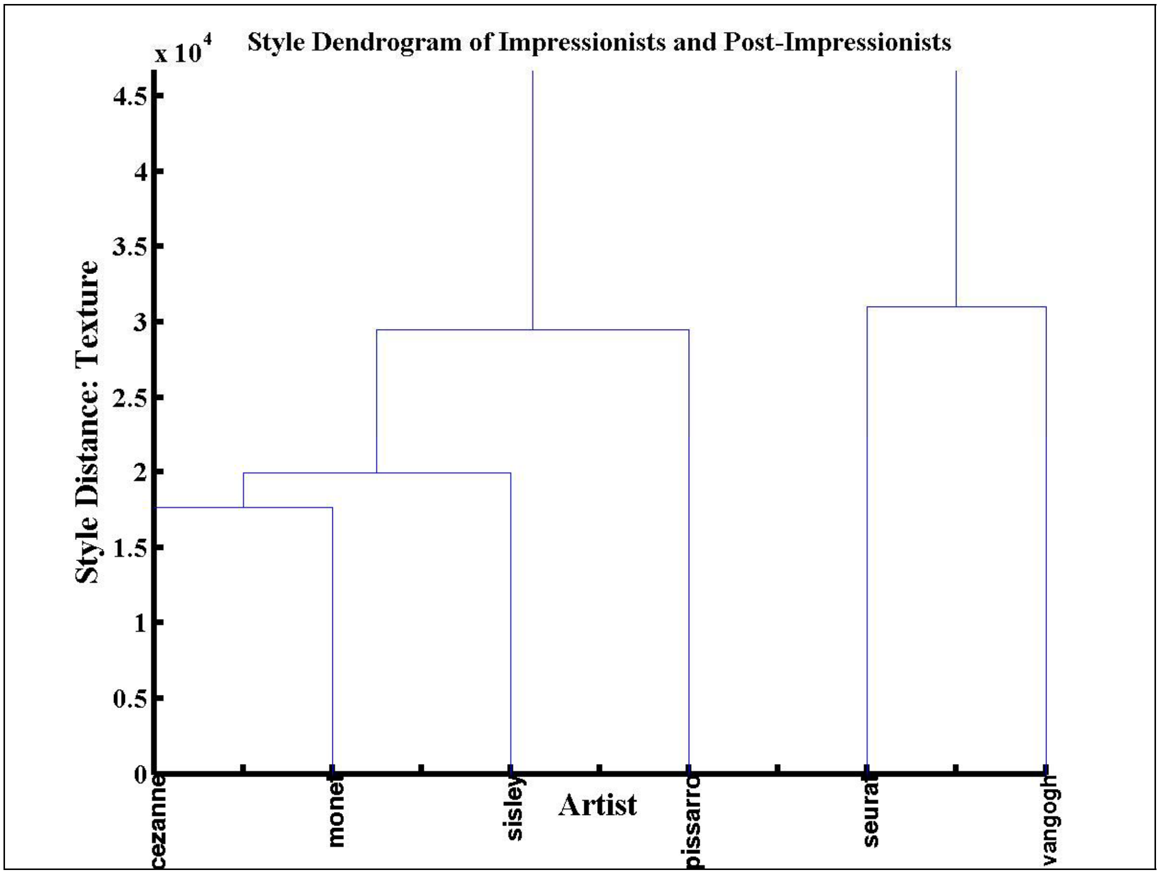


Figure 26: Hierarchical Cluster of Impressionist and Post-Impressionist Paintings

The clusters depicted in the dendrogram in Figure 26 were calculated in the following manner. The program implemented for this example extracted texture features from the images in the test database of Impressionist and Post-Impressionist painters aggregating these values by painter. A difference matrix of Euclidean distances was calculated as input to an agglomerative or bottom-up hierarchical clustering algorithm based on the farthest neighbor or complete-linkage algorithm [43]. The complete-linkage algorithm determines cluster distance by measuring the most distant nodes in two clusters. Formally, the complete-linkage algorithm [43] 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. According to the features measured, fractals, fast Fourier points, and intensity mean, Seurat and Van Gogh, both Post-Impressionists, are separated from the Impressionist painters and Cezanne.

4.3.3 Self-Organizing Maps

Although agglomerative clustering provides opportunities for organizing styles in a hierarchical way based on distance metrics, other approaches offer a greater range of analytical capabilities. Self-organizing maps [43, 93, 118] also known as, self-organizing feature maps, topologically ordered maps, or Kohonen self-organizing feature maps are one such unsupervised technique. Self-organizing maps transform all points in the feature space to points in a target space preserving the relative distances and proximities between instances as much as possible. The appeal of self-organizing maps derives from its advanced visualization capabilities and analytical techniques. Figure 27 displays a basic self-organizing map for the Impressionist and Post-Impressionist database considered in previous examples.

The basic self-organizing map represents clusters of each painting labeled by its painter. Every basic self-organizing map specifies characteristics describing its structure. The topology of a self-organizing map may be hexagonal as in Figure 27, a grid, or random. The number of nodes in the map is also configurable; the example in Figure 27 is a four by four configuration. In addition to these characteristics, self-organizing maps, as a type of neural network, specify other characteristics common to many learning algorithms including the number of epochs, initialization functions, and training algorithm. The self-organizing map in Figure 27 represents the results of a 5000 epoch training duration with a random initialization of map nodes. The self-organizing map was trained with the Levenberg-Marquardt backpropagation training function. A visual inspection of the self-organizing map reveals a reasonably clustered map with several nodes clearly dominated by a single painter. By simply changing the labels one can analyze the clusters according to style class, Impressionist or Post-Impressionist, painter, or painting title. Figure 27 demonstrates significant style overlap in the top center nodes labeled 10 and 8 as these nodes contain just under one third of the entire database and at least one painting from each painter.

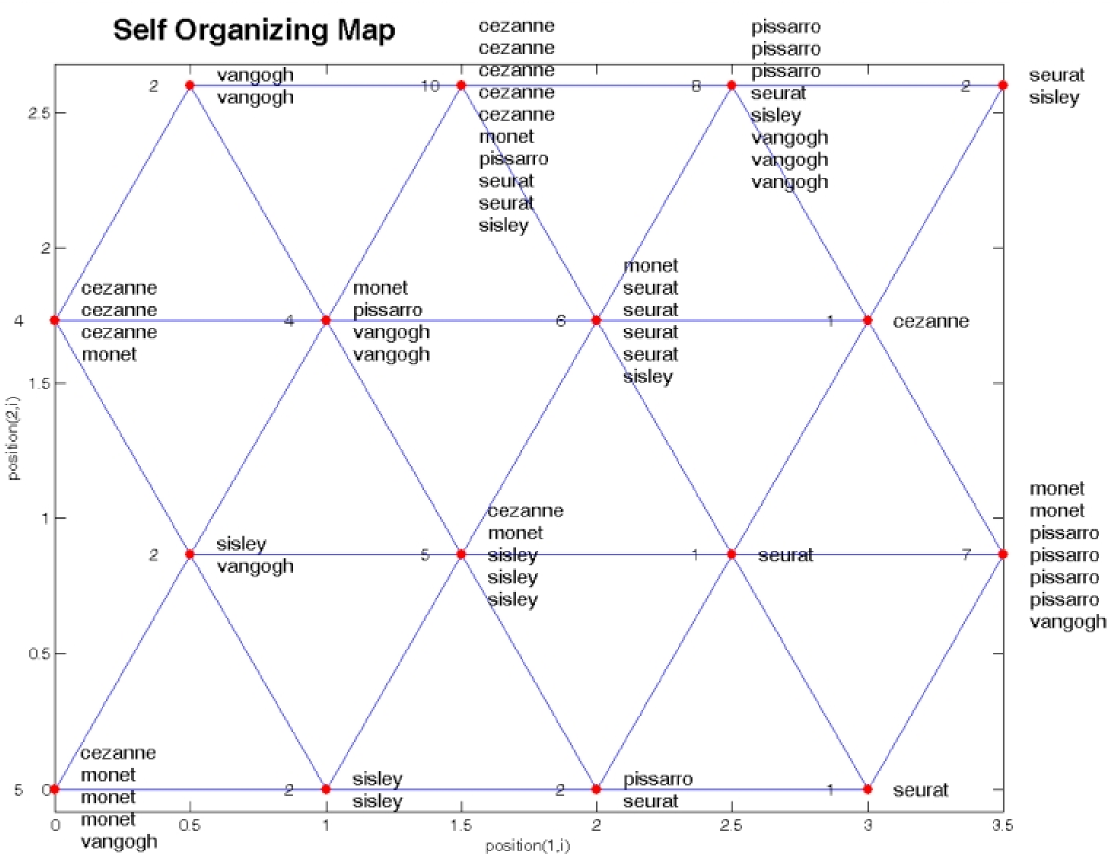


Figure 27: Self-Organizing Map

In addition to clustering samples of paintings, the basic self-organizing map organizes feature aggregates of a painter's style. Figure 28 shows a basic self-organizing map of two by two nodes arranged on a hexagonal sheet according to color and texture features. In this example, Cezanne, Sisley, and Van Gogh cluster at one node opposite Pissarro denoting that his work is farthest from the work of those at the cluster of three. Despite the potential of the basic self-organizing map, there are two questions worth considering when evaluating the quality of a map [118]. First, what features contribute to the organization of the map? Second, to what degree is the map organized and how do we recognize this degree of organization?

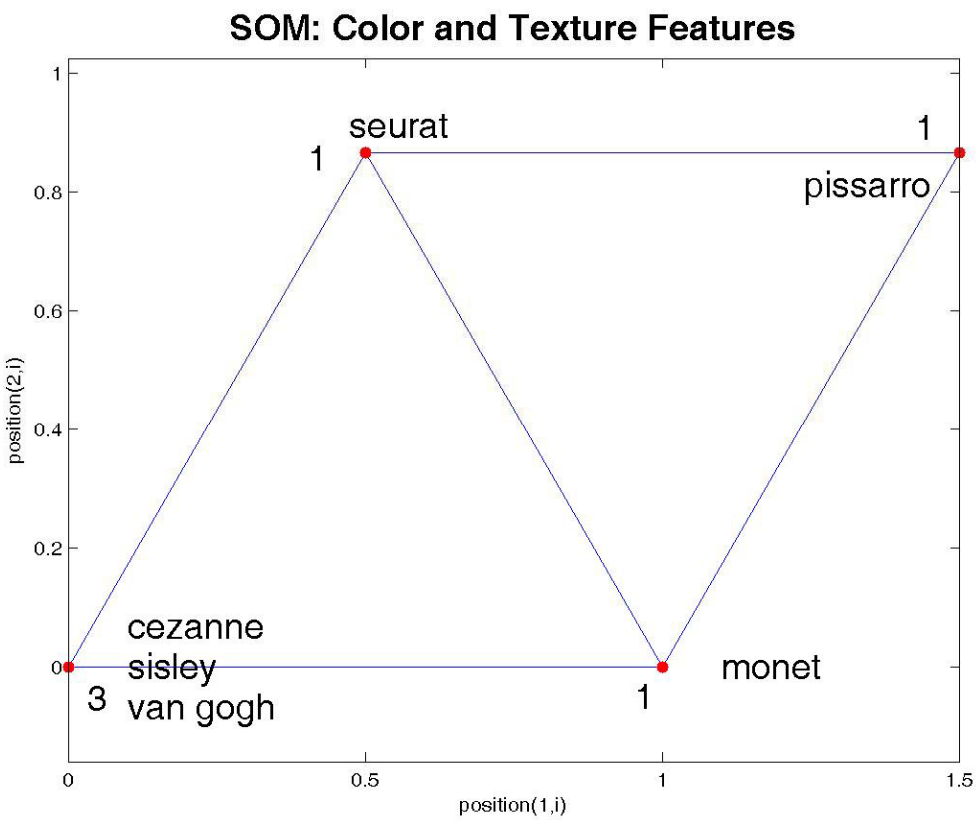


Figure 28: Self-Organizing Map of Aggregate Values

Advanced self-organizing map techniques answer both of these questions. The visualizations above suffer because they do not offer opportunities to identify cluster boundaries [93]. The unified distance matrix representation remedies this by illustrating the clusters of codebook vectors in the self-organizing map. This visualization technique shows the average distance between codebook vectors or neurons in a grayscale image. In Figure 29, light shades denote small average distances and dark shades identify large average distances. In essence, the dark nodes form boundaries between clusters.

