Digital analysis of paintings

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DIGITAL ANALYSIS OF PAINTINGS

Igor Berezhnoy

Stellingen

Behorende bij het proefschrift
"Digital Painting Analysis"
door Igor Berezhnoy

1. In the coming decades, computer techniques will conciliate the art-historian world. (This thesis.)
2. The opponency values of Van Gogh's paintings reflect his increased usage of complementary colors while moving from the Netherlands towards the South of France. (Chapter 4, this thesis.)
3. The prevailing orientation of brush strokes can be reliably detected using a combination of a circular filter and thresholding. (Chapter 5, this thesis.)
4. The second-order statistics of Gabor filters form a better representation of the characteristic features of authentic Van Gogh paintings than the first-order statistics. (Chapter 6, this thesis.)
5. Establishing a computer program that can detect all fakes is a *contradictio in terminis.*
6. Algorithms for the analysis of paintings are being developed to support art historians, not to replace them.
7. An extensive study of the relevant literature prevents scientists from reinventing old ideas but at the same time it prohibits the development of new ideas.
8. Carrying responsibility for ones own destiny is not a burden, but constitutes freedom.
9. The goal of all living creatures is to control their reality.
10. Boredom does not exist, instead it is a feeling which comes from the apathy when one realizes his/her incompetence to change reality.
11. If all alleged Van Gogh paintings would turn out to be authentic, the price of a Van Gogh will drop to almost zero.

DIGITAL ANALYSIS OF PAINTINGS

DIGITAL ANALYSIS OF PAINTINGS

PROEFSCHRIFT

ter verkrijging van de graad van doctor
aan de Universiteit van Tilburg,
op gezag van de rector magnificus,
prof. dr. Ph. Eijlander,
in het openbaar te verdedigen ten overstaan van een
door het college voor promoties aangewezen commissie
in de aula van de Universiteit
op maandag 7 december 2009 om 14:15 uur

door

Igor Berezhnoy

geboren op 23 januari 1975 te Lozovaya, Sovjet-Unie

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and patience in educating me about your whimsical world. Both museums are especially thanked for granting access to their extensive collection of Ektachromes of paintings (mis)attributed to Van Gogh. I also would like to thank professor Rick Johnson who voluntarily agreed to become an organizer of the first meeting of researchers working within the cultural heritage domain on paintings analysis. Our work on the automatic analysis of paintings became possible only because of his persistence in collecting the appropriate data sets.
Over the years, I was fortunate to be surrounded by several people from whom I learned always to use common sense, to ignore unimportant issues, and to focus on important things in life. Complementary to those already mentioned I would like to give my thanks and appreciation to Paul and Patricia van der Zee and Geer Janssen. I also would like to express my gratitude to my wife and son for their love and support. Finally, my respect and thankfulness goes to those without whom all this would not happen, to my best teachers, my parents. From them I learned to overcome things which one can overcome, to refrain from things one cannot overcome, and most importantly to distinguish the one from the other. They provided me with their unconditional love and support. Thank you.
Eindhoven, December 2009

Preface

Paintings are fascinating objects to study, in particular for computer scientists. In digital representations of paintings, the pigments are translated into numbers representing the amount of red, green, and blue light. In turn, the numbers can be processed by a computer in a way that is roughly similar to the human processing in the visual pathway. Computer vision is most successful in mimicking the lowest levels of human visual processing at that level, the computer-based visual analysis of colors, textures and basic shapes is performed quite well. So, there computers may support art historians in the analysis of low-level visual patterns.
The subject of the thesis is the development and evaluation of algorithms that perform low-level visual analysis of paintings. The hope and expectation is that ultimately these algorithms become standard tools for art experts.
For the writing of the thesis I received both mental and professional support from many people who deserve my sincerest gratitude. First of all, I would like to thank my supervisors Eric Postma and Jaap van den Herik. Against all odds, despite cultural differences and sometimes despite orthogonal points of view, both kept supporting me, guiding me, and - what is most important - believing in me, which gave me the strength and reason to continue my research. Next, many colleagues and in particular colleagues who became best friends are gratefully acknowledged for hours of inspiring discussions about the thesis and all other possible subjects ranging from common sense and the meaning of life to Middle Ages military tactics. Some may speculate that without those hours not directly spent on the thesis I would have completed it earlier. However, I take the liberty to disagree with such an opinion as I truly believe that a socially enjoyable working environment is a prerequisite for creative computing and thus for remarkable research since it is inspiring and simultaneously challenging. I would like to thank Evgueni Smirnov, Frank Claus, Joyca Lacroix, Jahn Saito, Andra Waagmeester, Guillaume Chaslot, and Sander Spek. My special thanks go to my roommates, comrades, and allies, Guido de Croon, Niek Bergboer, and Laurens van der Maaten for the fellowship that we still share. I also would like to thank Peter Geurtz for his on-demand help and his expertise in hardware I used for my research and for allowing me all the freedom I needed to do my work, Joke Hellemons for keeping an eye on me and for dealing with the overwhelming attention from the media.
My sincere acknowledgment goes to our allies Chris Stolwijk, Ella Hendriks and Louis van Tilborgh from the Van Gogh Museum of Amsterdam and Liz Kreijn and Luuk van der Loeff from the Kröller-Müller museum. Thank you for your passio

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Chapter 1

Introduction

The history of art goes hand in hand with the history of forgery in art. For a long time, the identification and attribution of paintings was exclusively performed by human visual analysis. Undoubtedly, the assessments of skilled art experts were (and still are) of great value to the domain of the visual arts. However, inevitably human judgments are highly subjective and prone to error. This study claims that recent advances in artificial intelligence (in particular in image recognition and machine learning) allow the art expert to be supported by digital image-analysis techniques. Quantitative and objective analysis facilitates the quality of the visual assessment and may reduce the number of errors due to subjective factors.

In this chapter the reader is introduced into the world of visual art. For a number of reasons, the advent of computers in the discipline of visual art happened later than in other disciplines. The domain of medicine was a front runner; the first expert systems, such as MYCIN (Shortliffe, 1976), were developed in the early 1970s. The domain of law followed closely by having the first expert system developed at the end of the 1980s (Clancy, Hoenig, and Schmitt, 1989). Whatever the case, the progress in visual art is fascinating and a well-founded motivation to continue is not only inspired by the continuously ongoing detections of forgery, but also by specific questions in the minds of art experts. The aim of the chapter is to structure emerging questions and to position them within the proper scientific context culminating in a problem statement and three research questions. In section 1.1 we provide background information on visual art and artificial intelligence. Then, in section 1.2 we formulate our problem statement and the three research questions. In section 1.3 we describe our research methodology. Section 1.4 gives the outline of the thesis.

1.1 Visual art and artificial intelligence

A systematic approach which served as source of inspiration for our study was *Pictology*, a systematic authentication procedure proposed in the early 1950s by Van Dantzig (1973). Pictology relied on the structured human analyses of various characteristics of the painting, such as the distribution of light, the composition, and the brush strokes. According to Van Dantzig, the maker (author) of a painting could be reliably determined in this manner. Of course, the unavoidable subjectivity introduced by the human expert forms the major impediment to the Pictology approach.

Probably the most dramatic example of an art expert's subjectivity is the so-called *Van Meegeren* case. In 1937 the reputable art historian Bredius, an expert of Vermeer's paintings, examined a new painting with the title *Christ and the Disciples at Emmaus* as depicted in figure 1.1. Having studied the works of Vermeer throughout his life, Bredius was eager to discover a new Vermeer. After a careful examination of the painting, Bredius decided that it was a real Vermeer. Later, it turned out that Bredius' decision was wrong. The alleged Vermeer was a fake created by Van Meegeren, an unknown Dutch artist. We suppress further details on this fraud since they are not relevant to our study. The interested reader is referred to Kreuger (2007) for a concise study of the Van Meegeren case.

Figure 1.1: *De Emmaüsgangers*, 1973, Museum Boymans van Beuningen, Rotterdam.

Obviously, the Van Meegeren case illustrates that art experts can be fooled despite their life-long experience. It may be even the case that experience itself may fool an expert. We provide an example of this statement that is based on the fact that pure exposure to an odd painting of a well-known painter may shift the mental reference to what is "standard" for that painter. So, the reader is invited to examine the portrait of Mona Lisa shown in figure 1.2 (Carbon and Leder, 2006). Evidently, the image seems to be a distorted version of the true Mona Lisa. Assume the reader examines the portrait for a few minutes. Even being exposed to the odd portrait for such a short duration, already affects his[1] reference to the "true" Mona Lisa.

The reader is now requested to inspect the two portraits shown in figure 1.3 (Carbon and Leder, 2006) and to decide which of the two corresponds to the real Mona Lisa.

[1]For brevity, we use "he" and "his" whenever "he or she" and "his or her" are meant.

Figure 1.2: A distorted version of the Mona Lisa.

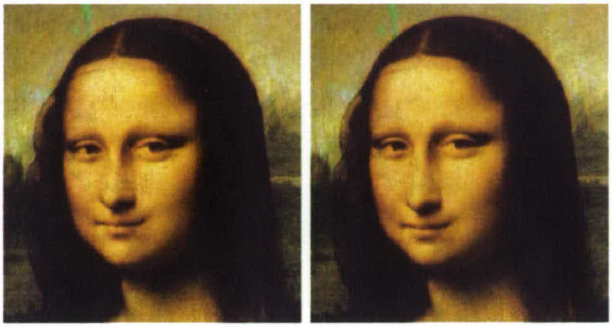


Figure 1.3: Two portraits of Mona Lisa. Which one corresponds to the true one?

As reported by Carbon and Leder (2006), subjects exposed to figure 1.2 tend mistakenly to identify the right portrait in figure 1.3 as being the true Mona Lisa, while in fact the left portrait is the real one. This tendency can be explained by the fact that the adaptation to the distorted portrait (figure 1.2) gives rise to a shift in the mental representation of the Mona Lisa towards a vertically slightly elongated face. As a consequence, the elongated portrait (i.e., the right portrait in figure 1.3) is mistakenly identified as being more like the true Mona Lisa.

The growing awareness of the fallibility of human judgment gave rise to sound scientific methods such as the Pictology procedure in the analysis of visual art. In 1968, the Rembrandt Research Project (Van de Wetering, 1997) set out to investigate and classify all of Rembrandt's known paintings. The Rembrandt Research Project employs an interdisciplinary scientific approach for the analysis of the paintings and their supporting materials. A wide variety of disciplines, such as dendrochronology, textile research, pigment analysis, and X-ray analysis, were combined with the traditional art-historian discipline. Each of the disciplines contributed to the overall goal of the attribution of paintings. In addition to these supporting disciplines, this thesis describes how computer science, more specifically, artificial intelligence, may become a new contributing discipline to the art-historian examination of paintings.

An early result, suggesting the feasibility of computer science as a contributing discipline, was reported by Postma, Van den Herik, and Hudson (1998) and Postma and Van den Herik (2000). They applied computer-science techniques to painting-classification tasks by extracting visual features from digitized paintings and applying machine-learning techniques to the feature-based representations of the paintings. Even with low-quality reproductions, promising results were obtained. Paintings could be correctly classified to one of six authors in more than 80 per cent of the cases. This early success was one of the inspirational sources for the ToKeN initiative, a funding programme launched by the Netherlands Organization for Scientific Research (NWO) that aimed at promoting computer science research for (amongst others) the cultural heritage sector. The research described in this thesis was funded by the ToKeN programme. In 2003, NWO launched the CATCH programme, a funding programme that tries to bring state-of-the-art computer science techniques to museums and other cultural institutions. Our motivation for the research performed is based on the above ideas, in particular on the help computers can offer to authenticate paintings.

1.2 Problem statement and three research questions

In the new world of visual art and artificial intelligence we have to explore the potential research topics from two sides. It only fits when the computer scientists show great interest in culture, in particular in visual art, and the cultural heritage specialist has a dedicated interest in technology. Understanding how far apart these worlds were, the NWO initiatives (ToKeN and CATCH) gave us the opportunity to make a step from computer science towards visual art in the AUTHENTIC project. Our ambitions are formalized in the problem statement (PS) below which deals with computer-based painting authentication. Three research questions (RQs) serve as guidelines for our investigations and for our attempts to answer the problem statement.

Problem Statement: *To what extent can recent advances in image processing and image analysis supplement art historians in their task of painting authentication?*

The three research questions read as follows.

RQ1: *How and to what extent can color analysis of the digitalized reproductions facilitate the authentication process?*

RQ2: *Which features of the brush work can be extracted effectively from the digital reproduction of a painting?*

RQ3: *Are there visual features which could serve as a fingerprint of the master and reveal his identity independent of his style or the scene of his work?*

In the line of our study we show that applying image-analysis techniques can be of great help to art historians. At the time of writing it is an open question to what extent our study is able to develop techniques to support art experts. We believe that we can show *how* the techniques may alleviate the skilled technician of some time-consuming manual tasks. We also believe to be able to show *which techniques* will support art historians to obtain quantitative representations of the nature and distribution of colors and texture in paintings. Overall, the methods developed during this study provide art historians with a new powerful tool to perform visual analyses of art works.

1.3 Research methodology

We operate within the cross section of two domains: cultural heritage (CH) and computer science (CS). Our work aims to create computer-based techniques for supplementing art historians in their studies.

In order to fulfill this aim we follow a methodology consisting of four steps:

1. *identifying* a task that can support art historians;
2. *developing* a technique that can perform the task automatically;
3. *applying* the technique to a collection of (parts of) paintings;
4. *evaluating* the results.

The identification of tasks is performed by (i) interviewing art experts, and (ii) reviewing the existing literature to establish whether techniques for automating the task already exist.

The development of techniques to perform selected tasks proceeds by standard methodologies for image analysis (see Jain and Healey, 1998; Gonzalez and Woods, 2001; Forsyth and Ponce, 2003) and machine learning (see Mitchell, 1997; Duda, Hart, and Stork, 2001; Hastie, Tibshirani, and Friedman, 2001; Bishop, 2006).

The application of the technique to real data (paintings) requires a properly digitized data set of paintings. For our research, we have digitized a collection of 169 paintings by Van Gogh. For each painting, an Ektachrome (photo positive film) was digitally scanned at 1200 dpi. Appendix 7.3 provides a list of the scanned paintings.

The evaluation of the techniques is performed by comparing the results obtained by (i) established knowledge, (ii) other results acquired via other techniques, (iii) human judgments, and (iv) ground-truth data (i.e., "authentic" versus "non-authentic").

Methods designed and created using the above-described methodology are based on standard CS techniques: machine learning, statistical analysis methods, and image processing.

1.4 Thesis outline

This dissertation is subdivided into seven chapters.

Chapter 1 contains an introduction, the problem statement, and the formulation of three research questions as well as a research methodology and a motivation to perform this research.

Chapter 2 presents the background materials necessary to position our study in the framework of digital analysis of the visual art. It gives an overview of how image processing techniques are applied nowadays within the cultural heritage sector.

In chapter 3, we describe authentication-related image-analysis work that has been performed so far. It contains the early work with respect to the main aim of this thesis, i.e., to develop technologies that may help art-historian experts to determine the authenticity of a painting.

Chapter 4 gives a thorough analysis of the colors employed by a painter. The notion of "opponency value" of a painting is introduced along with the quantitative techniques to obtain it. RQ1 is answered.

Chapter 5 describes the POET - a novel image-analysis technique for automatic extraction of the brush-strokes orientation. The technique described allows us to determine the orientation of the brushwork at any given point of the digital reproduction. RQ2 is answered.

Chapter 6 describes and compares two novel techniques for extracting features from the brush work. These features are used by machine-learning techniques in order to build a distance measure (in terms of brush work) for pair-wise painting comparison. The techniques are evaluated on prepared data sets of paintings (authentic ones and fakes). RQ3 is answered.

Finally, in chapter 7 we provide conclusions and give answers on research questions and the problem statement. Moreover, we provide directions for future research.

Chapter 2

A review of digital painting analyses

This chapter reviews digital analyses of paintings in three domains where the art expert may be supported. In section 2.1 we focus on content-based painting retrieval; in section 2.2 on digital restoration, and in section 2.3 on two different approaches of geometric painting analysis and painting-style analysis. In all three sections, we provide a vista towards using the techniques under investigation for an authentication procedure, viz. geometric painting analysis and painting-style analysis.

2.1 Content-based painting retrieval

In the art-historian domain, content-based image-retrieval (CBIR) focuses on the development of techniques that support the retrieval and automatic classification of paintings and other objects of art in large art image databases. There is an extensive body of literature on CBIR (see, e.g., Smeulders *et al.* (2000) for a review). In this subsection we review those studies that we consider to be most related to our research (Corridoni, Bimbo, and Pala, 1998; Chun, Seo, and Kim, 2003; Li and Wang, 2004; Chun, Sung, and Kim, 2005).

Large image databases of visual art works are becoming increasingly popular in the cultural-heritage domain. They are most frequently used for archiving and subsequent retrieval. Nowadays, the retrieval of images relies largely on manually entered metadata, such as captions or keywords (cf. Day, 2000; Lewis *et al.*, 2004). However, recent advance in image processing and machine learning allow to some degree the automatic generation of metadata (Sasaki and Kiyoki, 2005). Such techniques make use of a variety of features collected from images. These features fall into two main categories: color features (see 2.1.1) and texture features (see 2.1.2). Below, we discuss both types of features first separately and then in combination (see 2.1.3). The section is completed by mentioning the relevance of these algorithms for painting authentication (see 2.1.4).

2.1.1 Color

From a psychological point of view, the perception of a color depends on three main features: (1) perceptual features (brightness, chromaticity, and saturation), (2) spatial features (surrounding colors, spatial composition, and color texture), and (3) cognitive features (the memory or prior knowledge of the observer). Although the meaning of paintings is reflected in all three features, current CBIR techniques are confined to the perceptual and spatial features. Itten (1961) introduced a formalism to analyze the use of color in art and the impact of these colors on the observer. Corridoni *et al.* (1998) presented a system which translates Itten's theory into a formal language that allows to express the semantics associated with the combination of perceptual (color) and spatial features in images of paintings. Corridoni *et al.* use (1) fuzzy sets to represent low-level region properties and (2) a formal language that allows to define semantic clauses for querying and matching images.

2.1.2 Texture

The texture of an image or image region represents an important feature for the automatic retrieval of paintings. Texture refers to the local statistics or regularities of an image and is likely to vary with the painter or style of the painter. In plain CBIR, texture has proven to be an effective feature. For instance, Chun *et al.* (2003) and Chun *et al.* (2005) developed texture features based on statistical descriptors. Alternatively, texture features may be defined using filter banks or oriented pyramids (Forsyth and Ponce, 2003).

2.1.3 Color and texture

A straightforward extension of color and texture features is their combination. For instance, Chun *et al.* (2005) extended their textural features by adding color features. The efficient combination of color features and multi-resolution texture features yields a considerable improvement in retrieval performance when compared to the performance obtained from either color or texture in isolation (Liapis and Tziritas, 2004).

2.1.4 Relevance to painting authentication

The developments in the CBIR domain are directly relevant to the domain of paintings authentication. The color and texture features used in CBIR techniques offer an effective means to express the contents of image regions in a numerical representation. Images that are similar in terms of color or texture yield numerical representations (vectors) that are similar (near in terms of, e.g., Euclidean distance) in the color space or in the texture space. Hence, in CBIR applications, images that are perceptually similar can be retrieved. For the domain of painting authentication, perceptual similarity is also important. However, whereas in CBIR similarity is expressed relatively coarsely (e.g., paintings depicting the same scene), in painting authentication similarity refers to a much finer matching of, for instance, individual strokes. Therefore, the color and texture features used in CBIR may be used in painting authentication, provided that they are applied in a more subtle matching than is typically the case in CBIR applications.

2.2 Digital restoration of paintings

Digital restoration is the second domain in which digital analysis techniques are applied. As is well known, the visual appearance of art works changes over time, e.g., due to aging, storage conditions, physical damage, and improper conservation. In these cases, digital image analysis techniques can support the restoration of a painting, e.g., (1) by visualizing the effect of reversing the aging of the pigments in the painting or (2) by repairing deformations or damages to the painting. The first technique relies on elaborate models of aging of pigments and their interactions. For this purpose, special simulation models are developed that can run forwards and backwards in time. The second technique is called virtual restoration. It allows an art historian to see the painting in the state in which it was just after its creation. Although the investigations in the domain of virtual restoration are scarce, there are two main active areas of research: virtual cracks removal (see 2.2.1) and virtual cleaning (see 2.2.2). We complete the section by illustrating the relevance of virtual manipulations and painted images with respect to the task of painting authentication (see 2.2.3).

2.2.1 Virtual cracks removal

Virtual cracks removal deals with the cracks that have emerged on painted surfaces as a result of aging of the pigments and the painting support (Giakoumis and Pitas, 1998; Hanbury, Kammerer, and Zolda, 2003). The cracks form an interconnected structure called *craquele* that superimposes a textural pattern on the painting which interferes with the original brush work. The aim of virtual cracks removal is to remove the craquele and to reinstate digitally the original appearance of the painting as good as possible.

Giakoumis and Pitas (1998) presented a method for virtual cracks removal from digital reproductions of paintings. Their method consists of two stages: (i) crack detection and (ii) crack filling. In the crack-detection stage a high-pass filter called the top-hat transform is applied. This transform detects intensity discontinuities and isolates convex objects. The objects may be cracks or fine brush strokes. The authors employ HSI color information to distinguish between both types of objects. In the crack-filling stage, the cracks are filled using order statistics or anisotropic diffusion.

Hanbury *et al.* (2003) presented an alternative method for virtual cracks removal using information obtained from infrared images of paintings. They use a variant of morphological reconstruction, called viscous morphological reconstruction. Morphological reconstruction features two main components: a marker and a mask. Typically, the marker is smaller than the mask and located inside it. The marker is dilated repeatedly until it is constrained by a mask. Morphological reconstruction relies on the connectivity of similarly valued pixels. Since in paintings, pixels belonging to the same crack may be disconnected due to noise, viscous morphological reconstruction is introduced to "bridge" such disconnections. Exploiting the fact that cracks are generally thinner than strokes and occur in orientations that are consistent with the properties of wood panels, Hanbury *et al.* (2003) succeeded in achieving a good restoration performance.

2.2.2 Virtual cleaning

Virtual cleaning deals mostly with renewing colors and luminance of the art works to bring its appearance in the original stage right after its creation. Mostly, virtual clearing intends to foresee the results of the actual cleaning process or to support the decision whether such a process should take place at all.

The traditional cleaning of paintings is a trial-and-error procedure. Different cleaning substances are applied to small parts of the painting to assess their effectiveness. However, with such an approach it is difficult to guarantee that the chosen cleaning substance will work for the entire painting as good as it does for the probe surface. In contrast, in the virtual domain it is possible - based only on the reaction of the probe surface - to see how the entire painting will react on that particular cleaning substance. Once the painting and the probe surface to which the cleaning substance has been applied are digitized, a mathematical color-transformation function can be defined. Such a function transforms colors "before" cleaning to colors "after" cleaning in a pixel-wise manner. In addition, the function can be applied to the entire digitalized painting to visualize the predicted effect of applying the cleaning substance to the entire painting.

This basic idea is employed in Pappas and Pitas (2000). They presented several techniques of obtaining a virtual cleaning transformation function using the CIELab color representation (see 4.3.2). All methods are straightforward and easy to understand. Despite the apparent simplicity of the methods, simulations performed on a number of different paintings gave satisfactory results.

2.2.3 Relevance to painting authentication

Digital restoration techniques may be quite useful to automatic painting authentication. After all, the presence of cracks and other effects of aging, may interfere with the analysis algorithms and lead to misclassifications. However, notwithstanding their successes, the digital restoration techniques should be applied with care, because they add new information to the painting that is not directly related to the author of the painting. In our research, we do not apply digital restoration techniques.

2.3 Digital painting analysis

Painting-analysis approaches are highly relevant to our review. Within the domain of painting analysis we identify the following three sub domains: (i) geometrical painting analysis, (ii) painting-style analysis, and (iii) painting analysis for authentication. In this section we will focus on first two sub domains. For us, the third sub domain is most relevant since it deals with painting analysis for authentication.

So, it is at the center of the thesis, therefore it will be treated separately in chapter 3.

2.3.1 Geometrical painting analysis

Geometrical painting analysis studies the geometry of perspective paintings. More specifically, the development of perspective in medieval paintings is studied using digital-analysis methods (1) to learn about the skills of the artists and (2) to explore the evolution of linear perspective in history. The methods attempt (a) to detect the so-called vanishing points, (b) to assess the internal consistency of the geometry in a painting, and (c) to assess its conformity to the rules of linear perspective. Below we summarize the development of the scientific progress in this field by mentioning four (recent) breakthroughs.

First, McLean and Kotturi (1995) presented a method for the *automatic* detection of vanishing points. Image processing and image analysis are integrated into a coherent scheme which (1) extracts straight-line structures from images, (2) develops a measure of line quality for each line, (3) estimates the number of vanishing points and their approximate orientations, and then (4) computes optimal vanishing point estimates through combined clustering and numerical optimization. The performance of the developed algorithms has been evaluated both qualitatively and quantitatively.

Second, Criminisi, Kemp, and Zisserman (2002) analyzed the geometry of perspective paintings to explore the development of linear perspective in paintings. The authors presented seven algorithms used for: (1) assessing the internal consistency of the geometry in a painting and its conformity to the rules of linear perspective; (2) generating new views of patterns of interest; (3) reconstructing occluded areas of the painting; (4) measuring and comparing object sizes; (5) constructing complete three-dimensional models from paintings; (6) exploring, in a systematic way, possible ambiguities in the reconstruction, and (7) assessing the accuracy of the reconstructed three-dimensional geometry. The developed algorithms rely heavily on the use of algebraic projective geometry. They are rigorous and therefore easy to use.

Third, by using similar techniques, Criminisi and Stork (2004) showed how computers can be used to disprove (or at least question) a popular hypothesis of how early (i.e., 1420) European artists painted realistic three-dimensional scenes and portraits. According to the hypothesis, artists used optically projected images as a guideline for creating their paintings. By determining the geometric accuracy of Renaissance paintings, the hypothesis can be tested. In their work, Criminisi and Stork (2004) investigate new techniques for analyzing the perspective accuracy of paintings. Their analysis of the chandelier in Jan van Eyck's "Portrait of Arnolfini and his wife" revealed major geometric inaccuracies that are inconsistent with the projection hypothesis (Stork, 2004).

Fourth, we would like to draw the reader's attention to De Smit and Lenstra's (2003) study of the work of Maurits Cornelis Escher (1898-1972). De Smit and Lenstra studied the vanishing structure in Escher's lithograph *Prententententoonstelling* (see figure 2.1). The lithograph depicts a man in an exhibition gallery who is viewing a drawing of a seaport, which contains a man in an exhibition gallery who is viewing a drawing, and so forth.

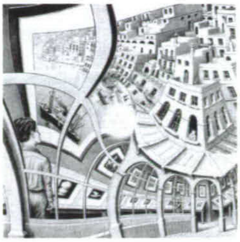
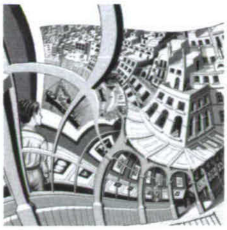
 

Figure 2.1: M.C. Escher's "Prententententoonstelling", before reconstruction (left) and after reconstruction (right).

Theoretically, this cyclic expansion could be expanded indefinitely. However, Escher was not able to figure out the required mathematics and terminated the expansion with a white patch in the center of the lithograph. De Smit and Lenstra (2003) succeeded in mathematically formalizing Escher's lithograph as composed on an elliptic curve over the field of complex numbers. Using this formalization, they were able to fill in the white patch.

2.3.2 Painting-style analysis

Painting-style analysis tries to detect changes in paintings associated with an artistic style, movement, or school. The methods employed may inspire techniques that can be used in authentication approaches. Below, we briefly review three distinctive approaches on classifying and explaining different painting styles.

First, Gribkov and Petrov (1996) developed a deductive model to explain structural properties of paintings. They examined the spatial composition of colored regions in paintings. Cultural-specific and school-specific color patterns were established for 822 paintings representing French, Italian, Spanish, and Russian national schools. The results obtained may be used for model purposes as well as for various studies in history of art.

Second, Icoglu, Gunsel, and Sariel (2004) distinguished between the works of three artistic movements using features largely related to luminance or gray scale. They are (1) the number of peaks in the gray scale histogram, (2) the deviation from the mean intensity in nine segments of the image, and (3) the skewness of the gray scale distribution. Using these global features, the researchers classified the paintings with various classifiers (naive Bayesian, k-nearest neighbor, and support vector machine). A classification accuracy of over 90 per cent is achieved with quite small false alarm rates. By indexing the paintings in a database with the gray-scale features, queries can be performed to search the database for paintings of the desired artistic styles.

Third, in Deac, Van der Lubbe, and Backer (2006) the selection of a small feature set for painting classification is performed by means of building an optimal pruned decision tree. The classification accuracy and the possibility of extracting knowledge for this method are analyzed. The results show that a straightforward small interpretable feature set can be selected by building an optimally pruned decision tree. Keeping in mind the parallel made between feature selection and decision-tree pruning, the focus of the study is directed onto the pruning of decision trees with an interpretation of the selected features.

As we already mentioned at the beginning of this section, the sub domain of main relevance to our study is the digital analysis of paintings to support art experts in their authentication. Chapter 3 reviews the most prominent studies performed in this sub domain, so far.

Chapter 3

Digital painting analysis for authentication

Even before the advent of powerful computers and advanced methods for image analysis, people started to realize that painting authentication may be supported by a formal analysis (see, e.g., Morelli (1893a) and Morelli (1893b) and, more recently Van Dantzig (1973)). The earliest works on digital painting analysis started to arise around the year 1995. In this chapter we review the studies that have been performed since then. Section 3.1 contains early works. Section 3.2 discusses color analysis. Section 3.3 reviews local texture analysis. Section 3.4 describes global texture analysis. Finally, section 3.5 contains challenges for authentication methods.

3.1 Early work

All approaches to the digital paintings analysis can be easily separated into two large categories: implicit approaches and explicit approaches. An *implicit* approach does not attempt to extract brush strokes or other (formal) elements for analysis (see 3.1.1). An *explicit* approach attempts to segment all elements and will use their properties for the analysis (see 3.1.2).

3.1.1 Implicit approaches

In the second half of the 1990s Postma *et al.* (1998) initiated their implicit approach at the authentication of paintings. The work was partly inspired by earlier work on a model of visual attention (Postma, 1994). Postma *et al.* (1998) surveyed a number of texture features to identify their ability to classify artistic styles by analyzing (1) oriented spatial features, (2) features derived from Fourier spectra, and (3) the independent components in an image. Oriented spatial features measured the local spatially oriented texture using Gaussian derivatives. The fast Fourier transform (FFT) could reveal spatially oriented features when sampled at a fixed distance from the center of the transformation. Finally, independent component analysis (ICA) could characterize texture in digital images. In particular, the Fast-ICA algorithm transforms two-dimensional vectors into components as independent from each other as possible. Postma *et al.* (1998) employed red-green-blue (RGB), hue-saturation-intensity (HSI), and hue histograms of 256 bins per channel in their survey of features. They found that, for their particular data set, color histograms based on the RGB color representation outperformed histograms based on the HSI color representation. More importantly, they found that texture features, such as fractal dimension and FFT coefficients, offer a clear advantage over color features in classification performance. However, Postma *et al.* (1998) refrained from normalizing the digital reproductions of the paintings for variations in physical size. As a result, the physical surface area of a painting as represented by a single pixel in its digital reproduction is not constant. Lombardi (2005) argued correctly that the lack of size normalization may have affected the FFT features and therefore the classification performance.

As stated in chapter 1, the study by Postma and Van den Herik (2000) was the first attempt to combine the worlds of art and computer science with the aim to authenticate paintings. In the Netherlands it was an important co-factor of starting the ToKeN programme, and later to the Authentic project as part of the ToKeN programme.

3.1.2 Explicit approaches

A variety of *explicit* approaches to painting analysis was proposed by Kammerer and colleagues. Kammerer, Langs, and Zolda (2003) presented an algorithm for the automatic segmentation of strokes in under drawings - the basic concept of the artist - in ancient panel paintings. The purpose of the stroke analysis is the determination of the drawing tool used to draft the painting. Information about the strokes facilitates the analysis of paintings. Up to now, the analysis has been done by human examination only. Subjective factors complicated the comparison of different under drawings with respect to drawing tools and stroke characteristics. Stroke segmentation in painting is related to the extraction and recognition of handwritings, therefore similar techniques to segment the strokes from the background incorporating boundary information are used. Following the segmentation, the approximation of the stroke boundary by a closed polygon was performed based on active contours. In brief, the approach was based on the traditional snakes moving over a Gradient Vector Flow field, initialized by an edge-based method. The main limitation of the approach is that crossed and bent strokes cannot be analyzed. Later, Vill and Kammerer (2006) dealt with this limitation by employing a combination of zip-lock and ribbon snakes. The results obtained by the improved segmentation technique are comparable to those obtained by humans. Still, the approach had four drawbacks. First, the technique involved manual labeling of the beginnings and ends of the strokes. Second, the user was required to set manually the constraints for detecting crossed strokes. (A crossing causes a larger difference in the directions at the right and left end points of a ribbon than a single stroke without crossing. If such a difference is larger than a user-set constraint, the directions with the larger difference to the main direction of the stroke are restricted to the main direction of the stroke.) This makes it a rule-based algorithm. Third, when the contrast of the background to a stroke is very low or if there is disturbing noise around the stroke, the snake can be misled. The correct segmentation depends on an appropriate preprocessing of the image, but is not always sufficient. However the algorithm produces good results on strokes which are continuously silhouetted against their background. Fourth, overlapping strokes even if they lie only partially over each other could not be detected.

From the review in the subsections 3.1.1 and 3.1.2, we may identify three main features used (with relative success) for painting analysis: color, local texture, and global texture. They are discussed below in three separate sections.

3.2 Color analysis for authentication

One of the prevailing elements in the authentication procedure of a painting is the analysis of colors. Currently, it is an important issue in the art-historian research (see chapter 4). Here we mention only the recent research effort that falls completely in this class. Widjaja, Leow, and Wu (2003) identified the authors of paintings from the color profiles of patches extracted from the paintings. After a series of normalization procedures, the colors were expressed in a range of well-known color representations (i.e., RGB, HSI, and CIELab, see, e.g., Gonzalez and Woods, 2001). The researchers used the features in combination with support vector machines to assign paintings to one of four classes, each of which represented a painter. Using a weighted voting system based on the best classifiers, they were able to reach a performance of 85 per cent correct classification.

3.3 Local texture analysis for authentication

There is a variety of local textures present in paintings. The term local implies that a particular texture feature does not hold for the whole painting. Examples of local texture features are: (1) the pattern of a single brush stroke, (2) the pattern of adjacent brush strokes, and (3) weave-like brush strokes. Below we discuss three approaches involving local features; they are different from Postma *et al.* (1998) (see 3.1.1).