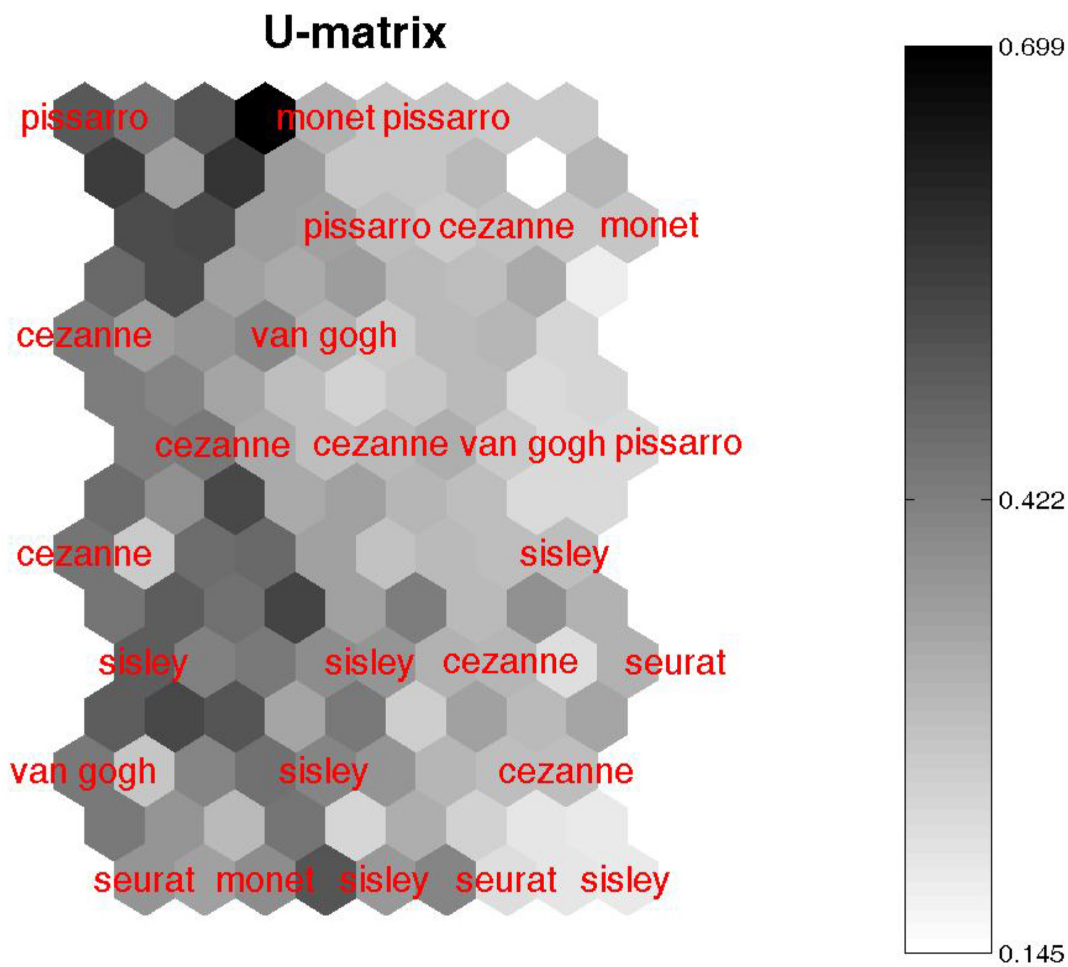


Figure 29: Unified Distance Matrix representation of Self-Organizing Map

The unified distance matrix visualization represents the average distance between codebook vectors or neurons considering all available features, which in this case included forty-three light features discussed in Chapter 3. In order to identify which features contribute to the clustering, it is possible to construct unified distance matrix representations for each feature as in Figure 30. In this example, eight of the forty-three light features considered are shown with the data labels mapped onto the representations. Each feature provides a different visualization of the data with the Peak Count, Global Standard Deviation, and the Global Kurtosis showing the most similarity to the unified distance matrix. By examining the clusters produced by individual features, we can see that little similarity or consistency exists in the clusters generated by these light features on the Impressionist and Post-Impressionist dataset.

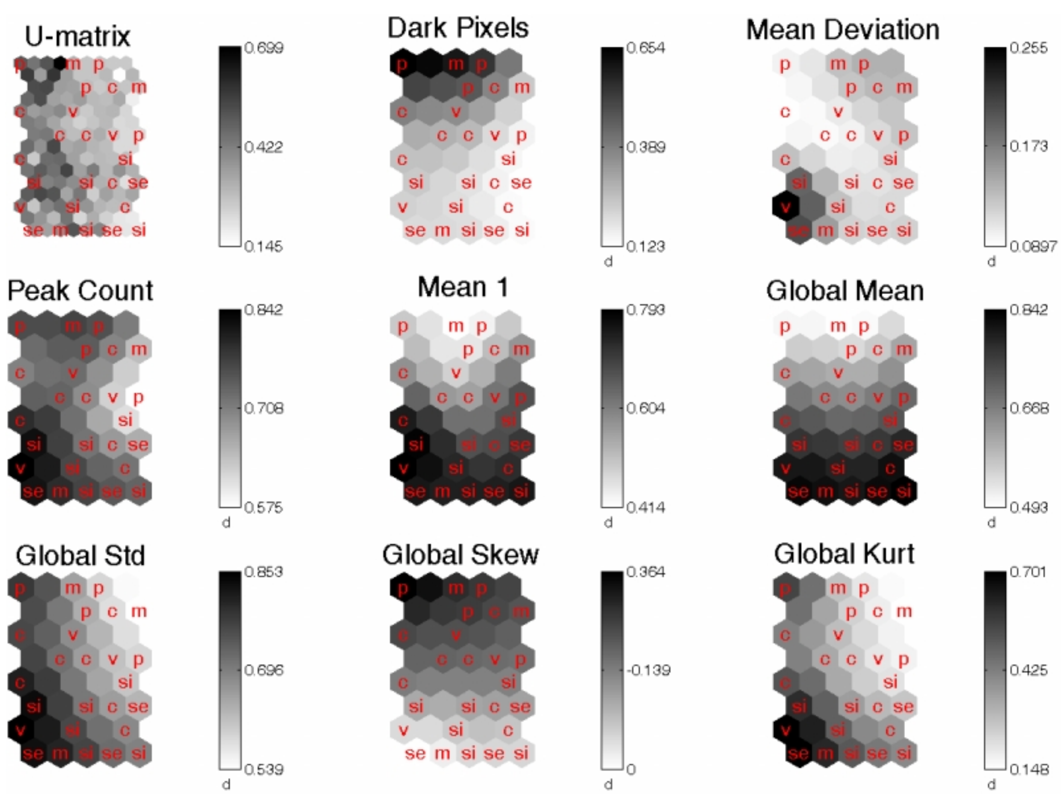


Figure 30: Unified Distance Matrix with Select Feature Components

The general impression offered by an analysis of individual features suggests that perhaps the light features in question are a poor basis for clustering this data. In order to gauge this question with more depth, we must consider the measurement of error found in the map. The quantization error or average unit of disorder is the average distance between each input data vector and its best matching unit or codebook vector. For the U-matrix in question the average unit of disorder is rather high (0.8395) confirming our intuited observation that this feature set does not lend itself well to clustering the work of these painters. Figure 31 displays the average unit of disorder for the unified distance matrix considered throughout this example.

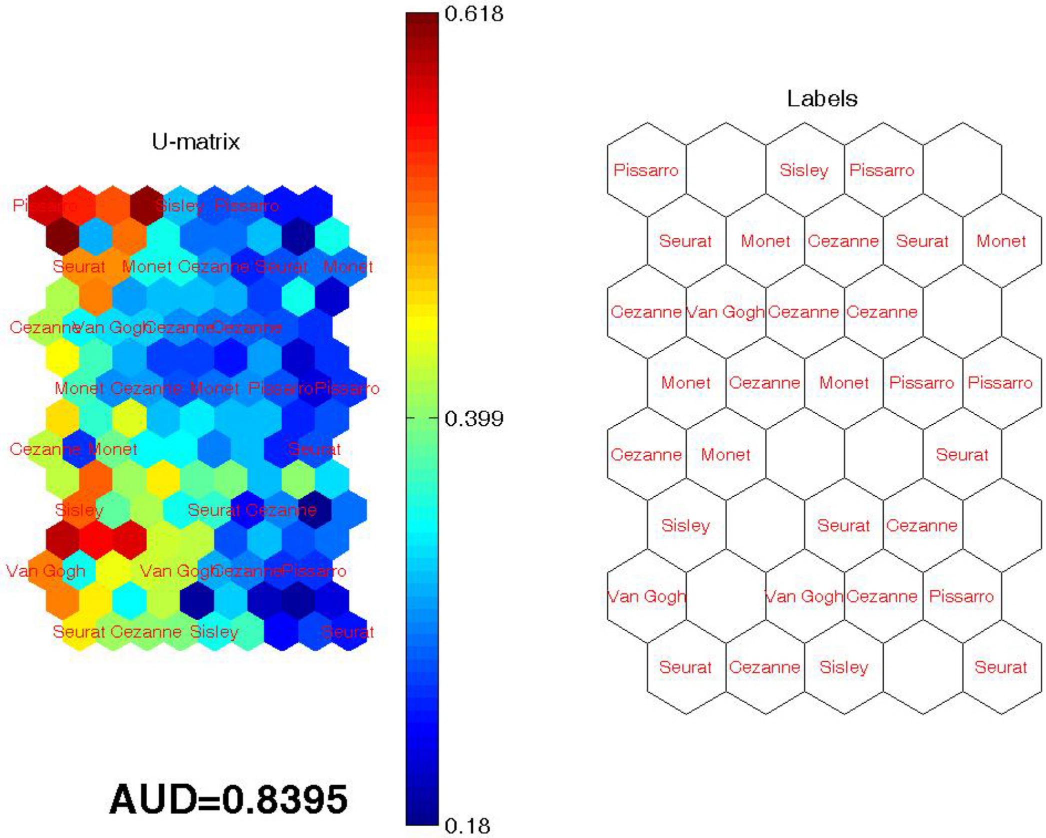


Figure 31: Unified Distance Matrix - Label Representation of Self-Organizing Map

Further evidence of the poor quality of this self-organizing map is gathered from the examination of the average unit of disorder after each epoch. Figure 32 displays two graphs tracking the quantization error. The top graph shows that the quantization error decreases slowly at first and then ever more quickly as the epochs progress. The pattern displayed is exactly the opposite of what should be happening: if the self-organizing map quality were better, there would be a period of rapid decrease in the early epochs when large global restructuring takes place and gradual refinement in the later epochs. The bottom graph displays the best matching units in red plotted against the input data vectors after the training period has completed. There are a number of data vectors quite distant from the best matching units.

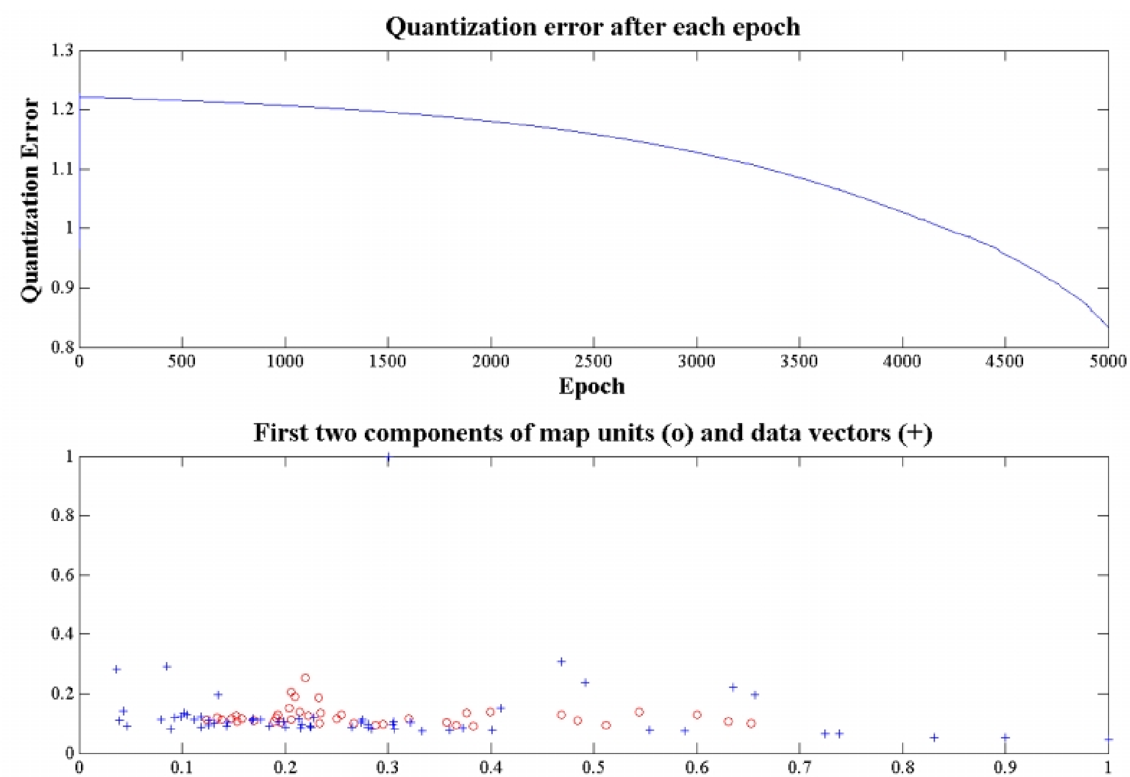


Figure 32: Self-Organizing Maps Assessment with Quantization Error

In order to improve the quality of the self-organizing maps, the algorithm must be tuned and a better basis for comparison (better features) selected. The more advanced implementations of self-organizing maps provide additional tunable parameters including additional neighborhood functions, initial neighborhood radius settings, final neighborhood radius settings, and additional topology options. The neighborhood function determines how codebook vectors are weighted. The implementation for the example in this study used the Gaussian neighborhood function. The initial and final neighborhood radius parameters determine the distances considered when applying the neighborhood function at both the beginning and the end of the training sequence respectively. The shape used in this example was a sheet but cylinder and toroid (donut) shapes are available as well. The self-organizing map and its representations provide opportunities to analyze and assess the role of individual features in style relationships.