Although Kammerer *et al.* (2003) and Vill and Kammerer (2006) only mention the final goal - drawing tools identification, they actually focus on local texture features by using stroke segmentation. Lettner and Sablatnig (2005) and Kammerer *et al.* (2007) followed up on earlier work (Kammerer *et al.*, 2003; Vill and Kammerer, 2006) by proposing an algorithm for the identification of the drawing material used for the creation of the strokes. As input for their algorithms, they used test panels deliberately prepared by a qualified restorer of paintings. These test panels contained strokes made by various drawing materials, both dry and fluid: graphite, black chalk, ink, quill, and so forth. The test panels were digitalized in two manners: (1) by scanning on the flat-bed scanner with 1200 dpi resolution, and (2) (in order to test the method on the real under drawing) the same test panels were covered by paint layers of different thickens and further photographed by an IR camera with a relative resolution of approximately 700 dpi. The identification algorithm proposed consists of three main stages: (1) stroke segmentation, (2) feature selection, and (3) classification. For the feature selection two techniques were used: (1) the Gray Level Co-occurrence Matrix and (2) the Discrete Wavelet Transformation. The results of the experiments showed that developed techniques managed to assign correctly 75 per cent of the brush strokes to 6 predefined classes.

In their more recent paper, Kammerer *et al.* (2007) extended their work on the drawing tools. They classified paintings on two stroke characteristics: (1) smoothness of the boundary and (2) the granularity of the stroke surface texture. The texture has been investigated by means of a discrete wavelet transformation. The smoothness features have been defined as the deviation of snakes of different elasticity. The techniques were tested both on scanned and IR images. Scanned images obtained about 89 per cent of correctly classified drawing materials, whereas IR images showed a lower percentage. Kammerer *et al.* assign this fact to a relatively low resolution of the IR images compared to the scanned ones.

The local texture analysis is naturally related to local fractal analysis. In this respect it is noticeable that Voss (1995) described a local fractal analysis of Chinese drawings. Voss applied fractal analysis to early and late Chinese landscape drawings (from 1000 A.D. to 1300 A.D.). The paintings from the early period were painted by artists living in the countryside, whereas the ones from the late period were painted by artists living in urban areas. James Watt, curator of Asian Art at the Metropolitan Museum in New York suggested that fractal analysis may provide a quantitative method of distinguishing between the early and late paintings. Voss showed that the visual differences apparent in both paintings indeed can be quantified using local fractal analysis.

3.4 Global texture analysis for authentication

Obviously, a global feature is a feature that holds for the whole painting, or even for the whole series of paintings (e.g., color: Picasso's blue period). An interesting global feature is the fractal dimension. It was used locally by Voss (1995), but usually it is used globally as is done by Taylor, Micolich, and Jonas (1999) (see below). Of course, there is a kind of area in between, i.e., a global texture feature composed of a number of local texture features. Below, we start with a telling example by Keren (2002), then discuss the fractal dimension and continue by the use of a stochastic model. Thereafter, we discuss three other global texture features.

First, Keren (2002) designed a classification scheme based on local features derived from the discrete cosine transformation. 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 calculates the probabilities of coefficients being associated with a particular painter. The probabilities are submitted to a naive Bayes classifier that is trained to classify test paintings. Using the technique, Keren accurately distinguished the work of five painters with an accuracy of 86 per cent.

Second, Taylor *et al.* (1999; 2002) demonstrated the fractal nature of Jackson

Pollock's work. Taylor *et al.* (2007) argued that the fractal dimension provides a measure of authenticity for works of Pollock. Recently, the work by Taylor has been criticized by Jones-Smith and Mathur (2006) who found that the paintings exhibit fractal characteristics over a range of spatial scales that is too small to be considered as fractal. However, as argued by R.P. Taylor and Jonas (2006), the range of scales over which the fractal dimension of Pollock's paintings was determined agrees with the typical ranges used in physics.

Third, Li and Wang (2004) developed a learning-based characterization of fine art painting styles. They claim that this research work has a potential to provide a powerful tool to art historians for studying connections among artists or periods in the history of art. The focus of their work is on comparing painting styles of artists. In order to do so, a mixture of stochastic models is estimated from images of paintings in a certain style. A two-dimensional (2D) multi-resolution hidden Markov model (MHMM) is used in the experiment. For every artist, these models form the artist's distinct digital signature. For certain types of paintings, only strokes provide reliable information to distinguish artists. Chinese ink paintings are a prime example of the above phenomenon; they do not have colors or even tones. The 2D MHMM analyzes relatively large regions in an image, which in turn makes it more likely to capture properties of the painting strokes. The mixtures of 2D MHMMs established for artists can be further used to classify paintings and compare paintings or artists. Algorithms presented in this study were tested using high-resolution digital photographs of some of China's most renowned artists. Experiments have demonstrated the potential of the approach for the automatic analysis of paintings. As stated above stochastic models form an artist's distinct digital signature. For certain types of paintings, such as the analyzed ancient Chinese ink paintings, the researchers claim that only strokes provide reliable information to distinguish artists and to arrive at authenticated art works.

As announced above, we now discuss three other global texture features. First, Lyu, Rockmore, and Farid (2004) designed authentication techniques which they applied to oil-on-canvas paintings. Lyu *et al.* (2004) subdivided images into non-overlapping sub-images and submitted these to a wavelet transform. The transform decomposed the images into five scales and three orientations, yielding 72-dimensional feature vectors of wavelet coefficients. Authentication was based on Hausdorff distances between the feature vectors. The result of their analyses was an $N \times N$ distance matrix, with N the number of paintings compared. The dissimilarities of paintings were visualized in a three-dimensional space using Multi Dimensional Scaling (MDS) (Kruskal and Wish, 1977). The visualization suggested a clustering by author.

Second, Lyu *et al.* (2004) applied the same technique to "'solve" the "many hands" problem. They submitted regions taken from painted faces to the wavelet transform and visualized the result. They found four distinct clusters, suggesting that the faces were painted by four different painters, which complies with claims by art experts. The work by Lyu *et al.* (2004) is highly relevant for our research. However, their paper raises two main questions. The first question is how the three-dimensional projection is obtained. More specifically, the authors fail to specify which feature vectors were included in the MDS procedure (Kruskal and Wish,

1977). The second question is why the authors did not normalize the sizes of the paintings by rescaling them to a common format. Since the standard wavelet transform does not generate a scale-invariant representation, differences in the sizes of paintings will lead to undesired considerable changes in the coefficients.
In Kroner and Lattner (1998) an authentication technique for drawings was presented. In this technique images of the drawings were scanned and transformed to binary images. Each image was subdivided into $M \times N$ non-overlapping sub-images. For each sub-image the ratio between black and white pixels was computed. Subsequently, the ratios for all sub images were represented in a eight-bin histogram. The bins represented the ratios ranging from zero to infinity. Kroner and Lattner (1998) extracted three features: (1) the difference between the counts of the third and fourth bins, (2) the quotient of the counts of the fifth and fourth bins, and (3) the product of the counts of the first and fourth bins. Additionally Kirsch masks (Pratt, 1978) were applied to extract oriented features (vertical, diagonal, horizontal, and anti-diagonal) from the drawn strokes. These features were submitted to a Bayes classifier, yielding a classification accuracy of 87 per cent.

3.5 Challenges for authentication methods

From the above review of digital painting analysis studies for the authentication of paintings we identify three challenges. These challenges are to perform:

1. automatic color analysis,
2. automatic brush stroke analysis, and
3. automatic authentication.

The challenges are motivated by the observation that (1) most color-analysis studies ignore the importance of calibrating the color spaces of the digitized paintings, (2) local texture analysis studies fail to evaluate their results with human experts, and (3) no study has attempted to perform automatic authentication.

We address these three challenges in the next three chapters. In passing we remark that the results achieved in those three chapters form the answers on RQ1, RQ2, and RQ3, respectively.

Chapter 4

Analysis of complementary colors

This chapter is based on the following publication[1]

- Berezhnoy, Postma, and Van den Herik (2007). Computer Analysis of Van Gogh's Complementary Colours. *Pattern Recognition Letters*, 28, 703-709.

This chapter addresses the first research question, RQ1: *How and to what extent can color analysis of the digitalized reproductions facilitate the authentication process?* Next to answering RQ1, we have two aims, viz. (1) to determine how successful the usage of complementary colors was in the oeuvre of Vincent van Gogh, and (2) to see whether this characteristic may make his paintings identifiable in time. It is commonly acknowledged that, especially in his French period, Van Gogh started employing complementary colors to emphasize contours of objects or parts of scenes. In this chapter we propose a new method called MECOCO[2] to measure complementary-color usage in a painting by combining an opponent-color space representation with Gabor filtering. To achieve the two aims, we undertook two actions (a) we defined a novel measure called the *opponency value* that quantifies the usage of complementary-color transitions in a painting (see 4.2.3), and (b) we studied Van Gogh's painting style (see 4.3). The result of our actions is two folded (A) MECOCO's analysis of a data set of 145 digitized and color-calibrated oil-on-canvas paintings confirmed the global transition pattern of complementary colors in Van Gogh's paintings as generally acknowledged by art experts. (B) MECOCO provided an objective and quantifiable way to support the analysis of colors in individual paintings.

[1]The first author would like to thank his co-authors for their permission to use parts of the publication in this chapter. Moreover, the Editors and the Publishers of the Journal are gratefully recognized for their permission to reuse essential parts of that publication in this chapter.

[2]MECOCO stands for Method for the Extraction of COmplementary COlors.

The outline of this chapter is as follows. Section 4.1 introduces the application of complementary colors by Vincent van Gogh, section 4.2 is a concise introduction to color and color perception. Section 4.3 presents our method MECOCO that analyses complementary colors in digital reproductions of paintings. In section 4.5 e provide the results of applying the method to a considerable part of Van Gogh's oeuvre. In section 4.6 we present to some extent a verification of our findings and discuss two critical factors which have a considerable impact on the results. Finally, section 4.7 gives an answer to RQ1 in the form of a conclusion and points to future work.

4.1 Complementary colors

Attempting to mimic and amplify the perceptual impact of natural scenes, Vincent van Gogh used complementary colors as a means to emphasize contours and to enhance the vividness of natural colors (Hulsker, 1996). Whereas early in his artistic career, Van Gogh refrained from using complementary colors, in his later career, while residing in Paris and the South of France, he made abundant use of complementary colors (Maffei and Fiorentini, 1999). Art experts analyzing the paintings by Van Gogh are quite interested in his usage of colors (cf. aim 1). In particular, they study the presence of complementary colors in his paintings (see, e.g., Badt, 1981). Focusing on aim 2, i.e., the viability of applying AI techniques with respect to colors we address the following question: can we establish an increase of complementary colors as used by Van Gogh in his paintings over his most active period (i.e., from 1885-1890)? To provide an answer to this question we performed a digital analysis of 145 of Van Gogh's oil-on-canvas paintings in an attempt to quantify and detect the transition in his usage of complementary colors.

4.2 The perception of complementary colors

The perception of colors can be best explained with the help of the color circle and the notion of color complements. The color circle is a circular arrangement of the spectral colors. Figure 4.1 shows an example of circularly arranged hues. The small circles arranged along the perimeter of the large color circle represent hues that match a standard set of color cards, the so-called Munsell cards (Munsell, 1923; Levine, 2000). The perceived color differences correspond to distances along the perimeter of the color circle. Colors on opposite sides of the color circle have the largest perceptual distance and are called complementary colors. The color pairs red-green and yellow-blue are well-known complementary colors. As can be seen in figure 4.1, these color pairs occupy approximately opposite sides of the color circle. Kuehni (2004) collected results on human variability in unique-hue perception for over 600 observers. The shaded circle segments illustrate the approximate variability of hues that were identified by human observers as the corresponding basic color. Although unique-hue variability is quite large, the ranges for the complementary pairs red-green and yellow-blue still occupy opposite segments of the circle as can be clearly seen in figure 4.1. The results indicate that different observers may assess the colors in a painting quite differently, whereas the same observers will largely agree on complementary color pairs.

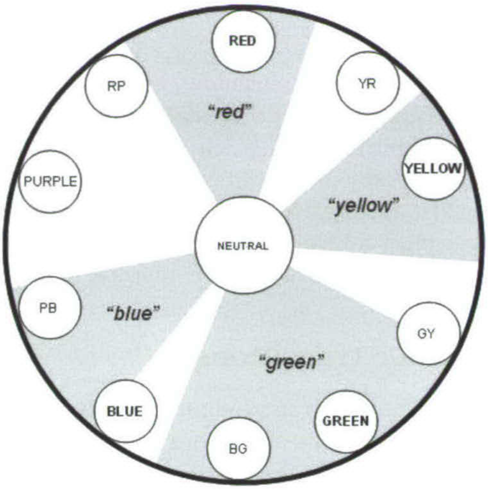


Figure 4.1: The color circle (reproduced from Kuehni, 2004).

Our analysis of Van Gogh's paintings is guided by neuro-scientific knowledge about the way how the human visual system processes complementary colors (Livingstone, 2002). Given the importance of complementary colors in Van Gogh's work and in the present study, we briefly discuss, in subsection 4.2.1, opponent channels which form the biological basis of complementary-color perception. Then, in subsection 4.2.2 we describe the color representation used in our study. Subsection 4.2.3 shows how complementary-color transitions are determined in our analysis.

4.2.1 Opponent channels

Color is a mental construct (see, e.g., Mollon, 1990). Therefore, when digitally analyzing color, the brain mechanisms responsible for generating a color experience have to be taken into account (insofar as possible). The human visual system processes chromatic signals using three types of retinal cone photo receptors. The neural transformation of the signals yields an opponent color representation in which chromatic information is expressed in three channels: a red-green channel, a yellow-blue channel, and a black-white (luminance) channel (Wandell, 1995; Zeki, 1999). The red-green and yellow-blue channels are very sensitive to complementary color pairs. For instance, the red-green channel is very sensitive to complementary color pairs that include red and green. Findings by Usui, Nakauchi, and Miyake (1994) suggest that the opponent channels arise naturally in artificial neural networks, namely that the opponent channels arise as the independent components of natural images (Lee, Wachtler, and Sejnowski, 2002). The latter statement is based on the fact that biological studies have revealed that individual neurons in the visual system respond to opponent colors (Valois and Valois, 2000).

4.2.2 Opponent-color space representation

Each of the three opponent channels can be regarded as forming the representation of an axis in an orthogonal three-dimensional color space. The values on the axis range from a minimum value representing one fully saturated color (e.g., green) to a maximum value representing its fully saturated opponent color (red). Halfway between these extremes, the value represents a shade of gray. Several opponent-color spaces have been defined (see, e.g., Wandell, 1995). The biological plausibility of opponent channels as the basis for the perception of complementary colors leads us to employ the CIELab color representation in our method of analysis (see section 4.3).

4.2.3 Opponent-color transitions

As stated in section 4.1, Van Gogh used complementary colors to emphasize contours in his paintings. Determining the usage of complementary colors requires a visual filter that responds to complementary-color contours. In the brain, neural cells that process colors exhibit a Gabor-like response sensitivity whereby the positive part of the Gabor function corresponds to one color of the opponent pair (e.g., red) and the negative parts correspond to the other color (green) (Valois and Valois, 2000). Figure 4.2 is an illustration of an idealized response profile of a red-green sensitive cell encountered in biological studies. It shows the response profile in the two-dimensional (image) plane against the red-green axis. The associated cell gives a maximal response when it is stimulated by a red-green contour in the proper orientation. In our analysis, we employ Gabor filters in combination with the opponent-color space representation yielding an opponent-color Gabor filter. In order to detect contours at several scales, we define such Gabor filters at four different scales (cf. Jain and Healey (1998); see also subsection 4.3.3). It enabled us to define a novel measure called *opponency value*. The definition is straightforward: the opponency value is the number of complementary color transitions in a painting. Of course, it is possible to subdivide this number into the transitions of the different complementary color transitions. We disregard this option for our research. Independent of the outcome of MECOCO's analysis, the experiments, and the results we may here already establish that the idea of using complementary colors by Van Gogh in his oeuvre was an eye-catcher in his time too and can be considered as quite successful (cf. aim 1 to be discussed below).

4.3 MECOCO's analysis of complementary colors

The first aim of our analysis is to determine how successful Van Gogh was in the usage of complementary colors over his most productive period. We use the *opponency value* as an indication that helps to measure the degree of success. The analysis of complementary colors is performed on digitized reproductions of oil-on-canvas paintings by Van Gogh. This section discusses the data set (in 4.3.1), the

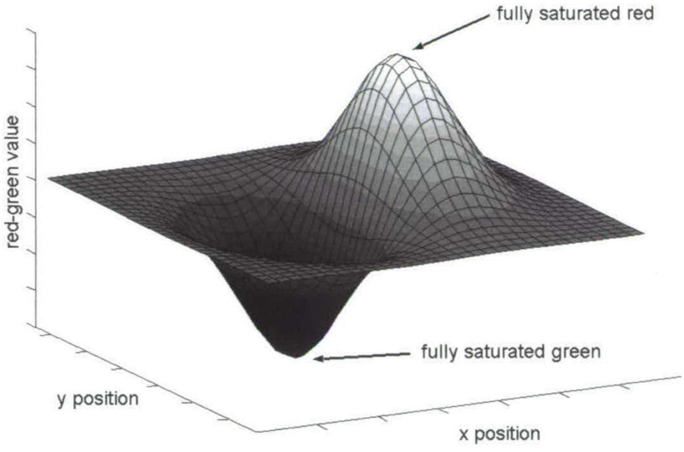


Figure 4.2: Illustration of the idealized response profile of a red-green sensitive cell in the visual system.

transformation of the data (in 4.3.2), and the method of analysis used to determine opponency values for each painting (in 4.3.3).

4.3.1 The data set

The digital analysis of colors from paintings depends critically on the quality of the data set. The appearance of colors in a digital reproduction of a painting is crucial. The two most important factors are: (1) the characteristics of the photosensitive film or CCD (charge-coupled device) element in the camera, and (2) the specific effects of the subsequent processes. In general, each operation (capture, reproduction, scanning) introduces distortions that may lead to a bias in the analysis. To minimize the effect of the distortions we used a high-quality color-calibrated data set consisting of Ektachromes provided by the Van Gogh Museum Amsterdam. Each Ektachrome contains a frontal photograph of a painting with a standard color calibration chart attached to it. The chart contains fully saturated reference colors for our analysis: red, green, blue, yellow, and white. The data set consists of 145 digitized Ektachromes of oil-on-canvas paintings made by Van Gogh during his stay in Antwerp (6), Paris (72), Arles (32), Saint-Remy (26), and Auvers-sur-Oise (9). All images were stored in uncompressed format and rescaled to a standard size. In the standard size, each pixel corresponds to a surface area of approximately 0.4 mm^2.

4.3.2 Data transformation

The RGB-coded images contained in the data set are transformed into CIELab color-space format that is based on the Munsell system (Forsyth and Ponce, 2003) and that was published by the *Commision Internationale de L'Eclairage* (CIE) in Paris. The CIELab space is spanned by the following three axes.[3]

- The luminance axis (L), with values ranging from 0 (black) to 100 (white),
- the red-green axis (a), with values ranging from -110 (green) to $+110$ (red), and
- the yellow-blue axis (b), with values ranging from -110 (blue) to $+110$ (yellow).

In contrast to RGB space, CIELab is a uniform color space in the sense that distances between points in that space correspond rather well to the perceptual differences of their color appearances. The CIELab transformation operates on images defined in XYZ color space. The coordinates in the CIELab space are obtained by a nonlinear transformation of the XYZ values (see, e.g., Wandell, 1995). The coordinates of the colors in the CIELab space are computed as follows (Forsyth and Ponce, 2003).

$$L = 116\left(\frac{Y}{Y_n}\right)^{\frac{1}{3}} - 16 \tag{4.1}$$

$$a = 500\left[\left(\frac{X}{X_n}\right)^{\frac{1}{3}} - \left(\frac{Y}{Y_n}\right)^{\frac{1}{3}}\right] \tag{4.2}$$

$$b = 200\left[\left(\frac{Y}{Y_n}\right)^{\frac{1}{3}} - \left(\frac{Z}{Z_n}\right)^{\frac{1}{3}}\right] \tag{4.3}$$

The CIELab transformation requires a so-called white point (X_n, Y_n, Z_n) as a reference (Forsyth and Ponce, 2003). The values X_n, Y_n, and Z_n represent the XYZ coordinates of pure white color. In our study, the white point was extracted from the white patch of the reference card. Subsequently, the (a, b) coordinates were computed for the red, green, yellow, and blue patches by averaging the RGB values of the corresponding image regions and transforming them into CIELab coordinates under the condition that $L > 0.3$. Figure 4.3(a) displays the (a, b) coordinates of the four patches for all paintings as points.

Ideally, all points representing reference patches of the same color should overlap since the same standard reference card was used for all paintings. However, a considerable scatter is observed, due to the different lighting and reproduction conditions during the photographing and Ektachrome creation of the paintings. Compensating for these variations is quite difficult because the exact conditions under which the photographs and the Ektachromes were created are unknown. Therefore, we

[3]For brevity, we denote the CIELab coordinates L^*, a^*, and b^*, by L, a, and b, respectively.

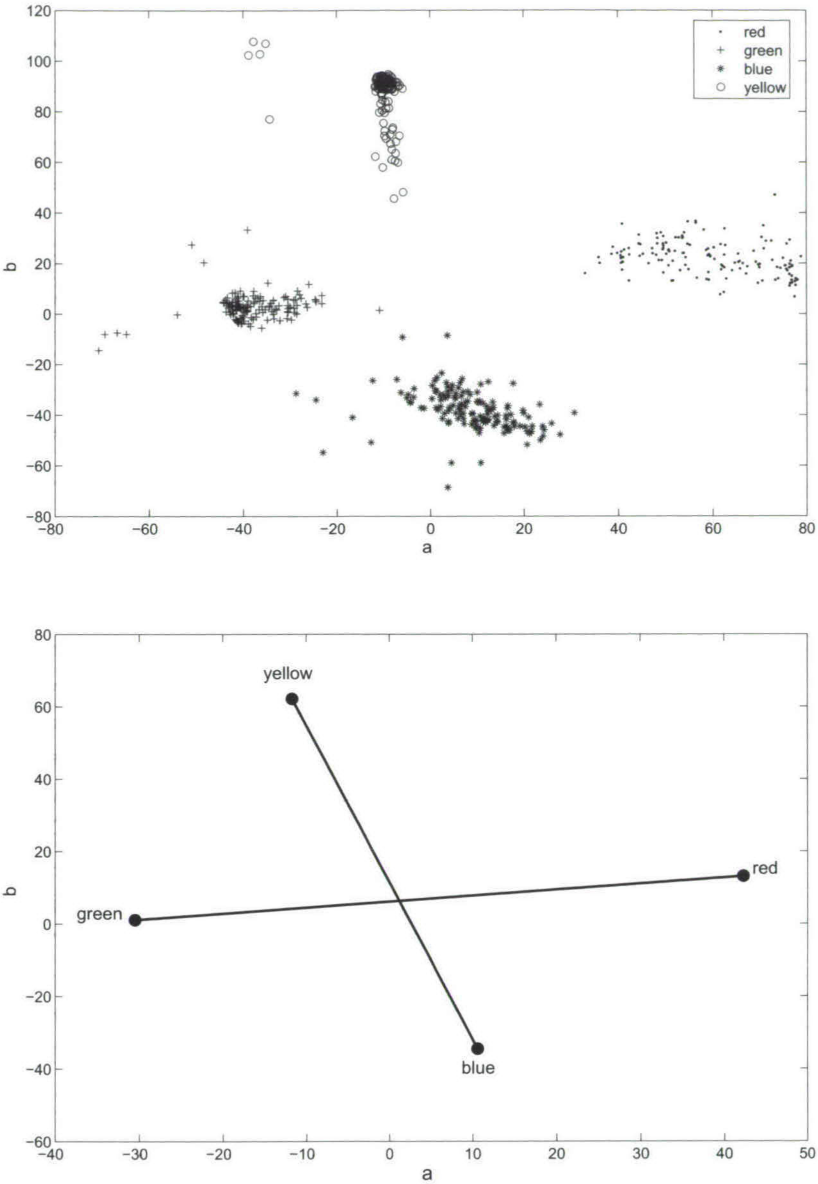


Figure 4.3: (a) Projection of the four reference color patches of all paintings on the $a - b$ plane. (b) Four reference color patches for a single painting. The axes represent the red-green (a) and yellow-blue (b) axis.

refrain from compensating these variations and only consider colors *within* paintings. In other words, we take the digitized colors of the reference card attached to a painting as reference colors for that painting only, since our main interest is in the faithful detection of the well-saturated colors red, green, blue, and yellow. The coordinates of these colors on the (a, b) plane reflect their appearance in the digital reproductions. Therefore, we take for each painting the coordinates of the four basic colors, i.e., (a_r, b_r), (a_g, b_g), (a_y, b_y), and (a_b, b_b), as anchor points for defining the opponent axes. Figure 4.3(b) shows an example for a single painting. All a and b components of the colors in the painting are interpreted in terms of their distance to the four reference points. To arrive at two opponent-color representations of a CIELab coded image I, we transform each pixel triplet (L, a, b) into two values F_{rg} and F_{by} representing the corresponding pixel values in the red-green and yellow-blue representations, respectively. The values are obtained by applying an attenuation function that enhances colors in the neighborhood of the reference colors and that suppresses unsaturated colors (i.e., colors for which (a, b) is near to the white point). The values F_{rg} and F_{by} are computed as:

$$F_{rg}(L,a,b) = H(L_{norm})\Big(G(a_r,b_r,a,b,\sigma_{att}) - G(a_g,b_g,a,b,\sigma_{att})\Big) \quad (4.4)$$

$$F_{by}(L,a,b) = H(L_{norm})\Big(G(a_b,b_b,a,b,\sigma_{att}) - G(a_y,b_y,a,b,\sigma_{att})\Big) \quad (4.5)$$

with $L_{norm} = (\frac{L}{L_{max}} - \Theta)$, L_{max} is the maximum luminance value, and Θ is a threshold value. $H(x)$ is the Heaviside step function that returns 1 if $x > 0$ and 0 otherwise, and G a two-dimensional Gaussian weighing function defined as

$$G(A,B,a,b,\sigma_{att}) = exp\left(\frac{-(\frac{a-A}{A})^2}{\sigma_{att}^2}\right) exp\left(\frac{-(\frac{b-B}{B})^2}{\sigma_{att}^2}\right) \quad (4.6)$$

with σ_{att} the standard deviation of the attenuation region ($\sigma_{att} = 0.4$). Applying these equations to the entire image yields two opponent-channel images I_{rg} and I_{yb}, the pixel values of which range from -1 to 1.

4.3.3 Opponent-color analysis

MECOCO's analysis measures opponent-color transitions by convolving both opponent images extracted from a painting with pairs of oriented Gabor filters (Jain and Healey, 1998). The pairs of Gabor filters, $Gabor_{even}$ and $Gabor_{odd}$, are defined as follows.

$$Gabor_{even}(x,y,\sigma,\alpha,\omega) = \cos(2\pi\omega(x\sin(\alpha) + y\sin(\alpha)))\exp\left(\frac{x^2+y^2}{2\sigma^2}\right) \quad (4.7)$$

$$Gabor_{odd}(x,y,\sigma,\alpha,\omega) = \sin(2\pi\omega(x\sin(\alpha) + y\sin(\alpha)))\exp\left(\frac{x^2+y^2}{2\sigma^2}\right) \quad (4.8)$$

In these equations, x and y are the spatial coordinates, σ the standard deviation of the Gaussian envelope, α the orientation of the filter, and ω the spatial frequency.

Each opponent image is convolved with odd and even pairs in four orientations (horizontally, vertically, diagonally, and anti-diagonally).
The opponency value for a painting is defined as the sum of the convolutions of the Gabor filter set with the images I_{rg} and I_{yb} divided by the number of pixels in the image. Appendix B-1 contains a flowchart of MECOCO.

4.4 Experiments

In all our experiments we defined the Gabor filters on a support of 32×32 pixels, and employed the following parameter values: $\sigma = 5$, $\alpha \in \{0, 0.5\pi, \pi, 1.5\pi\}$, and $\omega = 0.025$. We varied the scale of analysis by resizing the image by a factor 2^{-s+1} for scale $s \in \{1, 2, 3, 4\}$, while maintaining a fixed-sized filter set. For these parameter values, the Gabor profile falls well within the support (see figure 4.2).

4.5 Results

The second aim was to see whether using complementary colors made his paintings identifiable in time. We specify this question as follows: can we establish an increase of complementary colors as used by Van Gogh in his paintings over his most active period? For this purpose, we grouped the paintings by their year of creation. Each graph displays a scatter plot of the opponency values of the paintings created in the six years encompassing the period from 1885 to 1890. The four graphs of figure 4.4 show the results of the four spatial scales analyzed. In each graph, a dot represents a painting and its coordinates indicate the year of creation and the associated opponency value. Scale 1 represents the finest spatial scale of analysis for the detection of complementary-color transitions of a small size (e.g., adjacent brush strokes of red and green). Scales 2 and 3 are intermediate spatial scales, and scale 4 is the coarsest scale of analysis for the detection of complementary-color transitions of a large size (e.g., a yellow field against a blue sky).

Especially for the finer scales (scales 1 and 2) but also for the coarser scales (3 and 4), an increase in opponency values is observed over the period 1886 to 1888. These results are obtained with a threshold value of $\theta = 0.7$ (i.e., only colors with a normalized L of 0.7 or more were taken into account). Varying the threshold within the range $[0.6, 0.9]$ did not affect the main pattern of results.

A multiple comparison test (Liao, 2002) was performed to assess the statistical significance of the differences between the mean opponencies for each year. Table 4.1 lists the outcomes of the multiple comparison test for the four spatial scales of analysis. (Identical results were obtained for multiple comparisons using Tukey-Kramer and Scheffe's methods (Liao, 2002).) Each element within a sub table of Table 4.1 represents the comparison of the opponency values of paintings created in two years represented by the row and column labels. A +-sign represents a significant difference ($p \leq 0.05$) between the opponency values. For instance, in the upper sub table (scale 1), the +-sign in the third column (1887) and second row (1886) indicates that the observed difference in opponency values of paintings for these two years (1886 and 1887) is significant. This implies that Van Gogh increased his usage of small-scale complementary-color transitions from 1886 to 1887.

A significant difference in opponent-color transitions between early and later years is especially observed at the smallest scales examined. This suggests, that the increase in opponent-color contours are more prominent in the fine details, than in the coarse composition of the paintings.

Overall the results illustrated in figure 4.4 and listed in table 4.1 indicate that there is an increase of complementary-color transitions in Van Gogh's paintings in his most active period. This finding agrees well with the well-known increased usage of complementary colors by Van Gogh (Maffei and Fiorentini, 1999). These results help us to achieve our second aim of identifying Van Gogh's painting as accurately as possible in time.

Table 4.1: Results of multiple comparisons methods. Tukey-Kramer and Scheffe's methods yielded identical results for the four scales examined. Each element represents the comparison of the opponency values of paintings created in two years represented by the row (earlier year) and column (later year) labels. A "+"-sign represents a significant difference ($p \leq 0.05$) between the opponency values.

Scale 1	1885	1886	1887	1888	1889	1890
1885				+	+	+
1886			+	+	+	+
1887				+	+	
1888						
1889						
1890						

Scale 2	1885	1886	1887	1888	1889	1890
1885				+	+	
1886				+	+	+
1887				+		
1888						
1889						
1890						

Scale 3	1885	1886	1887	1888	1889	1890
1885						
1886				+	+	
1887				+		
1888						
1889						
1890						

Scale 4	1885	1886	1887	1888	1889	1890
1885						
1886				+		
1887				+		
1888						
1889						
1890						

4.6 A verification and a general discussion

The global pattern of our results supports the generally acknowledged increase in complementary-color transitions by Van Gogh. As stated in section 4.1, Van Gogh used complementary colors to enhance or emphasize the contours of the objects in his paintings. To verify whether large opponency values detected by MECOCO's analysis actually correspond to such enhanced contours, we modulated the intensity values of digitized paintings by the convolution values obtained by the convolution of the Gabor filter set at scale s with image I_{rg} (red-green opponency) or I_{yb} (yellow-blue opponency). In the modulated images, brightness is proportional to the local opponency value. Figure 4.5 shows two typical examples of paintings in which high opponency values detect detailed red-green contours (scale $s = 1$, top) and coarse yellow-blue contours (scale $s = 3$, bottom).

Despite these clear results, the validity MECOCO's analysis depends critically on two factors: (1) the biological plausibility of the opponent-space representation and the Gabor filtering, and (2) the quality of the data set. We are confident that the analysis is biologically plausible although further improvements may be obtained by deriving (a) the opponent-color space and (b) Gabor filters automatically from the images using statistical techniques based on independent component analysis and principal component analysis (Lee *et al.*, 2002). We are also confident about the quality of the Van Gogh data set since we were able to map the colors of the paintings in the painting-specific color space spanned by the four reference cards.[4]

In what follows, we discuss related work in content-based image retrieval and in image analysis. In content-based image retrieval, color represents an important cue for retrieving images. For the domain of the visual arts, special color representations have been proposed to facilitate the retrieval of paintings containing specified combinations of colors. A notable example is a representation due to Itten (1961) in which hues are arranged on the surface of a chromatic sphere, the so-called Itten sphere (Colombo, Bimbo, and Pala, 1999). Perceptual contrasting colors have opposite coordinates on the sphere. Itten's generalization of the color circle offers the advantage that it includes semantic interpretations of color contrasts that can support queries such as find all paintings that include warm colors. In addition, it can be included in art analysis systems to identify semantic or emotional characteristics in paintings.

In image analysis, color contrasts and opponent colors have been investigated by several researchers. A large number of studies have been performed on the automatic analysis and classification of color textures (see, e.g., Postma and Van den Herik (2000)). In the present context, the combination of spatial and chromatic features is of particular relevance. Jain and Healey (1998) proposed a multi-scale Gabor representation including monochrome and opponent features. Our multi-scale opponent-color representation is similar to that of Jain and Healey (1998). The main two differences are that (1) our color representation is defined relative to the painting-specific color cards, and (2) our representation emphasizes saturated colors (by means of equation 4.5).

As stated in subsection 4.2.3, the use of Gabor filters in our representation is motivated by biological insights. Single and multi-scale Gabor filters are widely used in image analysis and especially in texture analysis. Still, it may very well be the case that alternative representations such as co-occurrence matrices or the local binary pattern approach (Maenpaa, 2003) yield similar or even better results. This is left for future study.

[4]Of course, once more we owe much gratitude to the Van Gogh museum for providing high-quality material.