4.3.4 Multidimensional Scaling

Although self-organizing maps provide broad analytical powers for analyzing features and clusters of paintings, they often obscure 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 [43, 44] techniques serve rather well. Multidimensional scaling 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 33 shows a multidimensional scaling analysis of light features derived from ten paintings of Cezanne. Each circle in the plot represents a painting in the database. By averaging the values of the samples, the study constructs 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 an estimate of stylistic variance. Figure 33 displays the paintings that fall within the style variance with green circles and those outside of the style variance with blue circles.

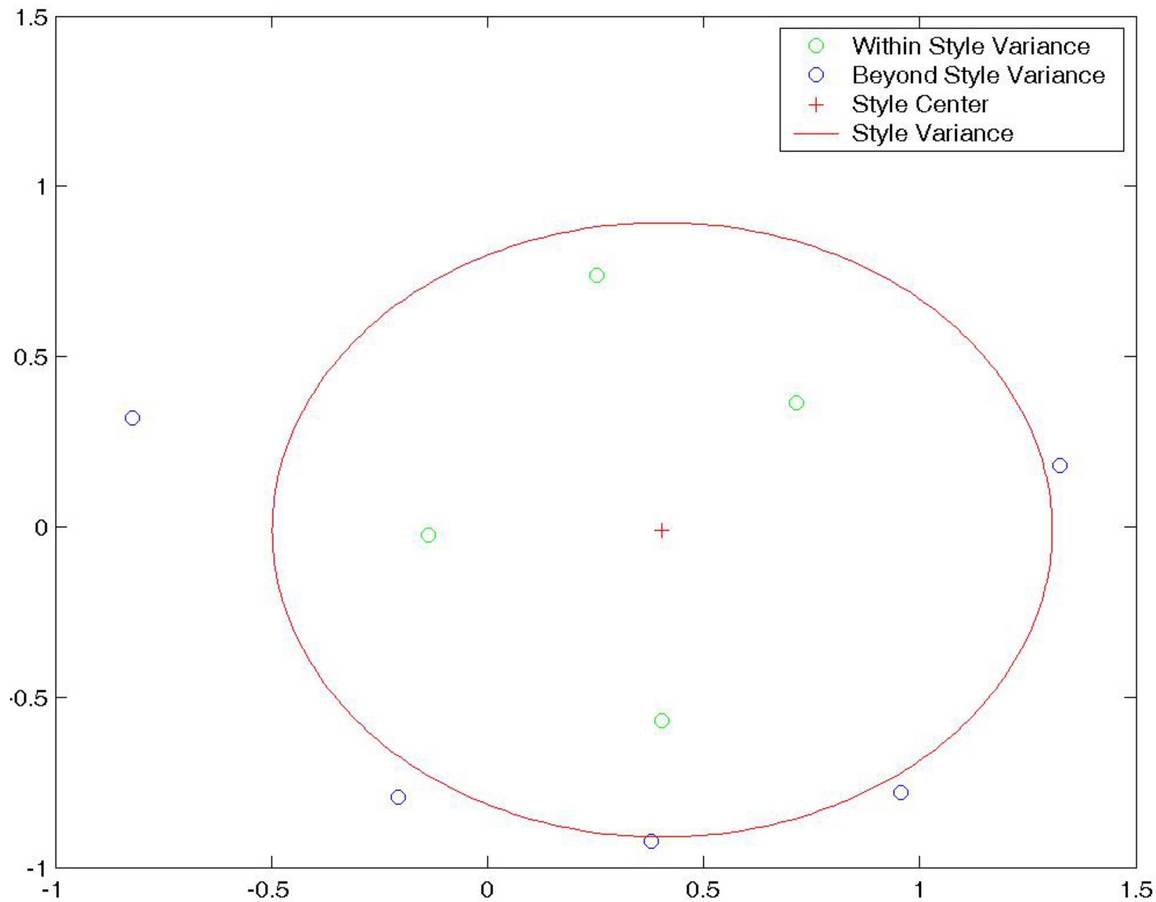


Figure 33: Multidimensional Scaling Analysis of Cezanne's Paintings

The style center and variance constitute a method of characterizing the style of an artist with respect to particular features. These style descriptors provide an entire range of analytical opportunities. For example, Figure 34 displays a list of the paintings plotted in Figure 33 ordered by their proximity to the style center. The first painting in this list therefore represents the closest to the theoretical stylistic center of Cezanne's work with respect to the light features measured.

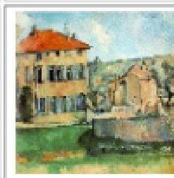
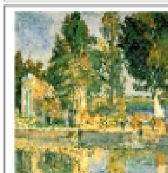
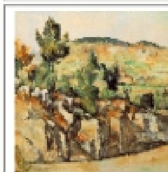
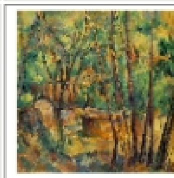
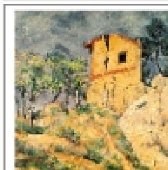
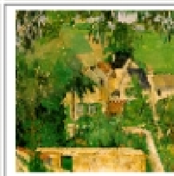
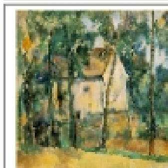
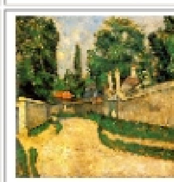
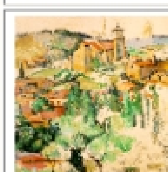
Painting Information	Painting Image	Painting Information	Painting Image
1 Painting: house-and-farm-at-jas-de-bouffan.jpg Distance from Style Center: 0.4839		2 Painting: jas-de-buffan-the-pool.jpg Distance from Style Center: 0.54223	
3 Painting: gardanne.jpg Distance from Style Center: 0.55894		4 Painting: 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 34: Paintings sorted by Distance from Style Center

The utility of multidimensional scaling extends to broader class considerations as well. Figure 35 plots the style centers of the six painters considered throughout this chapter against that of the theoretical style center for the entire class. With respect to the light features considered, Cezanne's style is the closest to the theoretical center of the entire group. As evidence of this, Cezanne's style center is closest to the overall style center and more of Cezanne's paintings are inside the overall style variance than the paintings of any other painter. Another interesting observation is that it is possible to draw a line from the Sisley style center to the Monet style center that divides Post-Impressionist painters from Impressionist painters albeit with several Post-Impressionists close to the demarcation.

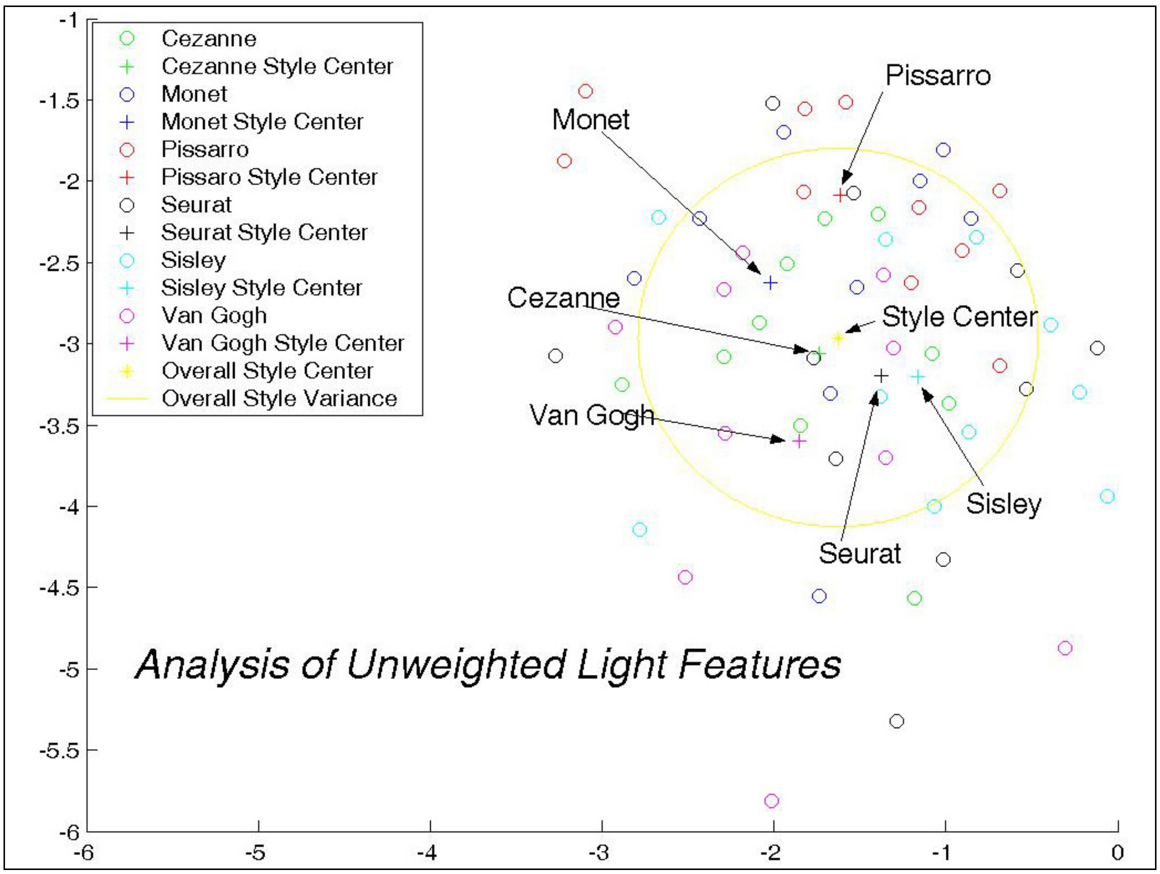


Figure 35: Multidimensional Scaling Analysis of Impressionist and Post-Impressionist Paintings

The multidimensional scaling approach to style classification allows for the comparison of theoretical style centers of painters and groups of painters. While this approach has important analytical significance in its own right, it also provides a technique for evaluating the quality of classifications and perhaps of the class definitions themselves. As will be considered in the next section, the style variance is one predictor of the classifiability of certain datasets.

4.4 Evaluation

4.4.1 Introduction

An interesting finding of this study is the wide range of success and failure in classification tasks. That is to say that the artwork of certain artists was considerably easier to classify than that of others. The study considered two possible explanations of this phenomenon: 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 Rembrandt is easier to classify because his style variance is smaller than that of other artists. Are classes with lower style variance easier to classify?

4.4.2 Data Quality

The nature of the data is a likely factor in classification accuracy. Several studies [60, 107] 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 image resolution measured in pixels, file size measured in bytes, and the ratio of bytes to pixels. Table 20 shows the data quality measurements and the accuracy of results for the test considered.

Table 20: Data Quality Measurements

Artist	Mean Pixels	Mean Bytes	Bytes per Pixel	Accuracy(%)
Cezanne	916,559	156,399	0.1706	100
Monet	729,664	179,350	0.2458	20
Pissarro	590,655	157,190	0.2661	0
Seurat	766,260	241,553	0.3152	60
Sisley	849,990	199,670	0.2349	20
Van Gogh	775,980	201,501	0.2623	0

The number of pixels proved to be the best predictor of classification accuracy of the data quality measures considered. Figure 36 plots the relationship between the average number of pixels in an image class against the accuracy of classification for that class. Figures 37 and 38 display similar graphs plotting the average bytes and bytes per pixel ratios of each class. Despite the relative success of this measurement, a few details of the data suggest that it is incomplete as an explanation of accuracy. For example, despite the fact that the images of Sisley are on average about 80,000 pixels (9%) larger than those of Seurat the system struggled to classify those images. Van Gogh and Seurat, on the other hand, have roughly equal (within 2% or 12,000 pixels) measurements and the system failed to classify a single painting of Van Gogh correctly.