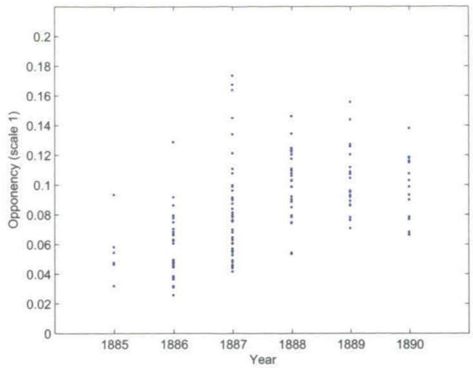
4.7 Chapter conclusion

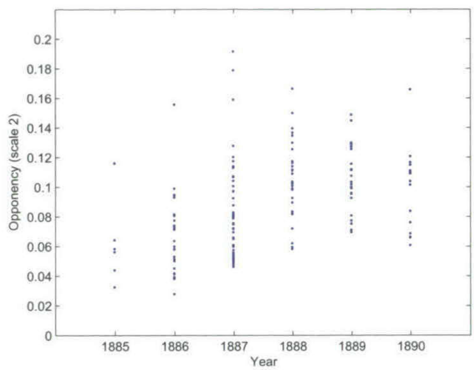
MECOCO's analysis of the usage of complementary colors by Van Gogh is mainly dependent on the color-reproduction quality of the digital images. However, since the projections of the detected complementary-color contours fully correspond to the contours of objects in the painting, we are confident that our analysis is fairly reliable.

Therefore, we complete the chapter by answering research question RQ1 as follows. From the results presented in this chapter we may conclude that the multi-scale Gabor transform (as employed by MECOCO) (1) is suitable for analyzing digital reproductions of paintings and (2) may facilitate the authentication process, e.g., by confirming the presence of complementary-color contours that are characteristic for Van Gogh. Moreover, we have seen that MECOCO clearly succeeds in establishing an increase of complementary-color usage by Van Gogh over his most productive period. Furthermore, the opponency values of individual paintings provide a hint to identify the time in which a painting by Van Gogh has been made. As is well known, the ordering of Van Gogh's work has been a challenge for many art experts over the years (Hulsker, 1996).

In summary, based on these results, we may come to a more general conclusion. We foresee an increasing use of AI techniques in the domain of visual arts to support art experts in their analysis of paintings. In our future work we will expand our investigations by covering the following four features: (1) color, (2) texture, (3) shape, and (4) composition of Van Gogh's paintings. In addition, alternative color-texture representation schemes will be explored.

Our conclusion reads that the digital analysis of Van Gogh's paintings provides an objective quantification of the complementary-color transitions that agrees qualitatively with the development of Van Gogh's painting style.


Opponency (scale 1)
0 0.02 0.04 0.06 0.08 0.1 0.12 0.14 0.16 0.18 0.2
1885 1886 1887 1888 1889 1890
Year


Opponency (scale 2)
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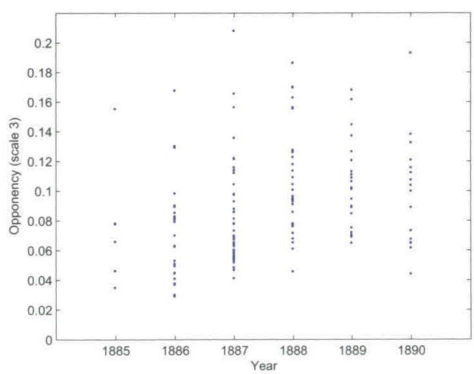
1885 1886 1887 1888 1889 1890
Year


Opponency (scale 3)
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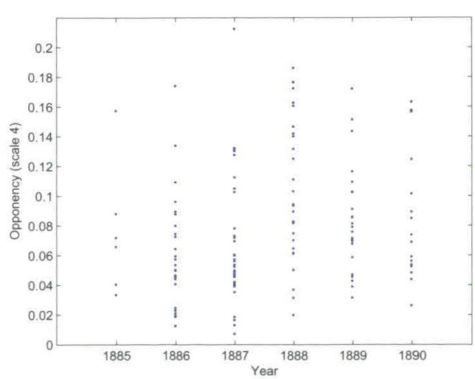
1885 1886 1887 1888 1889 1890
Year


Opponency (scale 4)
0 0.02 0.04 0.06 0.08 0.1 0.12 0.14 0.16 0.18 0.2
1885 1886 1887 1888 1889 1890
Year

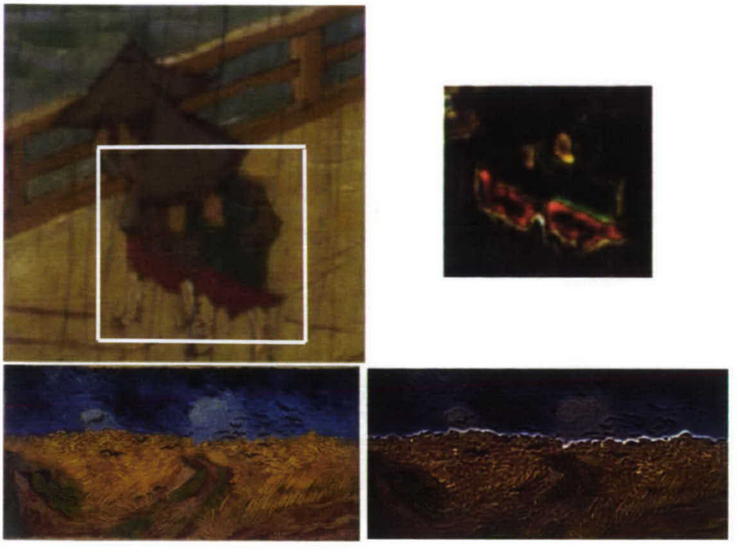


Figure 4.5: (Top) The detail of the painting "Bridge in the Rain", Paris 1887 (F 372), shown on the left, contains a clear red-green transition. The white rectangle indicates the area that is shown on the right as a red-green opponency-modulated image (scale $s = 1$) in which intensity is proportional to opponency. (Bottom) The painting "Wheatfield with Crows", Auvers-sur-Oise 1890 (F 779). The yellow-blue transitions between the wheat and the sky in the original painting on the left, yields a high yellow-blue opponency value (scale $s = 3$) in the yellow-blue opponency-modulated image on the right.

Chapter 5

Automatic brush stroke orientation extraction

This chapter is based on the following publication[1]

- Berezhnoy, Postma, and Van den Herik (2009). Automatic extraction of brush-stroke orientation from paintings. *Machine Vision and Applications Journal*, 20(1), pp. 1-9.

Spatial characteristics play a major role in the human analysis of paintings. One of the main spatial characteristics is the pattern of brush strokes. The orientation, the shape, and the distribution of brush strokes are important clues for analysis. This chapter focuses on the automatic extraction of the orientation of brush strokes from digital reproductions of paintings. It addresses the second research question, i.e., RQ2: *Which features of the brush work can be extracted effectively from the digital reproduction of a painting?* In an attempt to answer RQ2, we present a novel technique called the POET (Prevailing Orientation Extraction Technique). The technique is based on a straightforward circular filter and a dedicated orientation extraction phase; we aim at bringing the performance at a level that is indistinguishable from that of humans. From our experimental results we may conclude that the POET adequately supports the automatic extraction of the spatial distribution of oriented brush strokes. Such an automatic extraction will aid art experts in their analysis of paintings. Based on the results of the automatic extraction we will answer RQ2.

The outline of the chapter is as follows. In section 5.1 we emphasize the importance of brush strokes. In section 5.2, we present the data used for the empirical evaluation of the POET. Section 5.3 describes the POET and the procedure for

[1]The first author would like to thank his co-authors for their permission to use parts of the publication in this chapter. Moreover, the Editors and the Publishers of the Journal are gratefully recognized for their permission to reuse essential parts of that publication in this chapter.

obtaining orientation judgments of human subjects. Section 5.4 describes the experimental setup and section 5.5 presents the results. Section 5.6 discusses the results and section 5.7 provides conclusions and pointers to future work.

5.1 Brush strokes

When an art expert analyses a painting, a variety of techniques is available. They range from chemical analysis of pigments via analysis of visual observations to dendrochronological analysis of the panel supports (Van de Wetering, 1997). In this chapter we focus on digital visual-analysis techniques for oil-on-canvas paintings. In the analysis of an impressionistic painter of oil-on-canvas paintings, brush strokes play a key role. In particular, the spatial characteristics of brush strokes, such as (1) their orientation, (2) their shape, and (3) their distribution are important (Van Dantzig, 1973). Art experts believe that these characteristics hold a unique signature of the painter and, therefore, may aid judgments about the authenticity of a painting. Up till now the analysis of spatial characteristics was performed manually by skilled art experts. However, manual extraction of spatial characteristics is a difficult and time-consuming task (Van Dantzig, 1973).

As stated in chapter 1, recent advances in artificial intelligence (in particular in image processing) allow the art expert to be supported by digital techniques. Quantitative and objective analysis may facilitate the quality and consistency of the visual assessment. Our focus is on the texture orientation of brush strokes rather than on the brush strokes themselves (as in Lettner, Kammerer, and Sablatnig (2004)). Our research is motivated by the difficulty of segmenting individual brush strokes in Van Gogh's works. Van Gogh employed a painting style that gave rise to many overlapping brush strokes, making the identification of individual strokes very hard (Van Dantzig, 1973).

In order to be actually beneficial to the art expert, a computerized technique must perform at a level comparable to that of humans. Therefore we will evaluate the POET by comparing its orientation judgments to those produced by human subjects. We aim at showing that the POET performs at such a level.

5.2 The data

A good start to become acquainted with the main spatial characteristics of paintings is defining a data set of patches. They contain oriented brush strokes as a test bench for our technique. The data were produced from an image set of 169 digitized reproductions of paintings by Vincent van Gogh. The reproductions were obtained by scanning Ektachromes at a resolution of 2000 dpi with 48 bits color depth. To normalize the spatial scale of the paintings, all images were resized to match the resolution of the lowest-resolution painting: 196.3 dpi. Normalization is necessary for adequate comparison.

From the normalized image set, we randomly selected 200 gray-scale patches of 100 by 100 pixels each. Figure 5.1 shows nine examples of such patches. It should be noted that in most of these examples, clear prevailing brush-stroke orientation is difficult to determine.

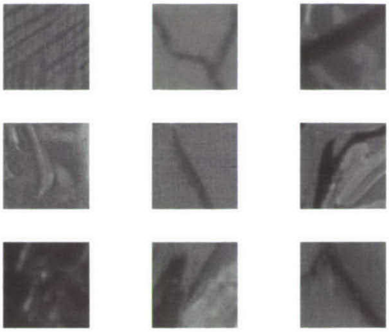


Figure 5.1: Nine examples of patches extracted from paintings by Vincent van Gogh.

5.3 Automatic orientation extraction

The design of the Prevailing Orientation Extraction Technique (POET) is inspired by observation and analysis of the human performance on the authentication task. It is in essence motivated by a failure and/or computational inefficiency of the traditional approaches (Knutsson, 1989; Felsberg and Sommer, 2001). The POET is designed after the empirical finding that the brightest and largest oriented contours within a patch of brush strokes determine the perceived prevailing orientation. Being more precise we may state that the design of the POET is motivated (1) by a failure to extract the prevailing orientation from the Fourier spectrum directly (Bigün and Granlund, 1987) as well as (2) by the desire to improve the performances of well-known techniques, such as orientation-estimation by means of smooth derivative filters (Farid and Simoncelli, 2004; Freeman and Adelson, 1991) and orientation estimation using multi-scale principal component analysis (Feng and Milanfar, 2002).

The POET consists of two stages: (1) a filtering stage and (2) an orientation-extraction stage. In the filtering stage the image is convolved with a Circular Filter (CF) yielding a convolved image in which oriented parallel contours are enhanced. In the orientation-extraction stage, the convolved image is processed to extract the prevailing orientation. Figure 5.2 illustrates the successive stages of an original image patch that is processed by the POET.

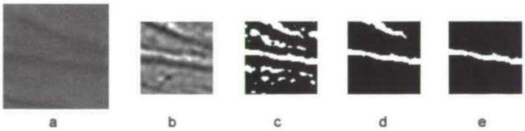


Figure 5.2: Illustration of successive steps in the POET consisting of the filtering stage (a-b) and orientation-extraction stage (c-e).

Figures 5.2(a-b) illustrate the filtering stage. Figure 5.2(a) shows the original image patch containing oriented brush strokes. The patch is convolved with a circular filter yielding the convolved image shown in figure 5.2(b). Figures 5.2(c-e) show the three steps constituting the orientation-extraction stage. This stage creates a binary representation of the convolved image containing oriented objects (the white shapes in figures 5.2(c-e)). In the following two subsections we describe both stages of the POET in more detail.

5.3.1 The filtering stage

The filtering stage is based on the application of a circular filter. The circular filter is a filter deliberately designed to satisfy two criteria: (1) orientation invariance, i.e., the filter should enhance oriented contours in all directions, and (2) a band-pass response, i.e., the filter should enhance contours within a specific range of spatial frequencies. Using the frequency sampling method (Gonzalez and Woods, 2001), the design of a filter meeting both criteria is straightforward. The method for designing the filter is illustrated in figure 5.3. In meeting the orientation-invariance criterion a circular band of frequencies is selected in the frequency domain. Two parameters define the orientation-invariant pass band of the filter, the pass-band width W, and the central spatial frequency R. The upper and lower cut-off frequencies of the filter are defined as $R - W/2$ and $R + W/2$, respectively. The pass-band criterion is met by selecting appropriate values for R and W. Figure 5.3(a) shows the idealized frequency domain response of the filter ($R = W = 0.5$). Figure 5.3(b) shows the actual response. The shape of the filter in the spatial domain is shown in figure 5.3(c).

We now return to figure 5.2. After setting up the parameters of the filter, an image patch (figure 5.2 (a)) is convolved with the filter. The resulting convolution image can be seen in figure 5.2 (b).

5.3.2 The orientation-extraction stage

The orientation-extraction stage transforms the convolved (filtered) image into a set of binary oriented objects which correspond to the bright brush strokes present in the patch. The properties of the objects will be used to extract the principal orientation of the brush strokes.

To obtain a binary image, we apply a simple and efficient multilevel thresholding (see Arora *et al.* (2008), for a recent overview). After mapping the convolution values onto the unit interval (in such a way that the minimum value equals 0 and the maximum value 1), all convolution values smaller than k/K are set to zero, and all others to 1, where K represents the number of threshold levels and k is an index for the threshold level. For an appropriate choice of k and K, the binary image contains oriented objects that correspond to segments of the brush strokes.

Figure 5.4 illustrates the binary maps obtained for the convolved image shown in figure 5.2 (b) for $k = 1, 2, ..., K$ with $K = 33$. Our objective is, given K levels, to select a threshold value k/K that maximizes the number of oriented objects in the binary image because these objects contribute to the perceived prevailing orientation.

An oriented object is defined as a connected cluster of at least eight non-zero pixel values of which the enclosing ellipse has a major axis length that exceeds 70 per cent of its minor axis length.

Our procedure to estimate the prevailing orientation of objects in the binary maps is based on two observations. The first observation is that for small and large values of k, the total number of objects is smaller than for intermediate values of k. The reason for this is obvious. For small k, many objects are connected forming larger objects (see the top row of figure 5.4), whereas for large k, only a few objects exceed the threshold (see the bottom row of figure 5.4). For intermediate values of k, there is a value of k for which the number of oriented objects is maximal (k still to be determined). The second observation, based on preliminary experiments, is that in general the value of k for which the number of oriented objects is maximal corresponds to the value of k for which the number of objects is maximal. The two graphs in figure 5.5 illustrate this for a single convolved image. The graphs show the number of objects (upper graph) and oriented objects (lower graph) as a function of k ($K = 33$). For this particular image, the maximum number of objects and oriented objects is reached for $k = 10$.

These two observations allow us to reduce the computational costs for determining the appropriate value of k. We simply select the value of k for which the number of objects is maximal.

Having established the appropriate value of k, we sort the oriented objects according to the major axis length of their enclosing ellipse. From the two front-ranked objects (i.e., the two objects with the largest major axis length of their enclosing ellipses), the one with the largest eccentricity of its enclosing ellipse is selected. The orientation of this object is defined as the prevailing orientation of the image patch. Appendix B-2 contains a flowchart of the POET.

In our experiments (see 5.4), human orientation judgments serve as a reference for evaluating the POET's performance. The procedure for acquiring the human judgments is described in subsection 5.4.2.

5.4 Experiments

This section describes the experiments and consist of three parts. In the first part (5.4.1) we describe the two main parameters of the circular filter and their constraints. The values of both parameters were optimized in order to achieve optimal performance by the POET. In the second part (5.4.2) the human-subject orientation-judgment procedure is explained. The third part (5.4.3) describes the techniques applied in order to evaluate the POET's performance.

5.4.1 The POET's parameter settings

To optimize the POET's performance, we did an exhaustive search in the parameter space. We systematically varied the two main parameters, the pass-band width W and the center frequency R of the circular filters' frequency response. Both parameters were varied by steps of 0.01 on the unit interval, where 0 corresponds to the minimum spatial frequency (zero or DC point) and 1 to the maximum spatial frequency. Both parameters were constrained to valid values, i.e., the following three conditions should all be fulfilled: $0 < R < 1$ and $R - W/2 >= 0$ and $R + W/2 <= 1$. The POET's performance is evaluated by comparing its orientation judgments to those of the human judges. The human orientation judgments were obtained in a separate experiment. The set-up of the experiment is described in the next subsection.

5.4.2 Set-up of the human orientation judgment experiment

In the human orientation-judgment experiment, 15 subjects took part. The procedure of the experiment was as follows. Individual patches were presented on a computer screen. The size of the patch on the screen was 0.2 by 0.2 meters and the subjects had a viewing distance of about 0.5 meter. Each subject had to specify two points: a beginning and an end of the line representing the prevailing brush stroke orientation of the patch. When the two points were specified, the line connecting the two points was superimposed on the patch to allow subjects to inspect and revise their orientation judgment visually. Subjects could revise their judgment as often as they desired. All subjects were instructed to complete the task at their own pace. In total, each subject judged the orientation of 200 patches. On average, they completed the task within 10 to 15 minutes. Figure 5.6 shows a typical example of a line superimposed on an image patch.

5.4.3 Criteria for the POET's performance

The evaluation of the POET is based on a comparison of its estimates of the prevailing orientation of image patches to those obtained by human judges. Our interest is in the smallest difference between the orientation judgments of the POET and a human subject assessing the same patch. In addition, we will compare the judgments of the POET also with two other techniques for estimating the orientation of textured patterns in a wider context.

Computing angular differences

The pair-wise comparisons of the POET's results and the human prevailing orientation judgments is performed as follows. The angular difference is defined as the smallest angle between the two orientations. Representing the orientations to be compared by α_i and α_j (with $\alpha_i > \alpha_j$) we define their angular difference D_α in degrees as:

$$D_\alpha(i,j) = \min\{d_\alpha(i,j), 180 - d_\alpha(i,j)\}, \tag{5.1}$$

where

$$d_\alpha(i,j) = \min\{(\alpha_i - \alpha_j)_{\mathrm{mod}360}, (180 + \alpha_i - \alpha_j)_{\mathrm{mod}360}\} \tag{5.2}$$

Using this definition, the angular difference is confined to the interval 0 to 90 degrees.

Criterion for success

The main criterion for the successful automatic extraction of brush-stroke orientation is a performance that is indistinguishable from human performances. To assess whether this criterion is met, we determine the differences between the judgments of the POET and those of the human subjects by means of the mean squared angular distance (MSAD).

5.5 Results

The presentation of results consists of three parts. In the first part, we present the results of the human orientation judgments (5.5.1). In the second part, these judgments are compared to those obtained by the POET (5.5.2). Finally, in the third part, we compare the performance of the POET to two other orientation estimation techniques (5.5.3).

5.5.1 The human-orientation judgment

Figure 5.7 displays the fourteen histograms of the human orientation judgments. Each histogram shows how often a patch was assigned a certain orientation (modulo 180 degrees) by a particular subject. The overall variety of the histograms suggests that the 14 subjects were not always consistent in their judgments.

Figure 5.8 shows the overall histogram of the human judgments, obtained by summing all histograms shown in figure 5.7. The histogram reveals that many patches were assigned a vertical (0 degrees) or horizontal (90 degrees) orientation. Visual examination of the data set revealed that the preference for these orientations stems from the orientation distribution of brush strokes in the data set rather than from a perceptual effect, i.e., the "oblique effect" (McMahon and MacLeod, 2003).

5.5.2 The judgments compared

The parameters R (central spatial frequency) and W (pass-band width) of the POET were optimized to match the human judgments as closely as possible. The optimization was performed for each subject separately yielding in total eight different pairs of optimized parameter values (four of these pairs were matched to more than one human orientation judgment, the remaining four to single human judgments). Table 5.1 lists the eight unique pairs of the optimized parameter values of R and W. Each pair is labeled with a separate label (a letter). The first column of the table indicates the filter labels (A to H). The second and the third columns show the values of the two filter parameters. These values indicate that spatial frequencies centered at 0.12 to 0.21 cycles per pixel yield the best match with human judgments. The corresponding brush stroke contours are about 4 to 8 pixels in width.

In table 5.2, the first column lists the human subjects; the second column gives the optimal filter for the human subjects. The third column displays the MSAD value (Mean Square Angular Difference) for the filter - human subject combination.

Table 5.1: Overview of the parameter values R and W that yield the best match with one or more human judgments.

FILTER	R	W
A	0.18	0.18
B	0.19	0.10
C	0.12	0.10
D	0.21	0.14
E	0.13	0.10
F	0.21	0.15
G	0.16	0.14
H	0.21	0.10

Table 5.2: Overview of the filters that yield the best match for a particular human subject.

HUMAN SUBJECT	FILTER	MSAD
hs1	A	697.00
hs2	B	532.00
hs3	C	878.00
hs4	C	861.00
hs5	D	396.00
hs6	D	464.00
hs7	B	785.00
hs8	E	756.00
hs9	B	807.00
hs10	F	675.00
hs11	G	695.00
hs12	E	709.00
hs13	B	584.00
hs14	H	471.00

Subsequently, we take these eight filters of which the performances match the human performances most closely and compute an average MSAD per filter over all human subjects. These averages are listed in table 5.3. The filter with the smallest average MSAD error is selected as the filter for the POET. From table 5.3 we may see that filter D, with $R = 0.21$ and $W = 0.14$ (see table 5.1), gives the lowest MSAD, and is therefore selected as the filter for the POET.

We cross-compared the judgments of the POET to those of each human subject (hs). It resulted in the matrix shown in table 5.4. Each entry specifies the MSE of the angular differences between the row and column judgments. We deliberately included entries below the diagonal to facilitate the interpretation of the results. Overall, from the values in this table we see that the POET judgments agree fairly well with those of most human subjects.

Figure 5.9 illustrates the differences between the human orientation judgments (gray dots) and the POET judgments (solid line). The graph shows the angular differences $D_\alpha(i,j)$ with respect to the horizontal axis ($\alpha_j = 0$) against all patches sorted in order of ascending orientation according to the POET. Evidently, the POET's judgments agree quite well with most human judgments.

INVITATION

to the open defense of my
PhD thesis

DIGITAL ANALYSIS OF PAINTINGS

on

Monday, December 7,

at 2 pm

in the Aula of

Tilburg University,

Warandelaan 2

5037 AB Tilburg.

The ceremony will end with
a reception.

IGOR BEREZHNOY

Table 5.3: Overview of the filters that yield the smallest average angular distance over all human subjects. Filter D showed the best performance.

FILTER	MEAN MSAD
A	709.79
B	680.93
C	841.36
D	463.07
E	858.5
F	755.36
G	869.86
H	573.79

Table 5.4: A cross-comparison of all judgments. Each entry specifies the mean squared angular distance (MSAD) between the row and column judgments.

	POET	MP	SF	hs1	hs2	hs3	hs4	hs5	hs6	hs7	hs8	hs9	hs10	hs11	hs12	hs13	hs14
POET	0	424	1841	584	271	464	490	396	464	559	313	560	426	541	354	616	445
MP	424	0	1947	680	463	587	647	504	521	597	439	808	524	538	466	783	451
SF	1841	1947	0	1893	1891	1902	1981	1922	2018	2091	1907	1844	1989	2051	1867	1948	1985
hs1	584	680	1893	0	675	486	876	629	630	898	532	846	582	629	660	1161	811
hs2	271	463	1891	675	0	578	533	456	483	595	350	678	528	734	459	710	539
hs3	464	587	1902	486	578	0	864	408	503	809	442	674	510	718	575	961	658
hs4	490	647	1981	876	533	864	0	583	658	619	616	673	893	818	616	779	593
hs5	396	504	1922	629	456	408	583	0	437	568	379	550	590	739	315	685	583
hs6	464	521	2018	630	483	503	658	437	0	509	343	733	493	545	444	911	625
hs7	559	597	2091	898	595	809	619	568	509	0	598	753	841	750	565	870	624
hs8	313	439	1907	532	350	442	616	379	343	598	0	600	418	511	361	792	523
hs9	560	808	1844	846	678	674	673	550	733	753	600	0	741	858	586	843	759
hs10	426	524	1989	582	528	510	893	590	493	841	418	741	0	685	564	907	521
hs11	541	538	2051	629	734	718	818	739	545	750	511	858	685	0	605	1057	667
hs12	354	466	1867	660	459	575	616	315	444	565	361	586	564	605	0	684	420
hs13	616	783	1948	1161	710	961	779	685	911	870	792	843	907	1057	684	0	866
hs14	445	451	1985	811	539	658	593	583	625	624	523	759	521	667	420	866	0

5.5.3 The POET versus standard techniques

In this subsection we compare the performance of the POET to two orientation-estimation techniques: (1) multi-scale principal components (MP) (Feng and Milanfar, 2002) and (2) single-scale steerable filters (SF) (Freeman and Adelson, 1991; Farid and Simoncelli, 2004). The two parameters for the orientation estimation with steerable filters are (a) the number of orientations and (b) the scale. The prevailing orientation is defined as the orientation with the maximum energy. In the MP the image patch was subdivided into 12×12 sub-images, for each of which the orientation was determined from the principal components at multiple scales. The prevailing orientation was defined as the most frequently observed orientation (the mode of a 60-bin histogram of the angles).

We optimized the parameters of these two techniques in a similar way as for the POET and obtained the results listed in the third and fourth rows and columns of table 5.4. The Mean Squared Angular Difference (MSAD) is smallest for the POET. The steerable filters clearly show the worst performance.
Table 5.5 shows the MSAD for each technique, averaged over all human subjects.

As an additional evaluation, we computed the correlation coefficients for the three techniques studied. In table 5.6, the correlations for each technique (columns) are listed per human subject (rows). All correlations are significant ($p < 0.001$), except for a subset of non-significant correlations obtained by the single-scale steerable filters. They are indicated by n.s. in table 5.6.

Table 5.5: Overview of the performance of the POET and two alternative techniques: the multi-scale principal components analysis (MP) and the steerable filters (SF).

METHOD	MEAN MSAD
POET	463
MP	572
SF	1949

Table 5.6: Agreement between automatic judgments of the three techniques (columns) and the human judgments (rows) expressed in terms of correlation coefficients. All correlations are significant ($p < 0.001$), except for those indicated by n.s.

	POET	MP	SF
hs1	0.75	0.69	0.23
hs2	0.86	0.75	0.23
hs3	0.76	0.70	0.23
hs4	0.76	0.65	0.22 n.s.
hs5	0.80	0.74	0.22 n.s.
hs6	0.74	0.73	0.16 n.s.
hs7	0.71	0.66	0.16 n.s.
hs8	0.84	0.77	0.24
hs9	0.77	0.65	0.23 n.s.
hs10	0.80	0.75	0.22 n.s.
hs11	0.76	0.74	0.17 n.s.
hs12	0.84	0.77	0.27
hs13	0.73	0.60	0.21 n.s.
hs14	0.80	0.78	0.22 n.s.
Mean	0.78	0.71	0.22

The bottom row of table 5.6 shows the average correlation coefficients. Again, the best correlation is obtained by the POET.

Figure 5.10 provides a visual illustration of the correlations by plotting the automatic judgments (horizontal axis) against the human judgments. The three groups of 14 plots display the correlations of the POET (left), the MP (middle), and the steerable filters (right), with the 14 human judgments. From a global visual examination, the relative performances of the three techniques are clear: the POET yields the best agreement (the points are nearest to the diagonal), the MP performs second best, and the steerable filters yield the worst performance.

5.6 Chapter discussion

In this chapter we presented a novel technique called the POET which generates orientation judgments. From the experimental results we may conclude that the judgments are indistinguishable from the judgments by human subjects. The success of the POET is likely due to the fact that it identifies the main oriented objects in the image and use these for estimating the prevailing orientation. The performance obtained by MP is only slightly worse than the performance obtained by the POET. However, MP is much more computationally demanding than the POET, partly due to the Eigenvalue decomposition required for computing the principal components.

Possible improvements

Below we address three points of discussion, viz. (1) improving the techniques used in the POET, (2) what we learn from the comparison with the two other orientation-estimation techniques, and (3) can statistical techniques contribute to the filtering technique used in the POET?

Improving the filtering technique

Although the performance by the POET was adequate, we still have attempted to improve the performance of the POET by enhancing the filtering stage using optimized Gabor filters, Gaussian Derivatives filters, and other edge-enhancing filters. None of these filters yielded an improvement over our circular filter. The orientation-extraction stage contains a number of parameters that may be further optimized (e.g, the number of levels K, and the object-defining parameters). Our preliminary experiments with these parameters revealed that the results are relatively insensitive to the specific choice of the parameters.

Improving the orientation estimation

We have compared the prevailing orientation judgments of the POET with those obtained by two other orientation-estimation techniques. The steerable filters did not show a very good performance. This is likely due to the fact that they compute the intensity gradient over the entire image so that local oriented structures can mask the prevailing orientation of the main objects in the image. As stated above, the performance by MP was only slightly worse than the performance by the POET. Apparently, the multi-scale estimation of local orientation yields a satisfactory estimate of the prevailing orientation. This suggests that a combination of the POET with a multi-scale approach may lead to a further improvement of POET's performance.

Introducing statistical techniques

The filtering technique underlying the POET may be contrasted to statistical techniques that rely on the distribution of gray values within the image regions. An interesting statistical technique for determining texture orientation analysis is based on *interaction maps*, i.e., two-dimensional maps that represent the pair-wise variations of pixel values (Chetverikov and Haralick, 1995). This technique is capable of extracting perceptual characteristics of a texture image: anisotropy, symmetry, and regularity. More importantly, it may be applied to our task to estimate the prevailing orientation of textured images. This idea and its implementation are left for future studies.

5.7 Chapter conclusion

From the results obtained we may conclude that POET has a performance indistinguishable from the performances of human subjects. The POET outperforms two alternative techniques: single-scale steerable filters and Multi-Scale Principal Components Analysis.

Although MP performed quite good it is computationally more demanding than the POET. Therefore, we may answer RQ2 by stating that the prevailing brush-stroke orientation can be effectively extracted from the digital reproductions of paintings.

Hence, we arrive at the conclusion that the POET offers an attractive and effective technique for extracting the specific feature of the brush work, i.e., brush-stroke orientation. Future research should focus on the shapes and distribution of brush strokes. We continue our research by analyzing the brush strokes with respect to other characteristics, viz. the textures and the patterns.

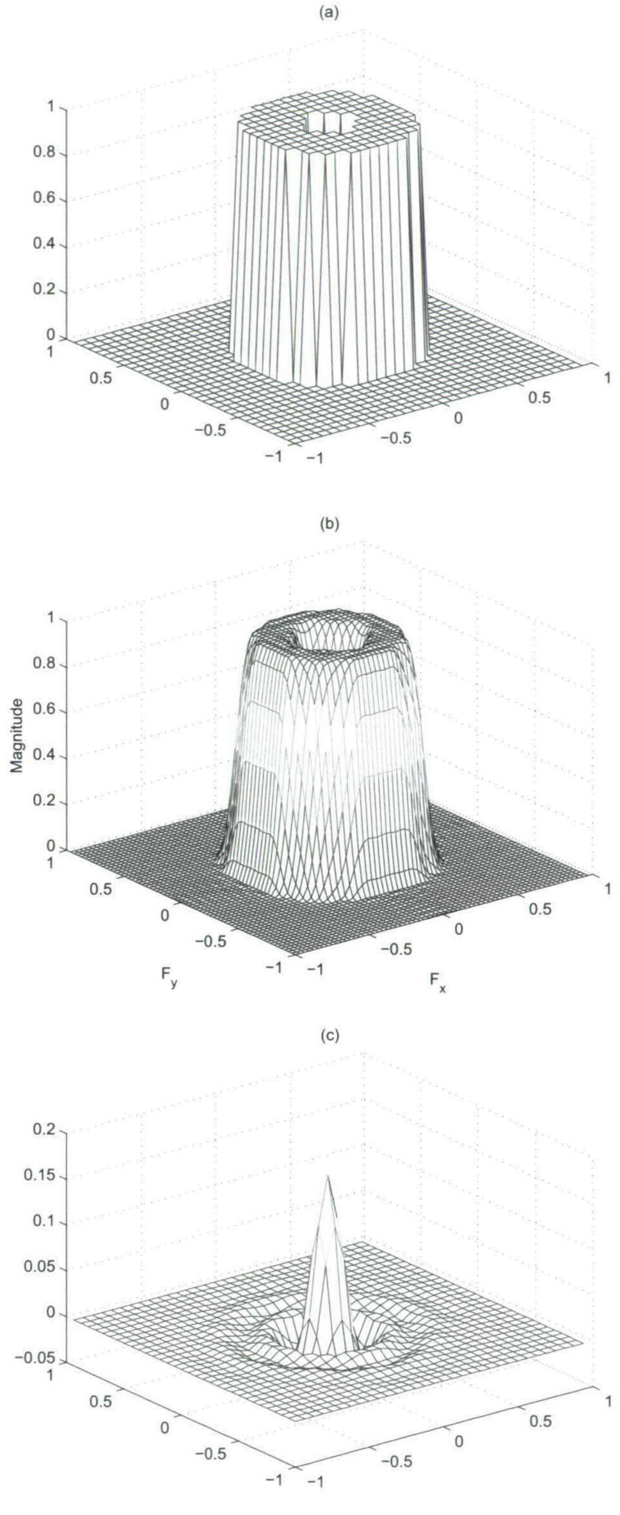


Figure 5.3: Illustration of the frequency sampling method. (a) Desired frequency response. (b) Actual frequency response. (c) The corresponding filter in the spatial domain.

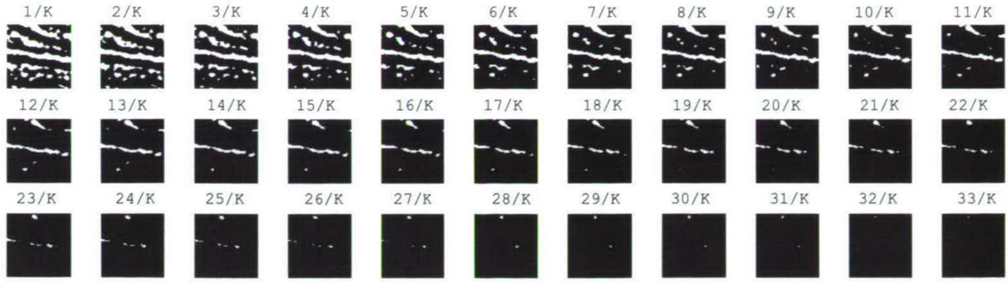


Figure 5.4: Thresholding the convolved image (shown in figure 5.2 (c)) for threshold values $1/K, 2/K, ...K/K$. $K = 33$

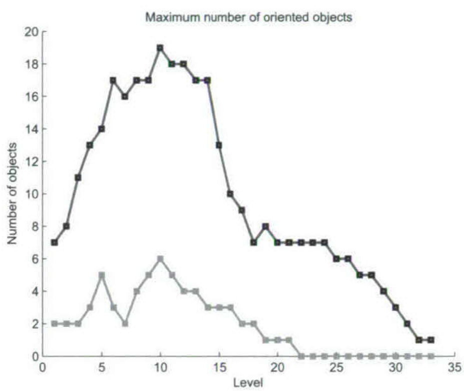


Figure 5.5: The number of objects (upper graph) and oriented objects (lower graph) as a function of k ($K = 33$) for a single image patch.