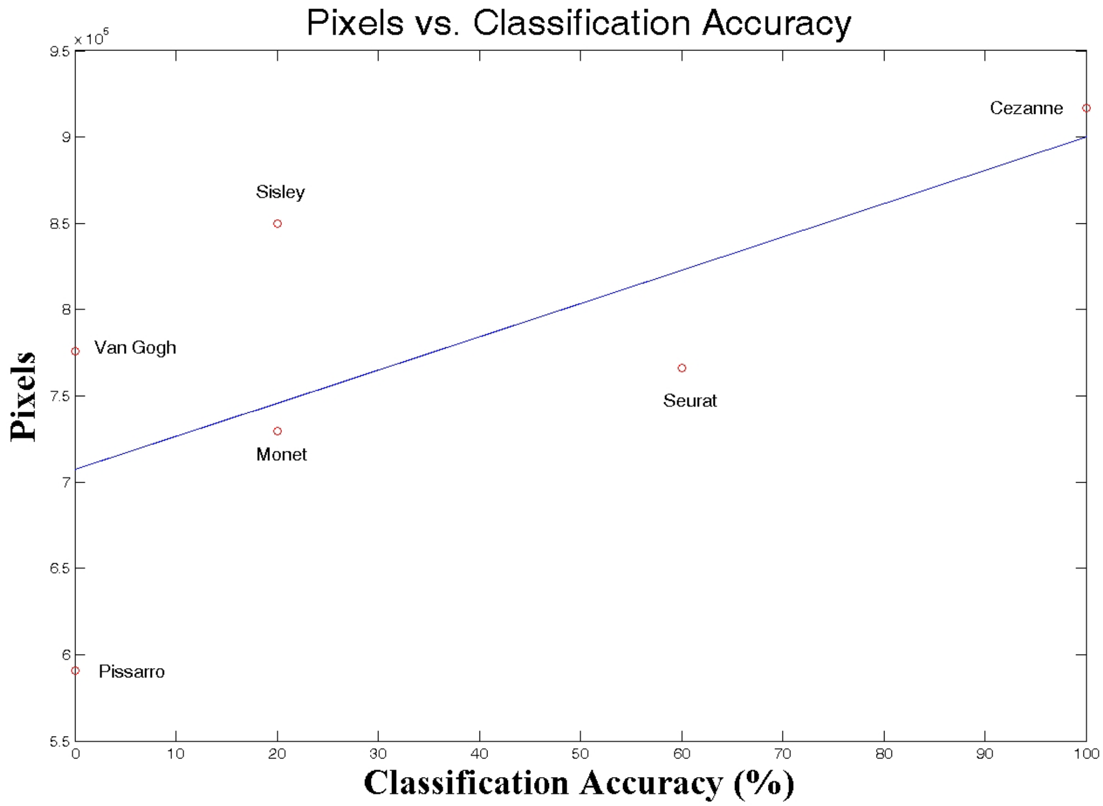


Figure 36: Pixels vs. Classification Accuracy

Neither bytes nor bytes per pixel provide a better explanation of the accuracy results for this test. The relationship of bytes to accuracy (Figure 37) is quite ineffective essentially cutting the data in two sets with no apparent relationship to accuracy. Although the bytes per pixel (Figure 38) measurement improved on bytes alone, it separates the two most successful classification results, Cezanne and Seurat, to a large degree. Therefore, despite these concerns, the data quality measured in pixels most likely holds some relationship to classification accuracy. Moreover, several aspects of the feature extraction and normalization phase, i.e. size normalization, suggest that there may be other predictors of classification accuracy.

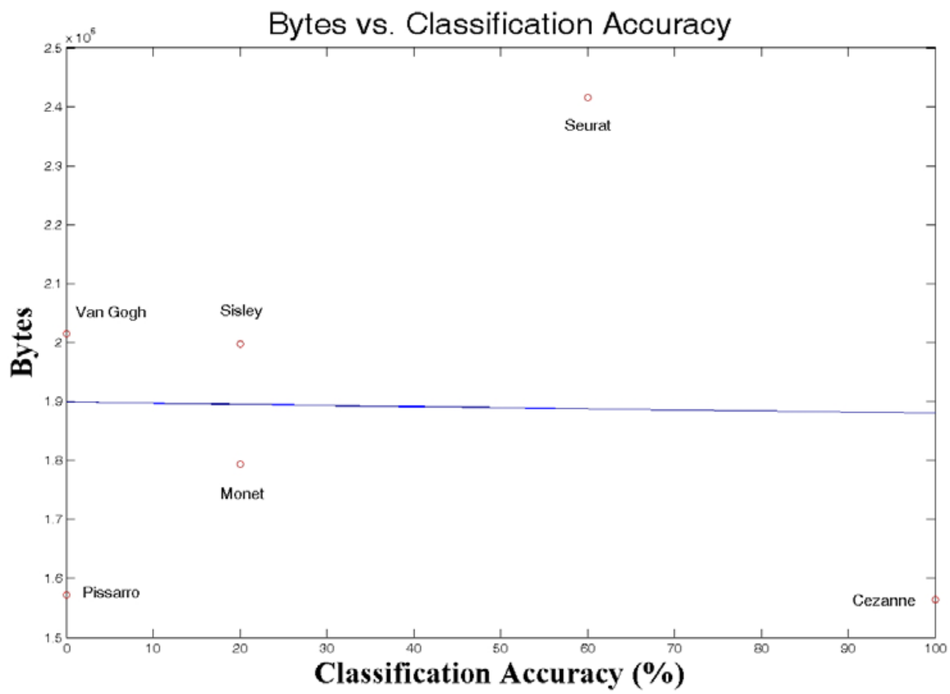


Figure 37: Bytes vs. Classification Accuracy

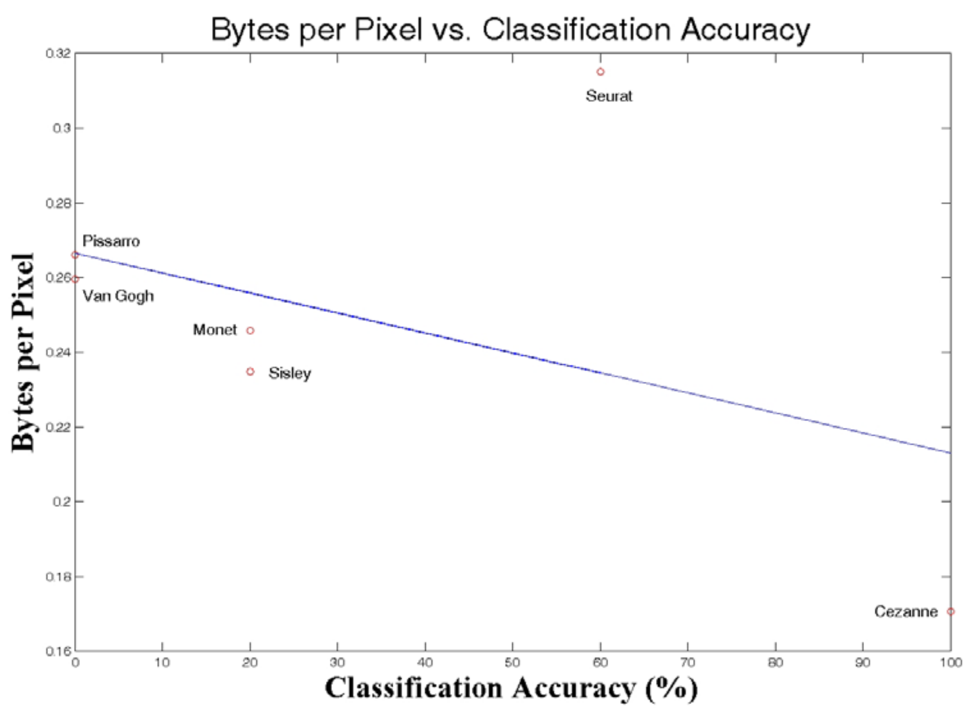


Figure 38: Bytes per Pixel vs. Classification Accuracy

4.4.3 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 style class including style variance and the distance between a class style center and the global style center. In this section, these metrics function as predictors of classification accuracy. Figure 39 shows the global style center and variance for the sixty samples in the Impressionist/Post-Impressioninst dataset detailed in Chapter 5. A yellow cross represents the global style center and a yellow ellipse represents the variance. The colored crosses depict the class style centers. Table 21 summarizes the class quality measurements for this example.

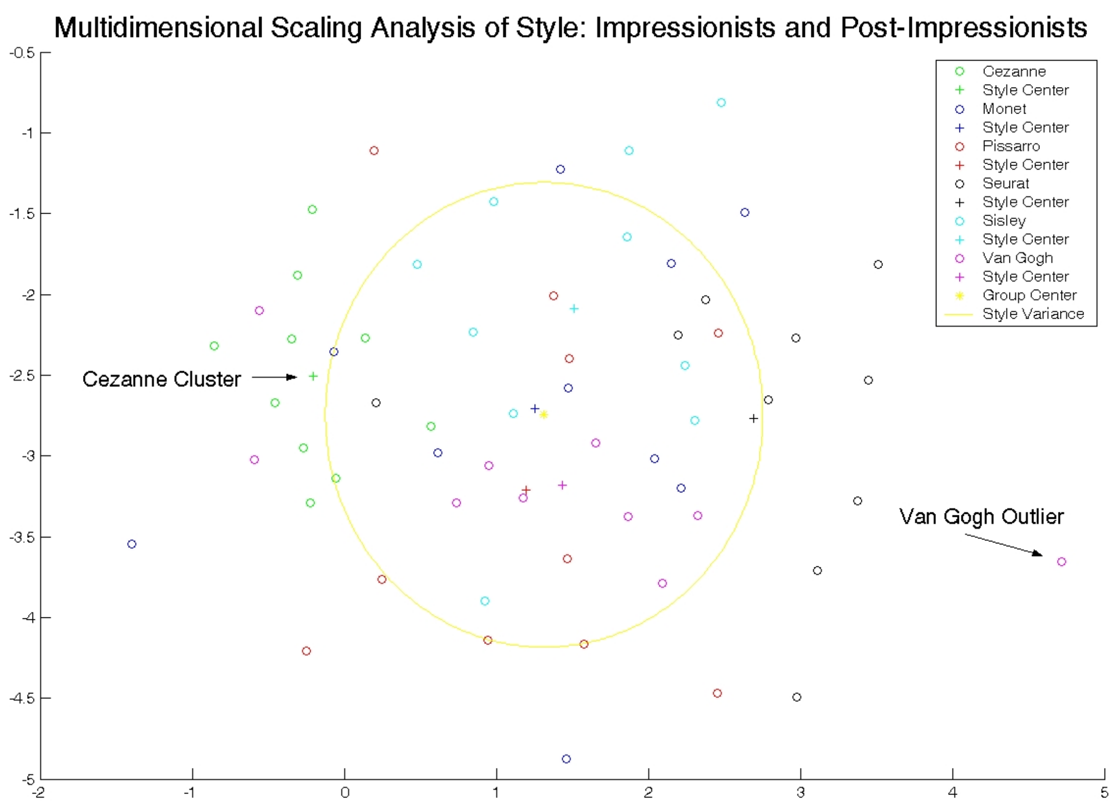


Figure 39: Multidimensional Scaling Analysis of Style

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 proposed in this study 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 center and global 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 depends 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 21: Class Quality Measurements

Artist	Style Variance	Distance from Global Style Center	Style Description Ratio	Accuracy (%)
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