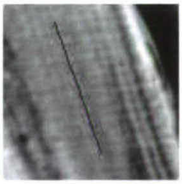


Figure 5.6: A typical example of a patch and the line reflecting a subject's judgment of the prevailing brush-stroke orientation.

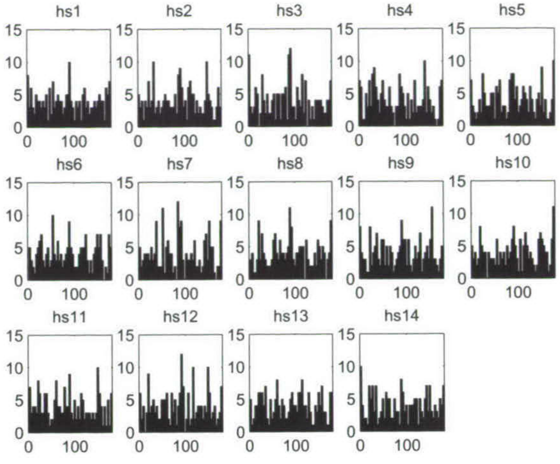


Figure 5.7: Histograms of the orientation judgments for the fourteen human subjects (hs1 to hs14). Each histogram shows the number of times a certain orientation (modulo 180 degrees) was assigned to a patch.

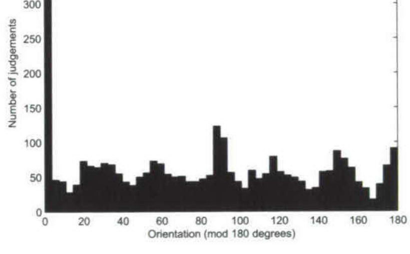


Figure 5.8: Histogram of the orientation judgments of all subjects.

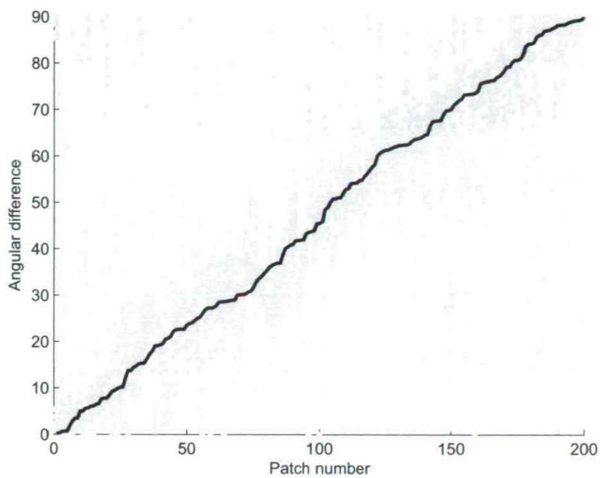


Figure 5.9: Graph of angular differences $D_\alpha(i,j)$ between orientation judgment α_i and the horizontal axis $\alpha_j = 0$ as a function of patch number (sorted in order of ascending orientation according to the POET). The solid line represents the POET's judgments, the gray dots are individual human judgments.

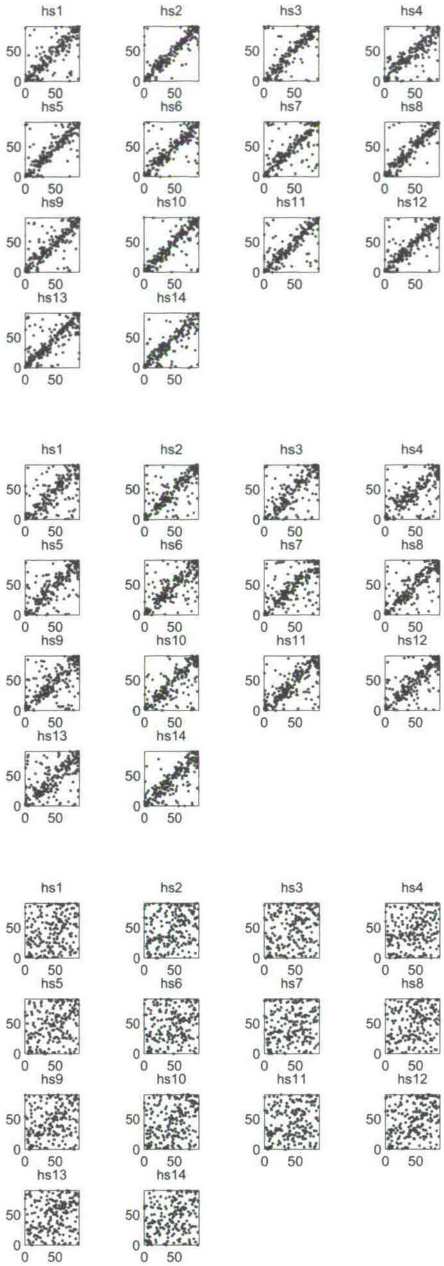


Figure 5.10: Plots of the automatic judgments (horizontal axis) against the human judgments (vertical axis) for the three techniques. From left to right: the POET, the MP, and the steerable filters.

Chapter 6

Brush-stroke analysis

In this chapter, we focus on the third research question, RQ3: *Are there visual features which could serve as a fingerprint of the master and reveal his identity independent of his style or the scene of his work?* In addressing this question, we present three methods that perform an analysis of the brush-stroke texture of a painting. They are called EXPRESS, IMPRESS, and IMPRESS2D.

Many art historians claim that the hand of the master is visible in his brush strokes. Physical characteristics and acquired skills contribute to the idiosyncratic application of brush strokes leaving a unique signature in the painting. While acknowledging the difficulty of establishing the extent to which this claim holds, in this chapter we aim at determining the nature and patterns of the brush strokes. First, we present two brush-stroke analysis methods that differ in their representation of the painted patterns: the EXPRESS method and the IMPRESS method. Then we present an enhanced version of the IMPRESS method, called IMPRESS2D.

The EXPRESS (EXPlicit REpresentation of StrokeS) method employs the circular filter described in chapter 5 to extract objects from a painting. The objects are assumed to correspond to (parts of) the brush strokes. Hence, they form an explicit representation of the strokes. The object properties reflect the characteristics of the brush strokes and will be used for analyzing the painting.

The IMPRESS (IMPlicit REpresentation of StrokeS) method employs a filter-based approach that transforms a region containing brush strokes into a vector of filter coefficients that constitute a feature-space representation. The coefficients contain information on the brush strokes and surrounding texture and therefore form an implicit representation of the brush strokes. The coefficients are aggregated in histograms that serve as representations of the paintings. Both methods will be applied to the task of brush-stroke analysis on small sets of paintings. The histograms obtained for the paintings within a set are compared in terms of their dissimilarity. The performances of the EXPRESS and IMPRESS methods will be evaluated by assessing to what extent the dissimilarities between histograms reflect the known differences in the authorships of the paintings. On the basis of the results obtained with the IMPRESS method, we decided to design and implement some enhancements, resulting in IMPRESS2D. The results of this third method were considerably better than the results of the original IMPRESS. So, we repeated our experiments for the improved version.

The outline of the chapter is as follows. In section 6.1 and section 6.2, the EXPRESS and IMPRESS methods are introduced. Then, in section 6.3 four painting classification tasks are presented to which both methods will be applied. Section 6.4 describes the experiments. Subsequently, the results of both methods on the four tasks are evaluated in section 6.5. In section 6.6 we describe the IMPRESS2D method and the corresponding experiments together with the results. A discussion over presented techniques and results obtained is given in section 6.7. Chapter conclusions are given in section 6.8.

6.1 The EXPRESS method

The explicit brush-stroke analysis method, EXPRESS, performs an analysis of brush work present in paintings. The analysis of brush strokes requires their segmentation. Although individual brush strokes are readily distinguished by humans, the automatic segmentation is quite difficult (see chapter 5, and e.g., Kammerer *et al.*, 2003; Kammerer *et al.*, 2007). Individual brush strokes that clearly contrast with their background in terms of color are easily segmented, but those that overlap and mix with other brush strokes are virtually impossible to isolate. Therefore, the EXPRESS method refrains from aiming to isolate brush strokes. Instead, it detects objects that are likely to form parts of the brush strokes. The method is mainly based on the Prevailing Orientation Extraction Technique (POET), described in the previous chapter.

The EXPRESS method consists of three stages: (1) filtering, (2) feature extraction, and (3) similarity measurement. In the following subsections, each of these stages is described.

6.1.1 Filtering

The gray-scale reproductions of the paintings are convolved with the circular filter described in subsection 5.3.1 and subsequently transformed into a binary image through thresholding. The circular filter enhances the contours and internal structure of brush strokes. Figure 6.1 illustrates the application of the circular filter on a detail of the Wacker painting (f418)[1]. Figure 6.1(a) displays the original image. Convolving the image with a circular filter yields the convolution matrix shown in figure 6.1(b). The convolution matrix is thresholded to obtain the binary image shown in figure 6.1(c).

6.1.2 Feature extraction

The filtering stage of the EXPRESS method is followed by a feature-extraction stage. This stage consists of two steps: (1) binary object extraction and (2) object measurements.

[1] f418 denotes the painting. The notation is adapted from the arts community. See 6.3.1.

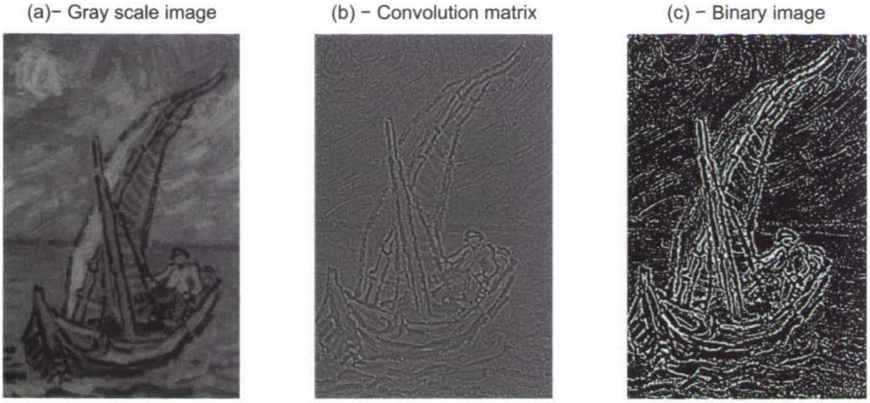


Figure 6.1: (a) detail of painting f418; (b) result of convolving the image with the circular filter; (c) thresholded convolution matrix.

(1) Binary object extraction. The binary object extraction is identical to the one employed in the POET described in subsection 5.3.2. It only differs in the way objects are accepted for or removed from further analysis. The object acceptation scheme employed makes use of the properties that are measured in the second step (see below). The scheme is defined as follows. For every object, its N_{ns} nearest objects (in terms of Euclidean distance) are determined. These neighboring objects are first ranked according to the area they occupy and then the front-ranked two objects are selected. The object with the largest eccentricity is accepted. This scheme is applied to every object and, therefore, yields as many accepted objects as the total number of objects. A large number of these accepted objects are repetitions which are removed so that a single copy of each accepted object remains.

In the acceptance scheme, the value of the parameter N_{nb}, determines the extent of the region over which objects are selected. The larger the value of N_{nb}, the larger the neighborhood of objects for determining the largest and most eccentric objects. Setting N_{nb} to its minimum value leads to the acceptance of all objects, whereas setting it to the maximum value leads to the (repeated) acceptance of the single largest object. Typically, N_{nb} is set to an appropriate intermediate value that filters out the smallest objects (noise) and retains the visually conspicuous objects.

Figure 6.2 shows all objects detected in f418. The result of the object extraction step is a (potentially long) list of objects that correspond to contiguous white regions in the painting.

(2) Object measurements. In the object measurements step, the properties (also called features) of each object are determined. The following five features are assumed to be indicative of the brush-stroke pattern. They will be extracted and studied in the experiments.

1. S - area occupied by the object (pixels),

2. E - eccentricity of the object,

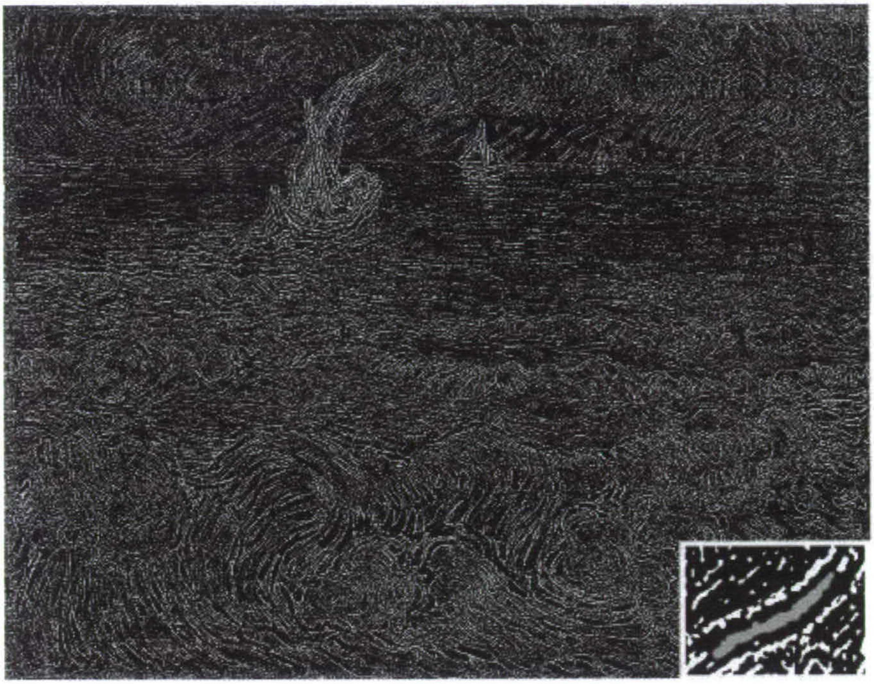


Figure 6.2: Objects extracted from f418. The inset at the lower right corner shows an example of an extracted object (shaded elongated shape defined by contiguous pixels).

3. A - major axis length of the ellipse circumscribing the object,
4. B - minor axis length of the ellipse circumscribing the object, and
5. α - orientation of the object (angle between A and the horizontal axis).

These measurements define the object features that represent the painting. The measurements on an object feature for a particular painting are summarized in a feature histogram.

6.1.3 Similarity measurements

The final stage of the EXPRESS method comprises the measurement of similarities between paintings. For any pair of paintings, P^a and P^b, the dissimilarity is computed by comparing their features F_i^a and F_i^b, respectively, where $i \in \{S, E, A, B, \alpha\}$. The dissimilarity D_i^{AB} between two histograms $H_A(i)$ and $H_B(i)$ of the i-th feature is computed by means of normalized histogram matching.

$$D_i(A,B) = \sum_{j=1}^{N_{bins}} \left| \frac{H_A(j)}{\sum_{k=1}^{N_{bins}} H_A(k)} - \frac{H_B(j)}{\sum_{k=1}^{N_{bins}} H_B(k)} \right|, \tag{6.1}$$

with N_{bins} the number of bins in the histograms. The last bin of each pair of histograms is centered at the maximum value of both paintings. By normalizing the histograms, we compensate for differences in the number of object properties (which may depend on the size of the painting) and emphasize differences in their distributions. Appendix B-3 contains a flowchart of the EXPRESS method.

6.2 The IMPRESS method

The purpose of the digital analysis is to compare (parts of) paintings in terms of perceptual meaningful similarities. Although perceptual meaningfulness is a human concept, rather than a physical concept, we can measure it using a computer by exploiting techniques derived from biological and psychological knowledge on the human visual system. In the IMPRESS method we combine three principles: (1) contours are important, (2) images are analyzed at multiple scales, and (3) similarities between paintings are reflected in the local patterns of the brush strokes. In the IMPRESS method, we combine these three principles by employing a Multi-scale Gabor Histogram Transform (MGHT) consisting of two components: (a) a multi-scale Gabor transform and (b) a histogram representation. The two components will be described in the following two subsections.

6.2.1 Multi-scale Gabor transform

In chapter 4, we already encountered the classical Gabor filter. The type of filters underlying the Gabor transform in the IMPRESS method differ from the classical ones in that they are defined as so-called log-Gabor filters (Field, 1987). We define these filters in polar coordinates by denoting the filter output by $G_{s,t}(\rho, \theta)$, where ρ and θ are the polar coordinates in the spectral domain (see below). In contrast to their classical counterparts, log-Gabor filters lack a DC component while allowing for a good coverage of all spatial frequencies when an appropriate multi-scale scheme is used. Typically, log-Gabor filters are defined directly in the Fourier domain as two-dimensional Gaussian functions (cf. Fischer *et al.*, 2007).

$$G_{s,t}(\rho, \theta) = exp\left(-\frac{1}{2}\left(\frac{\rho - \rho_s}{\sigma_\rho}\right)^2\right) exp\left(-\frac{1}{2}\left(\frac{\theta - \theta_{(s,t)}}{\sigma_\theta}\right)^2\right), \tag{6.2}$$

where $\rho_s = log_2(n) - s$, $\theta_{s,t} = \frac{\pi}{n_t} t$ if s is odd, and $\theta_{s,t} = \frac{\pi}{n_t}(t + \frac{1}{2})$ if s is even, and $(\sigma_\rho, \sigma_\theta) = 0.996(\sqrt{\frac{2}{3}}, \frac{\pi}{\sqrt{2} n_t})$. The log-polar coordinates (ρ, θ) are expressed in log_2 units (i.e., we employ octave scales). The number of scales n_s and orientations n_t are chosen in such a way that the relevant spatial frequencies are covered. The scales and orientations are indexed by s and t, respectively. The center coordinates and the bandwidths of the filters are defined by $(\rho_s, \theta_{(s,t)})$ and $(\sigma_\rho, \sigma_\theta)$, respectively.