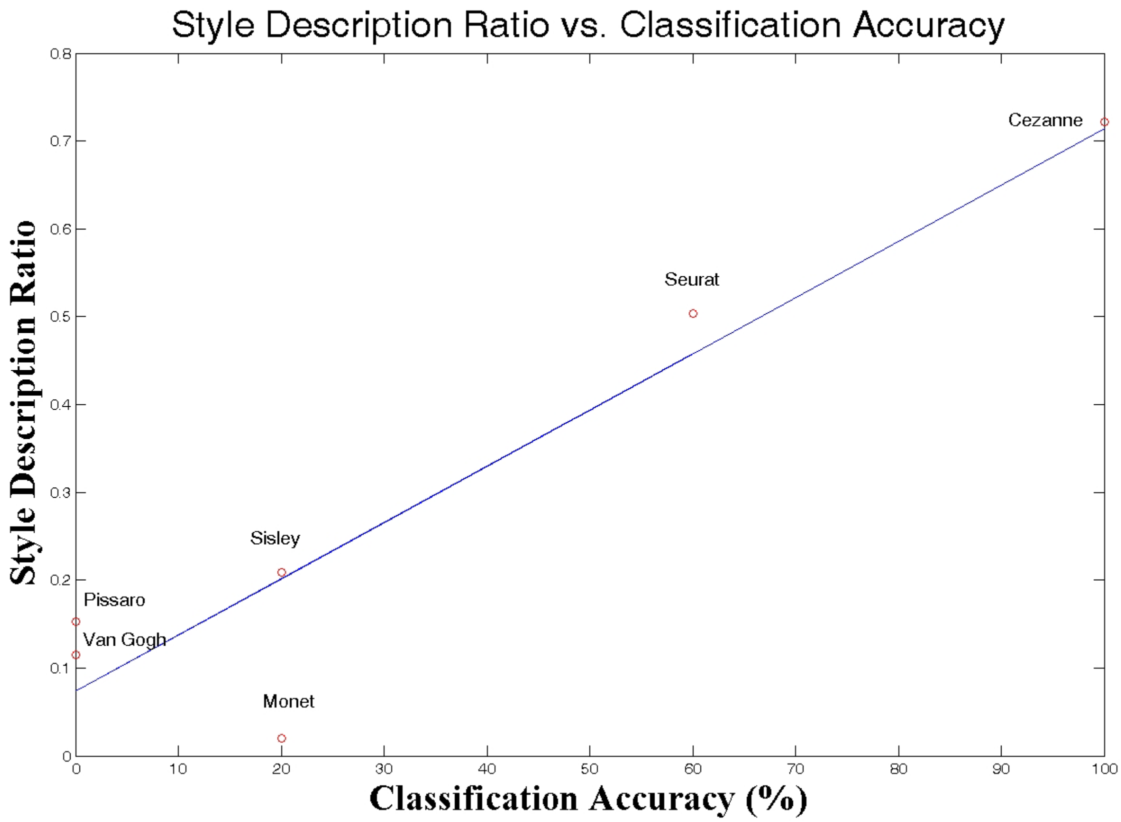


Figure 40: Style Description Ratio vs. Classification Accuracy

Figure 40 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 outlier in the data (Monet). The style description ratio is at least as effective as the pixel measurement in explaining the classification results presented.

4.4.4 Discussion

The evaluation technique discussed above has an important implication that deserves mention. In the test case examined in this chapter, the classes considered are fairly straightforward 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 period. For example, the introduction to this study mentioned that two reputable textbooks often categorized individual works and painters in different ways. The evaluation technique outlined above provides a basis for gauging the quality of these categories as well by defining a class variance and distance to a global style center. In effect, 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.

In particular, the other classification schemes discussed can offer additional insight into the class relationships by arranging the data in taxonomic formats. Consider the dendrogram of the aggregate test data in Figure 41. The graph reinforces many of the observations gleaned from the multidimensional scaling analysis of the same data. Monet’s style center is the closest to the global style center and Cezanne and Seurat are among the farthest apart. Another important aspect of the graph is the sub cluster comprising Cezanne and Van Gogh grouping two important Post-Impressionists together automatically. In fact, this visualization demonstrates that all three Post-Impressionists (Cezanne, Seurat, and Van Gogh) are roughly equidistant from the style center dominated by Monet and Pissarro. This type of analysis should be possible for aggregates of large groups of styles to identify and evaluate relationships among styles.

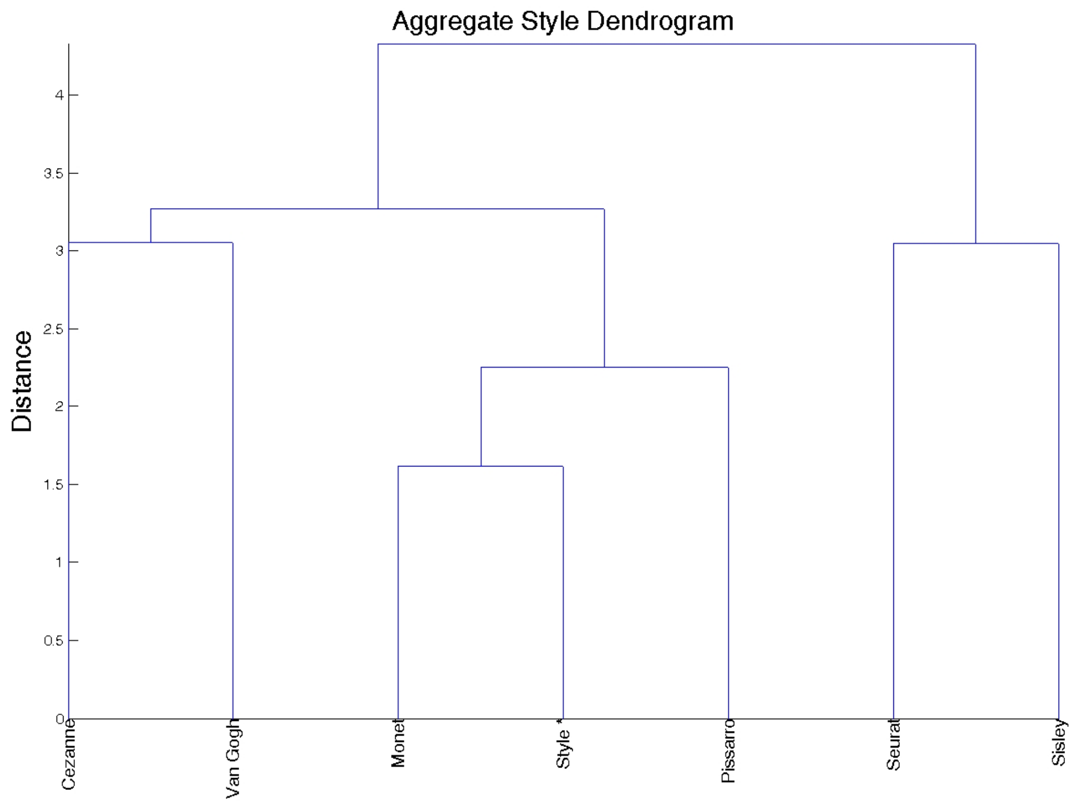


Figure 41: Aggregate Style Dendrogram

4.5 Conclusion

Classification accuracy has been the most important benchmark for computer science approaches to style classification. The focus on accurate classification assumes that problems of attribution are the only important questions related to style. A broader approach to style classification permits the analysis of the subtle relationships among styles. Unsupervised learning techniques provide the theoretical groundwork for complex style analysis including the visualization of style clusters, the construction of a taxonomic system of the formal elements of style, and the evaluation of classification results. These combined techniques form the basis for a general style classification system.

Chapter 5

Results

5.1 Introduction

The study conducted two types of tests run against two databases of paintings for each class of formal element: light, line, texture, and color. Feature tests identified the most effective features in a particular class with k-nearest neighbor and interactive tests. Integrated tests evaluated the features together to identify noise resistant features with little redundancy. In addition to these supervised learning tests, the study conducted unsupervised learning tests to visualize and evaluate the classification results. The chapter describes the data sources used for testing and presents the results in tabular form. Each section presents the result set with discussions of observations and concerns and summarizes the primary findings. The study conducted the tests on a Dell Latitude D600 with a 1700 MHz Pentium Processor and 1 GB of RAM. The study implemented the algorithms using Matlab 6.5.

5.2 Image Databases

5.2.1 Artist Database

The artist database stores the artwork of 52 painters from the Web Museum database published online (www.ibiblio.com/wm/paint) [127]. The database organizes JPEG images representing a broad range of painting styles from Medieval to Modern. The dataset comprised a training set and a testing set and served primarily for feature tests with k-nearest neighbor and interactive tests. Table 22 breaks down the training set of the artist database by artist. For each artist, the table reports the number of images, the vertical and horizontal resolution, and the mean file size. The final row in the table displays the total number of classes, the total number of images, the mean vertical and horizontal resolution, and the mean file size of the entire training set.

Table 22: Artist Database Description: Training Set

Class	No. of Images	Vertical Resolution	Horizontal Resolution	Mean File Size
Aertsen	9	849	919	171529
Altdorfer	10	725	674	95922
Ast	9	485	684	65099
Avercamp	10	623	959	125360
Bacon	11	1074	790	158827
Baldung	10	874	519	75161
Bassano	10	717	762	103849
Bosch	10	1164	647	191289
Bouguereau	11	561	331	40330
Bruegel	11	777	1021	195578
Caravaggio	10	823	790	89181
Cassatt	10	685	577	70128
Cezanne	10	819	994	158966
Chase	8	522	418	24130

Davis	10	906	961	135452
Degas	10	840	844	115021
Delacroix	10	733	809	125002
Durer	10	927	785	133435
Gauguin	10	807	857	128391
Gogh, van	10	801	971	183837
Greco	10	1046	707	162750
Gris	10	1026	757	143149
Hockney	10	869	995	143519
Hopper	10	803	1024	147145
Ingres	10	825	610	90868
Kandinsky	10	700	1035	150318
Kiefer	10	785	1097	282543
Klimt	10	774	816	105799
Malevich	10	952	715	84580
Manet	10	623	665	73382
Matisse	10	883	794	138214
Memling	10	631	563	66870
Modigliani	10	915	593	118500
Monet	10	833	811	166409
Morisot	9	583	601	66377
Munch	10	903	853	153951

Piero	10	950	882	198015
Pissarro	10	646	799	124991
Pollock	10	953	937	230366
Redon	10	968	884	202430
Rembrandt	10	929	783	106824
Renoir	9	696	527	67596
Rubens	10	662	685	84625
Seurat	9	704	790	108576
Sisley	10	813	956	177933
Toulouse-Lautrec	10	797	695	130843
Turner	9	685	851	94135
Velazquez	10	916	826	126063
Vermeer	10	985	850	128424
Watteau	9	667	695	76443
Weyden	10	884	698	123862
Whistler	9	954	660	67208
Total: 52 classes	*513*	*812*	*780*	*126553*

Table 23 summarizes the testing set of the artist database. For each artist, the table reports the number of images, the vertical and horizontal resolution, and the mean file size. The final row in the table displays the total number of classes, the total number of images, the mean vertical and horizontal resolution, and the mean file size of the entire testing set.

Table 23: Artist Database Description: Testing Set

Class	No. of Images	Vertical Resolution	Horizontal Resolution	Mean File Size
Aertsen	9	796	889	136798
Altdorfer	4	684	506	81911
Ast	2	278	234	12793
Avercamp	4	874	1375	227890
Bacon	2	1084	776	109381
Baldung	3	601	493	72469
Bassano	2	879	969	144542
Bosch	3	1087	776	189442
Bouguereau	2	597	292	44006
Bruegel	4	727	1020	175736
Caravaggio	3	899	932	99757
Cassatt	6	675	529	62104
Cezanne	8	890	872	145832
Davis	3	1026	816	134712
Degas	4	669	491	35282
Delacroix	7	704	779	108217
Durer	5	1031	827	145360
Gauguin	5	895	783	108927
Gogh, van	6	899	860	180627
Greco, El	8	1048	727	153263

Gris	6	1040	834	155725
Hockney	3	885	870	97936
Hopper	8	770	1046	166285
Ingres	4	697	541	70672
Kandinsky	7	709	754	111369
Kiefer	1	1128	767	207797
Klimt	7	884	714	118040
Malevich	11	892	744	62684
Manet	7	824	771	89194
Matisse	3	743	551	111444
Memling	2	600	461	35577
Modigliani	6	778	697	86973
Monet	10	733	769	117556
Morisot	10	603	619	64269
Munch	2	1019	808	169363
Piero	7	850	918	185343
Pissarro	4	822	900	191551
Redon	6	1053	810	203097
Rembrandt	34	853	789	100678
Renoir	37	722	629	92502
Rubens	7	587	747	95006
Seurat	3	837	809	136804

Sisley	3	655	685	102231
Toulouse-Lautrec	5	910	637	139041
Turner	10	640	851	104818
Velazquez	8	1038	819	128990
Vermeer	6	1055	963	165157
Watteau	4	631	724	83139
Weyden	1	1092	766	185467
Whistler	7	851	644	80984
Total: 50 classes	*319*	*813*	*758*	*115101*

5.2.2 Impressionist/Post-Impressionist Database

The Impressionist/Post-Impressionist database reconstructs the test database used by Herik and Postma [60] in the most thorough feature review to date. The database served for feature evaluation and all supervised and unsupervised tests. The set was divided in half for all supervised training tests. Table 24 summarizes the Impressionist/Post-Impressionist data by artist. For each artist, the table reports the number of images, the vertical and horizontal resolution, and the mean file size. The final row in the table displays the total number of classes, the total number of images, the mean vertical and horizontal resolution, and the mean file size of the entire database.

Table 24: Impressionist/Post-Impressionist Database Description

Class	No. of Images	Vertical Resolution	Horizontal Resolution	Mean File Size
Cezanne	10	889	1031	156399
Monet	10	832	877	179350
Pissarro	10	699	845	157190
Seurat	10	810	946	241553
Sisley	10	870	977	199670
Van Gogh	10	810	958	201501
Total: 6	*60*	*818*	*939*	*189277*

5.3 Feature Evaluation

The feature evaluation rated features according to the following criteria: execution time, storage requirement, semantic relevance, interactive classification, and two k-nearest neighbor tests. The execution time measures the average time in seconds required to extract the feature from the image including size-related normalization. The storage requirement lists the number of doubles required to describe the feature. The semantic relevance of a feature describes the proximity of a feature to its analogue in formal art-historical terms. For example, many color features exhibit a high semantic relevance in that HSV color metrics closely correspond to the language used in the description of painting, but features like the discrete cosine transformation coefficients exhibit low semantic relevance because there is little direct connection to art-historical concepts. The classification results represent the percent correct for each class given a particular test. In test results, the notation of NA indicates that the test was not applied.

5.3.1 Light

5.3.1.1 Artist Database

Table 25 displays the results of tests conducted for light features against the artist database. The elapsed time column measured the average time required to extract the feature from images in the training set. The storage requirement measured the number of doubles necessary to store the feature. The semantic relevance field describes the proximity of the feature to its analogue in art-historical terms. The interactive test measured the accuracy of classification in percent correct in a test scenario simulating an image retrieval system. The result of pure guessing for the interactive test yields an accuracy of 20%. The k-nearest neighbor tests measured the accuracy of classification in percent correct for tests with k equal to 5 and 54. The result of pure guessing for the k-nearest neighbor tests yields an accuracy of 2%.

Table 25: Results of Light Features applied to Artist Database

Feature	E Time	Storage	Semantic	Interactive	kNN5	kNN54
% of Dark Pixels	0.11	1	Medium	28.46	NA	NA
Luminance Peaks	0.13	1	Medium	NA	NA	NA
Mean Deviation Intensity	0.12	1	Medium	30.71	NA	NA
Segmented Mean	0.12	9	Medium	30.33	9.14	11.28
Segmented Variance	0.12	9	Medium	31.83	5.18	6.09
Segmented Skewness	0.12	9	Medium	33.33	6.70	6.40
Segmented Kurtosis	0.12	9	Medium	31.46	7.01	4.57
Global Mean	0.11	1	Medium	27.34	6.70	8.84

Global Variance	0.11	1	Medium	21.34	7.01	3.35
Global Skewness	0.11	1	Medium	25.46	5.18	3.35
Global Kurtosis	0.11	1	Medium	22.09	5.48	2.74
IXY	0.54	5	Low	42.32	14.02	6.70
Intensity Histogram	0.11	256	Medium	33.70	9.45	6.70

Table 25 demonstrates four points concerning the relationship of these features to discussions of light in art-historical terms. First, none of the features surveyed measure light in a semantically-relevant manner. In part, this results from the relationship between light and content in a painting. Particular objects cast shadows and therefore the accurate measurement of light depends to some extent on an interpretation of context not compatible with the general classification system proposed in this study. Second, the IXY feature measuring the spread of intensity in X and Y coordinates in the image outperformed the other features despite its low semantic relevance. This result challenges this study's assertion that semantically-relevant features provide the best basis for style classification systems. Third, features extracted from segmented images perform better than their global equivalents. For example, the global kurtosis feature performed just slightly better than guessing, but the segmented kurtosis feature showed improved accuracy in all tests. Fourth, despite the high storage needed for the intensity histogram, the additional information carried in this feature did not improve classification accuracy over other features. In other words, additional information is less important than pertinent information to style classification tasks.

5.3.1.2 Impressionist/Post-Impressionist Database

Table 26 displays the results of tests conducted for light features against the Impressionist/Post-Impressionist database. The k-nearest neighbor tests measured the accuracy of classification in percent correct for tests with k equal to 1 and 13. The result of pure guessing for the k-nearest neighbor tests yields an accuracy of 16.7%.

Table 26: Results of Light Features applied to Impressionist/Post-Impressionist

Feature	kNN1	kNN13
% of Dark Pixels	10	20
Luminance Peaks	26.7	13.3
Mean Intensity Deviation	33.3	23.3
Segmented Mean	33.3	16.7
Segmented Standard Deviation	23.3	36.7
Segmented Skewness	16.7	23.3
Segmented Kurtosis	13.3	20
Global Mean	16.7	16.7
Global Standard Deviation	6.7	16.7
Global Skewness	23.3	20
Global Kurtosis	6.7	16.7

Table 26 reinforces some earlier observations related to Table 25. The features extracted from image segments classified images at higher rates of accuracy than the same features extracted from the entire image. In fact, many of the global features failed to perform as well as blind guessing casting into doubt the utility of these features. In this test, the mean intensity deviation performed better than other features in the group.

In an integrated test of light features run against the Impressionist/Post-Impressionist database, the light features considered in Table 26 were combined and weighted according to each feature's distance from noise and redundancy compared to other features. The integrated tests confirmed the resilience of the mean intensity deviation demonstrating its resistance to noise and its lack of redundancy with other features. Of the features surveyed, the mean intensity deviation has the broadest applicability and is the most appropriate for general tasks in style classification.

5.3.2 Line

5.3.2.1 Artist Database

Due to time considerations, the survey tested only those line features with high semantic relevance: Canny contour measurements. The feature classified paintings in the artist database at an accuracy of 44% in interactive tests. The result supports the argument that features with high semantic relevance provide a strong basis for classifying style in painting.

5.3.2.2 Impressionist/Post-Impressionist Database

Table 27 presents the results for line features tested against the Impressionist/Post-Impressionist database. The k-nearest neighbor tests confirmed that the Canny contour features performed well when compared to other features in the class. In this test case, the accuracy of classification was proportional to the semantic-relevance. The study rated the block difference of inverse probabilities moments, gradient coefficients, and intensity edge ratio as features with medium semantic relevance.

Table 27: Results for Line Feature Tests

Feature	kNN1	kNN13
BDIP Mean	20	30
BDIP Variance	20	26.7
Canny Contour Lines: Number	20	23.3
Contour Lines: Mean Length Major Axis	33.3	30.0
Contour Lines: Std Length Major Axis	23.3	23.3
Contour Lines: Mean Length Minor Axis	23.3	10.0
Contour Lines: Std Length Minor Axis	23.3	20.0
Contour Lines: Mean Area	13.3	30.0
Contour Lines: Std Area	20	20
Contour Lines: Mean Eccentricity	23.3	30.0
Contour Lines: Std Eccentricity	33.3	26.7
Contour Lines: Orientation Histogram	26.7	30.0
Gradient Map Coefficient	26.7	23.3
Intensity Edge Ratio	13.3	20.0

The test of integrated line features confirmed the observations previously discussed. The Canny contour features exhibited the most distance from noise and the least redundancy when measured against other features in the class. Although the integrated tests do not surpass the results obtained by the most effective features, the test confirmed that the Canny contour measurements performed the best of those surveyed according to classification accuracy, semantic relevance, noise resistance, and reduced redundancy.

5.3.3 Texture

5.3.3.1 Artist Database

Table 28 summarizes the results of texture feature tests conducted against the artist database. The elapsed time column measured the average time required to extract the feature from images in the training set. The storage requirement measured the number of doubles necessary to store the feature. The semantic relevance field describes the proximity of the feature to its analogue in art-historical terms. The interactive test measured the accuracy of classification in percent correct in a test scenario simulating an image retrieval system. The result of pure guessing for the interactive test yields an accuracy of 20%. The k-nearest neighbor tests measured the accuracy of classification in percent correct for tests with k equal to 5 and 54. The result of pure guessing for the k-nearest neighbor tests yields an accuracy of 2%. The results indicate that wavelet statistical moments provide the quickest and most accurate basis for classifying style.

Table 28: Results for Texture Features

Feature	E Time	Storage	Semantic	Interactive	kNN5	kNN54
Fractal: Box Counting	1.06	9	Medium	34.1	6.7	8.2
Fractal: Hurst Coefficient	1.98	27	Medium	40.8	NA	NA
Fast Fourier Transformation: 100	0.71	50	Low	27.7	NA	NA
Gabor Statistical Moments	21.9	64	Medium	48.3	NA	NA
Wavelets: Statistical Moments	0.62	36	Medium	48.3	14.9	11.2

5.3.3.2 Impressionist/Post-Impressionist Database

Table 29 displays the test results of texture features for the Impressionist/Post-Impressionist database. The k-nearest neighbor tests reinforce the notion that features based on wavelet transformations are the most effective style classifiers. In fact, the results confirm the assumptions of many researchers in the field: texture features provide the most accurate basis for style classification. For example, Gabor transformation moments and two types of fractal measurements outperformed features in other classes.

Table 29: Results for Texture Features

Features	kNN1	kNN13
BVLC Mean	23.3	30.0
BVLC Variance	26.7	30.0
Fractal: Box Counting	33.3	46.7
Fractal: Hurst Coefficient	40	36.7
Fast Fourier Transformation: 100	20.0	16.7
Gabor Transformation: Mean	36.7	33.3
Gabor Transformation: Variance	50.0	30.0
GLCM: Contrast	16.7	23.3
GLCM: Correlation	16.7	26.7
GLCM: Energy	26.7	23.3
GLCM: Entropy	20.0	26.7
GLCM: Homogeneity	20.0	30.0
GLCM: Inertia	16.7	23.3

GLCM: Inverse Difference Moment	20.0	26.7
GLCM: Maximum Probability	20.0	23.3
Wavelet Transformation: Mean	43.3	36.7
Wavelet Transformation: Variance	50.0	30.0

The results of the integrated texture feature tests, revealed a less consistent view of the texture features than previous integrated tests for light and line features. For example, in previous integrated tests the feature with the highest accuracy of classification was also the feature most distant from noise and the least redundant feature. The texture features, on the contrary, demonstrate a broad range of responses. Although the wavelet-based features are the most accurate classifiers, they exhibit high entropy and mutual information. The box counting fractal measurements were the most distant of the features from noise. The correlation of the gray level cooccurrence matrix was the most independent of the features and yet was a rather poor classifier.

5.3.4 Color

5.3.4.1 Artist Database

Table 30 summarizes the results of color feature tests conducted against the artist database. The elapsed time column measured the average time required to extract the feature from images in the training set. The storage requirement measured the number of doubles necessary to store the feature. The semantic relevance field describes the proximity of the feature to its analogue in art-historical terms. The interactive test measured the accuracy of classification in percent correct in a test scenario simulating an image retrieval system. The result of pure guessing for the interactive test yields an accuracy of 20%. The k-nearest neighbor tests measured the accuracy of classification in percent correct for tests with k equal to 5 and 54. The result of pure guessing for the k-nearest neighbor tests yields an accuracy of 2%.

The results provide evidence for three themes discussed throughout this paper. First, the HSV-based features performed better than their RGB equivalents in a number of cases. Second, color features preserving frequency and spatial information do not improve the accuracy of style classification. For example, the static histograms of an image map performed better in every category than the equivalent static histogram of an image index and the dynamic spatial chromatic histogram. Third, the results indicate that the HSV palette description provided an accurate basis for classifying style with high semantic relevance and a low storage requirement. In general, color features with high semantic value perform as well as those with medium or low semantic value.

Table 30: Results of Color Features

Feature	E Time	Storage	Semantic	Interactive	kNN5	kNN54
HSV Static Histogram: Index	1.72	768	High	47.9	11.9	9.7
RGB Static Histogram: Index	0.49	768	Medium	44.6	11.6	9.1
HSV Static Histogram: Map	0.29	768	High	49.1	14.9	15.9
RGB Static Histogram Map	0.29	768	Medium	44.2	9.1	5.5
HSIXY	1.42	5	Low	42.3	16.1	10.3
RGBXY	0.65	5	Low	49.1	14.6	8.8
HSV Palette Description	0.32	50	High	53.6	NA	NA

HSV DSCH16	2.35	112	High	31.1	6.1	5.9
RGB DSCH16	2.33	112	Medium	32.9	7.0	4.9

5.3.4.2 Impressionist Database

Table 31 displays the test results of color features for the Impressionist/Post-Impressionist database. The k-nearest neighbor tests reinforce the notion that color features designed to preserve spatial information in the color channel do necessarily improve style classification. For example, the HSV palette description performed slightly better than color coherence vectors, dynamic spatial chromatic histograms, and autocorrelograms. Although the results were somewhat less convincing than those for the artist database, color features with high semantic relevance performed well for this classification task. The integrated feature tests did not provide conclusive results for the color features.

Table 31: Results of Color Features

Feature	kNN1	kNN13
Hue Static Histograms: Index	16.7	23.3
Saturation Static Histogram: Index	30.0	30.0
Value Static Histogram: Index	26.7	10.0
RGB Static Histograms: Index	33.3	23.3
HSV Dynamic Histograms: Index	43.3	23.3
Hue Static Histogram: Map	26.7	16.7
Saturation Static Histogram Map	20	20
Value Static Histogram: Map	16.7	13.3

RGB Static Histogram: Map	33.3	13.3
HSV Color Coherence Vectors	23.3	23.3
RGBXY	30.0	26.7
HSIXY	36.7	26.7
HSV Palette Description	36.7	30.0
HSV DSCH 16	20.0	23.3
HSV Autocorrelogram 16	10	20

5.4 Overall Classification Results

The overall classification results record classification accuracies for features integrated from the four feature groups: light, line, texture, and color. Conducted against the artist database, the interactive test measured an unweighted combination of three features: HSIXY, HSV histogram of the color map, and Wavelet Moments. Conducted against the Impressionist/Post-Impressionist database, the k-nearest neighbor tests used thirteen extracted features: palette description, color coherence vector, HSIXY, correlation of the gray-level cooccurrence matrix, fractal dimension by box counting, fractal dimension by Hurst estimation, wavelet moments, contour line measurements, mean deviation of intensity, segmented mean and standard deviation of intensity, and static hue and saturation histograms obtained from the image index. The test defined four values for k with the unweighted features and with features weighted by the mean entropy value of all fields comprising the feature.

5.4.1 Artist Database

The interactive test achieved an overall accuracy of 59 percent where the accuracy of pure guessing is 20 percent. Although the overall result was disappointing, the results represent a wide variance of success when considering each artist separately. Table 32 reports the interactive test results organized by artist.

Table 32: Results of Integrated Interactive Test

Artist	Interactive Test Accuracy
Altdorfer	25
Klimt	28.57
Manet	28.57
Sisley	33
Renoir	35
Monet	40
Ast	50
Avercamp	50
Bassano	50
Bruegel	50
Cezanne	50
Van Gogh	50
El Greco	50
Kandinsky	57.1
Toulouse-Lautrec	60

Hopper	62.5
Whistler	62.5
Baldung	66
Bosch	66
Cassatt	66
Gris	66
Modigliani	66
Seurat	66
Delacroix	71.42
Rubens	71.42
Degas	75
Ingres	75
Aertsen	77.7
Gauguin	80
Pissarro	80
Malevich	81.8
Turner	81.8
Vermeer	83.3
Piero	85.7
Rembrandt	85.7
Velazquez	87.5
Morisot	90.9

Bacon	100
Bouguereau	100
Caravaggio	100
Chase	100
Davis	100
Durer	100
Hockney	100
Kiefer	100
Matisse	100
Memling	100
Munch	100
Redon	100
Watteau	100
Weyden	100
Total	*59.9*

5.4.2 Impressionist/Post-Impressionist Database

Table 33 displays the overall results of the integrated k-nearest neighbor feature tests. Again, the overall results failed to produce high levels of accuracy and yet demonstrated a wide variance of classification accuracy when analyzed by artist.

Table 33: Results of Integrated Feature Test

Test	kNN1	kNN8	kNN13	kNN21
Unweighted	43.3	46.6	23.3	30.0
Entropy Mean Weighting	50.0	40.0	33.3	36.7

Table 34 reports the variance of results from the entropy-weighted tests analyzed by artist. Just as in the results for the artist database, some artists were easier to classify than others given a particular set of features. The evaluation results reported in section 5.5 suggest that the nature of the classes account for this disparity at least as much as the quality of the images in the test set.

Table 34: Results of Integrated Feature Test Organized by Artist

Artist	kNN1	kNN8	kNN13	kNN21
Cezanne	80	100	100	100
Monet	20	40	20	20
Pissarro	40	20	0	0
Seurat	60	60	60	60
Sisley	20	0	20	20
Van Gogh	80	20	0	0

5.5 Visualization Results

The classification results obtained from supervised methods like those discussed in section 5.4 provide information similar to forensic applications: they categorize paintings and researchers measure the quality of those categories in terms of classification accuracy. Supervised methods, on the other hand, contribute little to the understanding of how the classes in question relate to each other. In terms of painting, supervised techniques provide little information about how a particular style relates to other styles. Unsupervised learning techniques provide precisely this information including methods to present these relationships visually. The present study proposed statistical descriptors of style based on the mean and variance measurements derived from features extracted from paintings. The results below represent the application of these analytical techniques to the Impressionist/Post-Impressionist database. The study suggests that these visualizations supplement and provide context for understanding the classification results.

5.5.1 Style Variance Results

Figure 42 displays the multidimensional scaling analysis applied to the paintings of Cezanne. The red plus in the figure represents the theoretical style center of the paintings in the database. The red ellipse marks the theoretical style variance of the paintings. Figure 43 displays the same type of analysis applied to the paintings of Monet. The juxtaposition of these figures provides an important point of comparison that sheds light on the integrated classification results reported in section 5.4. The scale of the Monet figure is almost twice that of the Cezanne figure. As one might expect, the style variance of Monet is also larger than that for Cezanne: where Cezanne's style variance is 2.1, Monet's is 3.5. The fact that the Cezanne paintings cluster tightly around the mean helps to explain the higher accuracy of classification achieved in supervised tests.

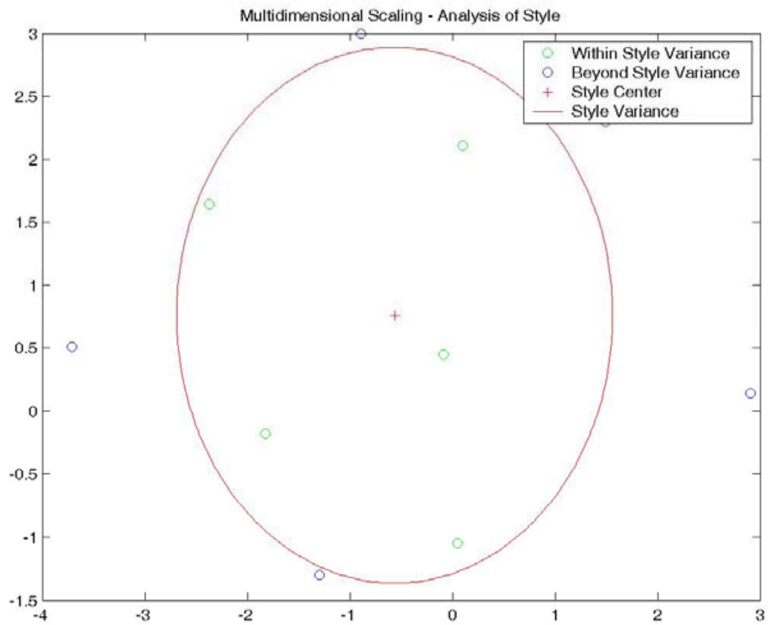


Figure 42: MDS Analysis of Cezanne

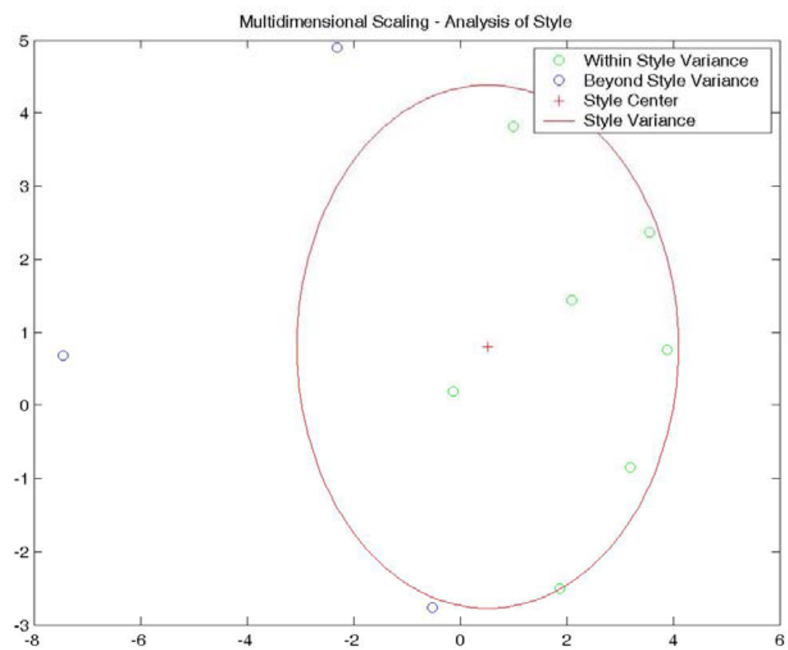


Figure 43: MDS Analysis of Monet

5.5.2 Global Variance

Figure 44 demonstrates how this analysis applies to style relationships. The yellow star denotes the theoretical global style center and the yellow circle marks the global style variance. According to the features used in the integrated feature test, Monet's style center is the closest to the global style center explaining further Monet's poor classification results. On the other hand, Cezanne's style center is the most distant from the global style center and the only style center outside of the global style variance. In other words, the supervised techniques achieved higher degrees of accuracy for Cezanne because his work was most dissimilar from that of the other painters considered.

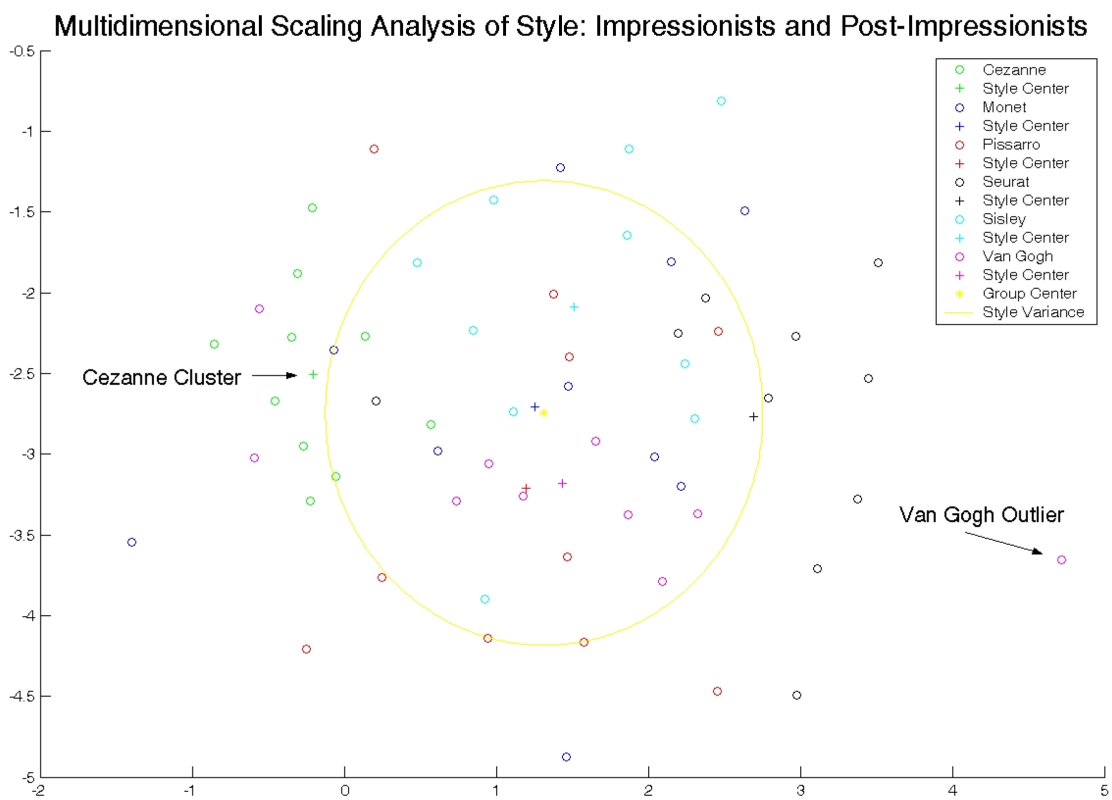


Figure 44: MDS Analysis of Style Group

Table 35 summarizes the results of the multidimensional analysis of these artists reporting the style variance, the distance of each style center from the global style center, the style description ratio, and the classification accuracy obtained from the k-nearest neighbor test discussed in section 5.4. The data recorded in this table supports the notion that classification accuracy depends to some degree on class quality. The two artists with the highest classification rates exhibit similar class quality descriptors: low style variance, large distance from the global style center, and high style description ratios. In essence, the style description ratio indexes how accurately our features describe the style of a particular artist.

Table 35: Class Quality Descriptors

Artist	Style Variance	Distance from Global Style Center	Style Description Ratio	Accuracy (%)
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

These metrics offer additional analytical and visualization options. Figure 45 displays a dendrogram of the artists' stylistic centers along with the global style center. As expected, Monet is closest to the global style center and Cezanne is among the most distant. Figure 46 depicts a dendrogram of the data extracted from the paintings in the

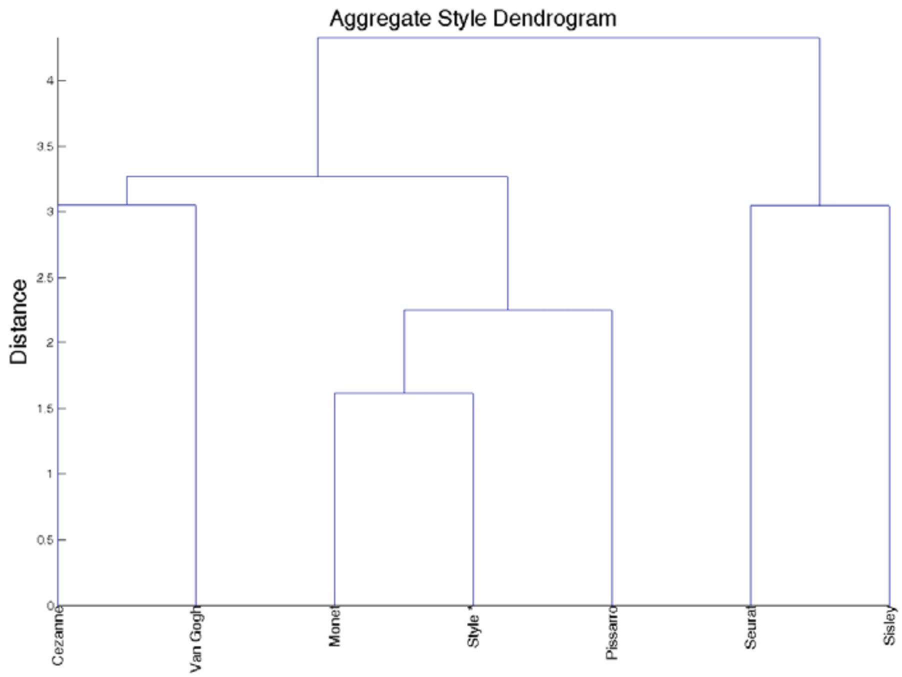


Figure 45: Aggregate Style Dendrogram

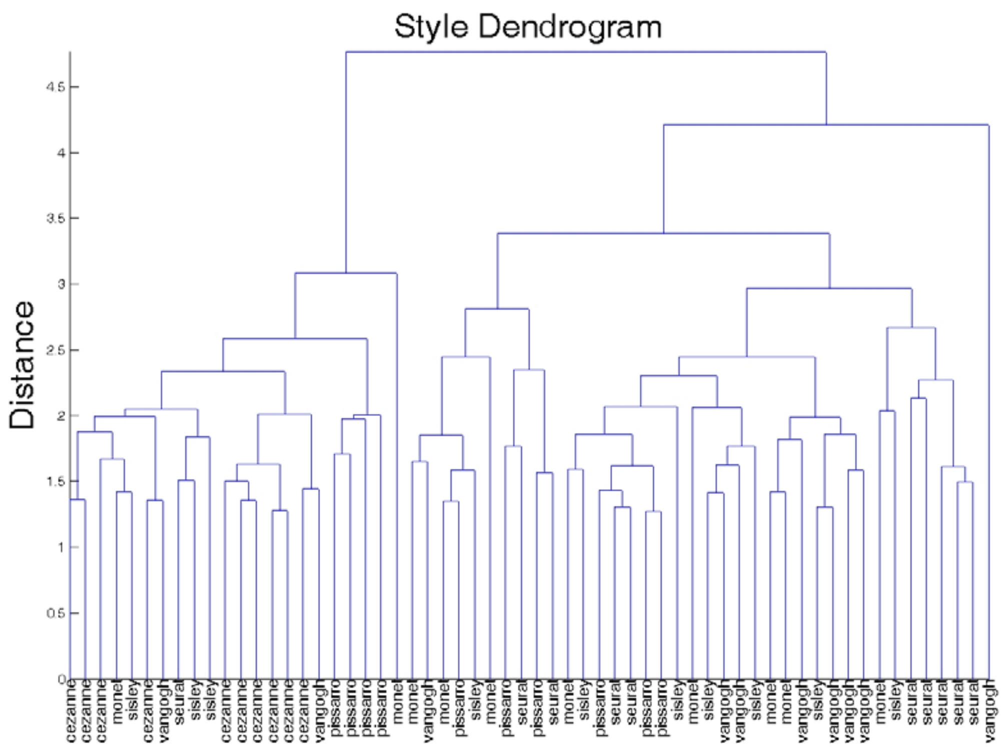


Figure 46: Style Dendrogram of Paintings

database. Although far from a perfect cluster, the dendrogram demonstrates properties consistent with previous observations: the Cezanne paintings cluster tightly on the left and Monet's are almost evenly distributed throughout the dendrogram.

5.6 Evaluation

The study considered two possible explanations for classification accuracy: data quality and class quality. Although both types of measurement probably contribute to classification results, the class quality measurements showed as strong a correlation to classification accuracy as data quality measurements. Figure 47 plots the average number of pixels for each class against the classification accuracy of that class. The graph demonstrates a proportional relationship between these two variables. Figure 48 plots the style description ratio for each class against the classification accuracy of that class. This graph also demonstrates a proportional relationship between the variables with a much tighter correlation and fewer outliers. The style description ratio measures the relative quality of the defined style classes, in effect providing feedback concerning the quality of the feature measurements.

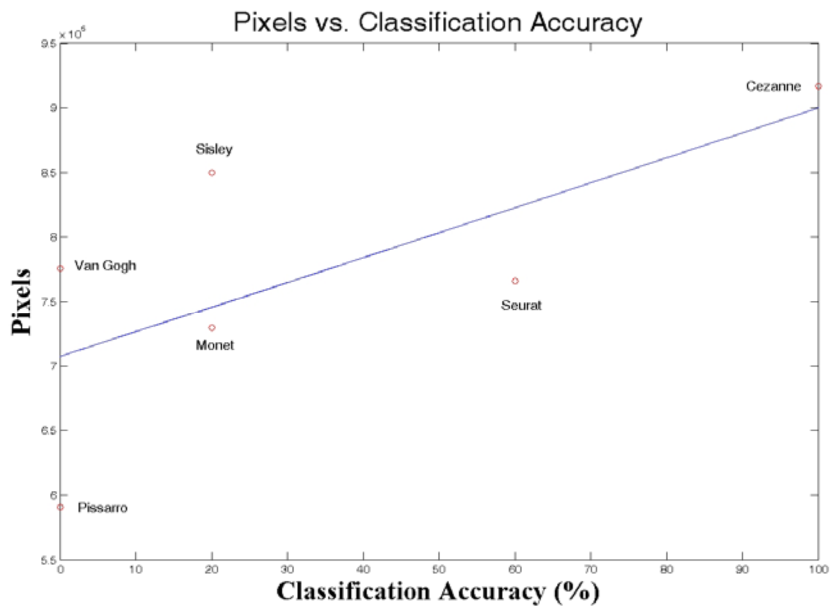


Figure 47: Data Quality Evaluation

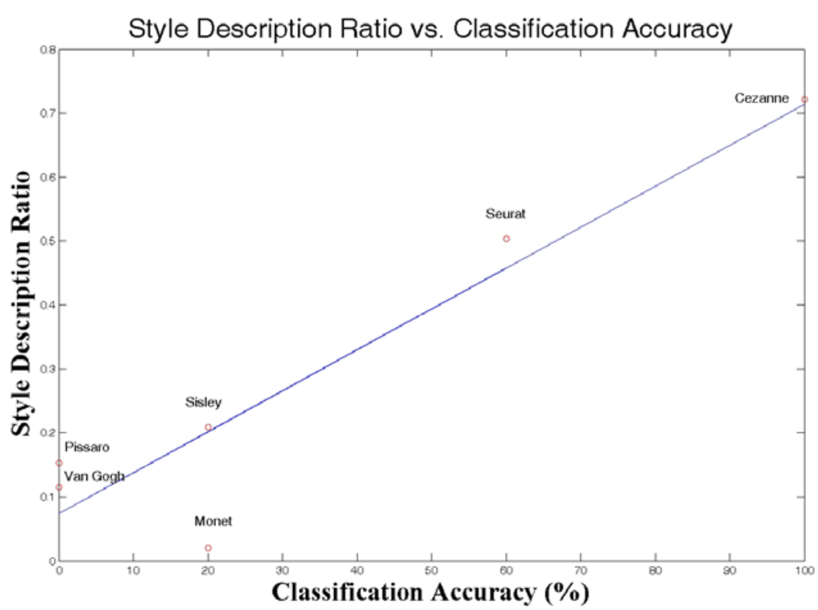


Figure 48: Class Quality Evaluation

Chapter 6

Conclusion

This study reviewed the approaches of computer science to the classification of artistic style. In general, these approaches have focused on a narrow set of problems related to the attribution of works of art and in many cases the solutions proposed are of a limited scope. In contrast to these approaches, this study proposed a general classification system for style based on the formal elements of artistic style in painting. The evidence gathered in this study suggests that it is possible to design a general style classification system that supports a broad range of activities including style identification, the mapping of style relationships, and the visualization and evaluation of classification results.

A broad feature survey revealed a distinct bias in the literature for texture features. Although in certain contexts texture features were most effective for classifying style, this survey revealed that this was not always the case. In fact, when considering databases with larger numbers of classes such as the artist database, the best color features perform comparably to the best texture features. The feature survey also revealed that semantically-relevant features often perform as well as those with less direct relevance to the domain.

The feature survey also identified an important difference between feature extraction for image retrieval and feature extraction for style classification. Features that improve image retrieval do not necessarily improve style classification. In particular, this proved to be the case for color features. Color features that preserve frequency and spatial information do not necessarily improve style classification. Although advanced color features such as spatial chromatic histograms, color coherence vectors, and color autocorrelograms have all been shown to improve image retrieval accuracy, the same cannot be said for style classification. In fact, color metrics that ignore frequency and spatial information altogether often outperformed the more advanced features in classification tasks.

This observation concerning the role of color in style classification suggested the development of a palette description feature. The palette description feature and its associated palette comparison method capture the color information inherent in a painting with significant reduction in the storage requirement. The palette description feature described style as well as similar color measurements in this domain. The feature leverages the HSV color model and conic geometry to define the central tendency of a palette without the loss of information resulting from separating the hue and saturation measurements or the translation of polar coordinates into Euclidean spaces.

This study has further shown that artistic style is generally classifiable using a broad range of features and can support such tasks as the identification of relationships between styles, the visualization of these relationships, and the evaluation of classification results. As examples of these abilities, the study reviewed three visualization techniques. A style dendrogram displayed the hierarchical relationship between styles including their proximity to a theoretical style center. A visualization, based on a self-organizing map, identified cluster boundaries inherent in the sample of given styles. Multidimensional scaling analysis provided the basis for an evaluation technique that defined the following style descriptors: theoretical style center, theoretical style variance, and a style description ratio. The style description ratio proved to be an effective predictor of classification accuracy.

The results of the study suggest several avenues for further research in image processing and machine intelligence. First, the role of filtering in this domain remains only partially addressed. The affect of filtering on the classification accuracy and feature extraction in this domain certainly warrants additional attention. Second, the role of optimization in this domain has also received little attention. It should be possible to optimize feature weights for classification accuracy and perhaps even for style description ratios thus providing a basis for improved class definition. Third, texture features in this domain will improve when researchers can adequately distinguish between actual and perceived texture. An explicit formulation of techniques to extract and separate these different types of texture should improve the analysis pursued by researchers. Fourth, the development of a style taxonomy based on the formal elements inherent in a style should provide a map of many style relationships. In addition to this taxonomy, it should be possible to identify the features most associated with specific styles. Fifth, the measurements in this study assume that paintings are the best measuring sticks for identifying and classifying other paintings. Approaches based on abstract image databases are also possible and would provide a static and universal basis for comparing paintings. For example, when measuring texture features in paintings, a system could just as easily measure the distance between a painting and images from the Brodatz texture database, which would serve as a benchmark for texture measurements. Similar techniques could be applied to color and other classes of features discussed in this study.

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