In the MGHT, the log-Gabor filters at several scales and orientations are convolved with the (parts of the) images of the paintings. This yields a large number of coefficients g in the spatial domain. For each image location, the MGHT returns

$n_s \times n_t$ coefficients (i.e., energy values in the spatial domain). The energy value $E(x, y)$ reflects the presence of an oriented visual structure (e.g., oriented brush strokes) of a certain spatial frequency (e.g., the width of the strokes) at the spatial coordinates (x, y) of the painting. The large number of coefficients requires some form of reduced representation. In IMPRESS, the reduced representation is achieved by means of histograms of the coefficients.

6.2.2 Histogram representation

We apply the MGHT to the entire painting. The result of MGHT is a histogram of the energy values, each within a corresponding region. It is a numerical representation of the perceptually meaningful features of the painting. The brush strokes are implicitly represented in the numerical representation along with other textural or shape characteristics. The MGHT histogram can be considered as a "signature" of the painter under investigation. Assuming an invariant pattern of brush strokes employed by a painter, the histograms of two different paintings of the same painter should be similar. Of course, the MGHT histograms of two distinct regions within the same painting may differ due to the different styles or brushes employed in these regions. By comparing the overall MGHT histograms of the same painter across paintings, the differences are expected to average out. Each painting is analyzed at multiple spatial scales.

The visual similarity of each possible pair of paintings is measured by comparing the corresponding histograms. The comparison yields a dissimilarity value of zero when there is a perfect match and a dissimilarity value larger than zero when there are many differences. Appendix B-4 contains a flowchart of the IMPRESS method.

6.3 Four painting classification tasks

The automatic recognition of painter-specific patterns of brush strokes by both methods will be evaluated on four tasks. Each task consists of a small set of five to six paintings that are similar in style or time and location of creation. The use of small sets is motivated by art-historian considerations. The evaluation of the authenticity of a painting is typically performed by selecting a small set of highly similar paintings. Visual examination of the details of the painting under consideration and the closely related paintings provides an effective means to assess similarities and differences in brush-stroke patterns and other relevant characteristics.

The four sets are composed by Ella Hendriks, an experienced art historian of the Van Gogh Museum. In each set, all paintings except one have been painted by Van Gogh. The odd painting has a style very similar to that of Van Gogh, but is painted by another artist. The tasks are described in subsections 6.3.1 to 6.3.4.

The reproductions were obtained in the same way as described in chapter 5, i.e., by scanning Ektachromes at a resolution of 2000 dpi with 48 bits color depth. Again, all images were resized to match the resolution of the lowest-resolution painting: 196.3 dpi.

6.3.1 The first painting classification task

Table 6.1 provides an overview of the first set of paintings. The table lists the codes (f numbers), the titles, the dimensions, the year and month (or period) of creation, and the authors of the paintings.

Table 6.1: The first set of paintings.

Code	Title	Dimensions	Year	Author
f418	*The Sea at Saintes-Maries*	430 × 560 mm		Wacker
f412	*Harvest at La Crau*	730 × 920 mm	1888 (June)	Van Gogh
f415	*Seascape at Saintes-Maries*	510 × 640 mm	1888 (June)	Van Gogh
f511	*Orchard in Blossom*	725 × 920 mm	1888 (April)	Van Gogh
f618	*Wheat Fields with Reaper at Sunrise*	730 × 920 mm	1889 (Sept.)	Van Gogh

Figure 6.3 depicts the paintings of the first set. Painting f418 is a deliberate imitation of Van Gogh's style and belongs to the so-called Wacker group of forgeries produced in the latter part of 1920s (Berge *et al.*, 2003). The Wacker forgery is painted in a typical Van Gogh style. The long curvilinear strokes in the waves of f418 bear some resemblance to those used in f618, which is also included in the set. Moreover, the strokes resemble Van Gogh's pen and ink drawings of the same scene created in June 1888 in Arles (f1431; Hulsker, 1996). Van Gogh started to use these strokes in his paintings after his move from Arles to Saint-Rémy in May 1889, whereas the alleged Van Gogh should have been created in Arles around 1888. This is one of the many reasons, why f418 is generally acknowledged to be a forgery.

Paintings f412, f415, and f511 were all painted in the Spring and Summer of 1888 and are included as references for Van Gogh's painting style during the Arles period. In addition, f415 depicts a seascape scene that is similar to that of f418. Finally, f618 is added because it has a similarity in composition to the other paintings in the set.

The first classification task is to distinguish between f418 and the rest of the paintings in the data set using the EXPRESS and IMPRESS methods.

6.3.2 The second painting classification task

Table 6.2 lists the paintings in the second set. Figure 6.4 depicts the paintings.

Table 6.2: The second set of paintings.

Code	Title	Dimensions	Year	Author
s251v	*Vase with Flowers*	510 × 390 mm		Monticelli
f243a	*Vase with Myosotis and Peonies*	345 × 275 mm	1886 (June)	Van Gogh
f248a	*Vase with Gladioli*	465 × 385 mm	1886 (late Summer)	Van Gogh
f234	*Vase with Asters and Phlox*	610 × 460 mm	1886 (late Summer)	Van Gogh
f218	*Glass with Roses*	350 × 270 mm	1886 (Summer)	Van Gogh

The second painting classification task focuses on Monticelli's Vase with Flowers (s251v), which was in the collection of Theo van Gogh and therefore it was known to Vincent. Monticelli had a strong influence on Van Gogh as can be read in Vincent's letters to Theo and seen in his paintings. Being in Paris in the summer of 1886, Van Gogh painted a number of floral still lives which share some similarities with Monticelli's work. The paintings f243a, f248a, f234, and f218 have the same rich

(a) f418

(b) f412

(c) f415

(d) f511

(e) f618

Figure 6.3: The first set of paintings centered around the Wacker forgery f418. The painting f418 is one of the so-called "Wacker" group of forgeries produced in the latter part of the 1920s.

impasto texture and (except for f248a) a dark background as has s251v. However, there are also differences. The strokes by Monticelli overlap more and are more disordered than those by Van Gogh.

The second classification task is to distinguish between the Monticelli painting and the other paintings using the EXPRESS and IMPRESS methods.

(a) s251v

(b) f243a (c) f248a (d) f234 (e) f218

Figure 6.4: The second set of paintings is centered around Monticelli's painting s215v.

6.3.3 The third painting classification task

The third painting classification task involves a single work by Gauguin and four works by Van Gogh. The paintings are listed in table 6.3 and displayed in figure 6.5.

Table 6.3: The third set of paintings.

Code	**Title**	**Dimensions**	**Year**	**Author**
s225v	*Portrait of Van Gogh Painting the Sunflowers*	730 × 910 mm	1888	Gauguin
f546a	*Portrait of Paul Gauguin*	375 × 330 mm		Van Gogh
f482	*Vincent's Bedroom in Arles*	720 × 900 mm	1888 (October)	Van Gogh
f451	*The Sower*	320 × 400 mm	1888 (November)	Van Gogh
f499	*Paul Gauguin's Armchair*	905 × 725 mm	1888 (December)	Van Gogh

Gauguin painted s225v during the period that he shared a study with Van Gogh in Arles. Both this painting and Van Gogh's portrait of Gauguin (f546a) are painted on the same coarse jute. However, both paintings differ in their use of ground layer which may have impact on the brush-stroke texture. The three other paintings in this set (f482, f451, and f499) originate from the same period, have a similar application of broad and more or less homogeneous areas of bright color, and were painted on canvas.

The third classification task is to distinguish between the painting by Gauguin from the paintings by Van Gogh using the EXPRESS and IMPRESS methods.

(a) s225v

(b) f546a

(c) f482

(d) f451

(e) f499

Figure 6.5: The third set of paintings, centered around Gauguin's painting s225v.

6.3.4 The fourth painting classification task

In the fourth painting classification task a single painting by Toulouse-Lautrec (s274v) is compared to five paintings by Van Gogh. The paintings are listed in table 6.4 and shown in figure 6.6.

Table 6.4: The fourth set of paintings.

Code	Title	Dimensions	Year	Author
s274v	*Young Woman at a Table; Poudre de Riz*	560 × 460 mm	1887	Toulouse-Lautrec
f292	*Boulevard de Clichy*	425 × 555 mm	1887 (Feb.-March)	Van Gogh
f347	*Street Scene in Montmartre: Le Moulin a Poivre*	345 × 645 mm	1887 (Feb.-March)	Van Gogh
f337	*Flowerpot with Chives*	315 × 220 mm	1887 (March-April)	Van Gogh
f370	*Woman Sitting in the Cafe du Tambourin*	555 × 465 mm	1887 (Feb.-March)	Van Gogh
f369	*Woman Sitting by a Cradle*	610 × 455 mm	1887 (Spring)	Van Gogh

Toulouse-Lautrec was Van Gogh's younger friend and colleague. He is generally believed to have had a strong influence on Van Gogh's style. The paintings by Toulouse-Lautrec and those in which Van Gogh employed his style have thin washes with touches of bright color (i.e., *l'essence* technique) applied to an absorbent substrate.

The paintings in the set are all from the first half of 1887. The paintings depict three types of scenes: portraits (s274v, f370, f369), cityscapes (f292 and f347) and a flower (f337).

In this fourth classification task, the brush stroke analysis methods should distinguish the Toulouse-Loutrec painting from the other ones.

The four tasks will be used for the evaluation of the explicit and implicit brushstroke analysis methods, EXPRESS and IMPRESS. Before turning to the experimental evaluation of the methods, the next section describes the experiments.

6.4 Experiments

The parameter settings for the EXPRESS and IMPRESS methods are listed in table 6.5.

Table 6.5: Parameter settings for the evaluation of the EXPRESS and IMPRESS methods.

Method	Parameter	Description	Value
EXPRESS	N_{nb}	number of neighbors	2
IM/EXPRESS	N_{bins}	number of bins	1000
IMPRESS	n_s	number of scales	4
IMPRESS	n_t	number of orientations	6

The experiments are executed by method (EXPRESS and IMPRESS) and evaluated by task (1 to 4). Ideally, we would perform a typical machine-learning experiment in which a classifier is trained on examples of paintings by Van Gogh (positive instances) and by other painters (negative instances). Subsequently, the generalization performance of the trained "Van Gogh detector" could then be evaluated on unseen

(a) s274v

(b) f292

(c) f347

(d) f337

(e) f370

(f) f369

Figure 6.6: Case study 4, set of five Van Gogh paintings centers around the painting by Toulouse-Lautrec (S274V) who was Van Gogh's younger friend and colleague.

instances. However, such an experiment is premature for two reasons. The first reason is that the number of positive (and especially) negative instances is too small to obtain reliable results. The second reason is that the appropriate features for classification are unknown. At this moment, the scientific research in this domain is in the phase of identifying useful features. Once visual feature have been identified that allow for distinguishing paintings by Van Gogh from paintings by other authors, a machine-learning experiment becomes feasible.

6.5 Results

The results of the application of both methods to the four painting classification tasks are presented in the form of distance matrices that express the dissimilarity between each pair of paintings in each set. Each dissimilarity expresses the normalized histogram distance which can assume values between 0 (complete agreement) and 2 (complete disagreement). We assess the ability of both methods to detect the odd painting by evaluating the average dissimilarity of each painting with respect to all other paintings within a set. The odd painting should have the largest average dissimilarity from all paintings within the set to be detected by the method.

6.5.1 EXPRESS results

The results obtained are presented for each task separately in the form of tables. Each table shows five dissimilarity matrices, one for each feature (area, eccentricity, major axis, minor axis, and orientation (S,E,A,B,α); see subsection 6.1.2). In the rows and columns the paintings of the set are listed. Each matrix specifies the dissimilarities between the paintings in the matrix. The last column (avg) specifies the average dissimilarity and corresponds to the mean of the non-zero dissimilarities in the associated row. The values in this column indicate the extent to which the painting in that row, is different from the rest of the paintings. The largest average dissimilarity value is typed in boldface.

Task 1

The results of the EXPRESS method on painting task 1 are presented in table 6.6. For the area feature (S), the largest average dissimilarity value is obtained for the Wacker painting (f418) which implies that this forgery can be detected from the magnitude of this feature only. The Wacker painting gives rise to objects occupying a larger surface area (in terms of pixels) than the other four paintings.

Similarly, the other four features (E,A,B,α) for this painting also yield the largest average value indicating that the forgery differs in the distribution of the features eccentricity, and major and minor axis length, and orientation.

Task 2

The results of the EXPRESS method on painting task 2 are presented in table 6.7. Examining the average value for the area feature (S) reveals that f248a has the largest

Table 6.6: The results obtained with the EXPRESS method on set 1.

area	**f412**	**f415**	**f418**	**f511**	**f618**	**avg**
f412	0	0.04561	0.30325	0.13108	0.17802	0.16449
f415	0.04561	0	0.32147	0.1103	0.19795	0.16883
f418	0.30325	0.32147	0	0.42289	0.14292	**0.29763**
f511	0.13108	0.1103	0.42289	0	0.29631	0.24014
f618	0.17802	0.19795	0.14292	0.29631	0	0.2038
eccentricity						
f412	0	0.14464	1.73796	0.18632	0.98336	0.76307
f415	0.14464	0	1.7474	0.19933	0.96986	0.76531
f418	1.73796	1.7474	0	1.7955	1.75507	**1.75898**
f511	0.18632	0.19933	1.7955	0	0.86457	0.76143
f618	0.98336	0.96986	1.75507	0.86457	0	1.14321
major axis						
f412	0	0.0812	0.30584	0.15257	0.19007	0.18242
f415	0.0812	0	0.33717	0.14317	0.21471	0.19406
f418	0.30584	0.33717	0	0.42768	0.15989	**0.30764**
f511	0.15257	0.14317	0.42768	0	0.30341	0.25671
f618	0.19007	0.21471	0.15989	0.30341	0	0.21702
minor axis						
f412	0	0.09671	0.31698	0.16501	0.19381	0.19313
f415	0.09671	0	0.34587	0.15377	0.22308	0.20486
f418	0.31698	0.34587	0	0.44659	0.16273	**0.31804**
f511	0.16501	0.15377	0.44659	0	0.31054	0.26898
f618	0.19381	0.22308	0.16273	0.31054	0	0.22254
orientation						
f412	0	0.96663	1.69006	0.33054	0.2556	0.81071
f415	0.96663	0	1.29896	0.67949	1.50506	1.11253
f418	1.69006	1.29896	0	1.64031	1.78964	**1.60474**
f511	0.33054	0.67949	1.64031	0	0.35707	0.75185
f618	0.2556	1.50506	1.78964	0.35707	0	0.97684

value, whereas the odd painting (Monticelli's s251v) has the second largest value. Apparently, Monticelli's painting cannot be distinguished from the Van Gogh's by means of the area feature. The same holds for the other four features (E,A,B,α).

Task 3

Table 6.8 lists the results obtained by the EXPRESS method on painting task 3. Also here, Gauguin's painting (s225v) cannot be distinguished from Van Gogh's paintings using the EXPRESS features. In all cases, Van Gogh's paintings deviate more in value from the rest than Gauguin's painting as evidenced by the average dissimilarity values. Clearly, the EXPRESS method is not sensitive to the visual features distinguishing the Gauguin painting from the Van Gogh paintings.

Task 4

The results of the EXPRESS method on painting task 4 are shown in table 6.9. As with the previous two tasks, the odd painting (Toulouse-Loutrec's s274v) cannot be distinguished from the Van Gogh paintings in the set on the basis of the average

Table 6.7: The results obtained with the EXPRESS method on set 2.

area	**f218**	**f234**	**f243a**	**f248a**	**s251v**	**avg**
f218	0	0.18167	0.24662	0.39017	0.25594	0.2686
f234	0.18167	0	0.30871	0.47872	0.21171	0.2952
f243a	0.24662	0.30871	0	0.18328	0.4595	0.29953
f248a	0.39017	0.47872	0.18328	0	0.62917	**0.42034**
s251v	0.25594	0.21171	0.4595	0.62917	0	0.38908
eccentricity						
f218	0	1.72966	1.81507	1.82173	0.41749	1.44599
f234	1.72966	0	1.81246	1.79485	1.6676	**1.75114**
f243a	1.81507	1.81246	0	1.01057	1.76796	1.60152
f248a	1.82173	1.79485	1.01057	0	1.77278	1.59998
s251v	0.41749	1.6676	1.76796	1.77278	0	1.40646
major axis						
f218	0	0.24865	0.29798	0.4067	0.32209	0.31885
f234	0.24865	0	0.37109	0.50599	0.26298	0.34718
f243a	0.29798	0.37109	0	0.23995	0.48678	0.34895
f248a	0.4067	0.50599	0.23995	0	0.63932	**0.44799**
s251v	0.32209	0.26298	0.48678	0.63932	0	0.4278
minor axis						
f218	0	0.26678	0.33068	0.43718	0.34845	0.34577
f234	0.26678	0	0.38267	0.53082	0.26342	0.36092
f243a	0.33068	0.38267	0	0.25791	0.52912	0.37509
f248a	0.43718	0.53082	0.25791	0	0.67324	**0.47479**
s251v	0.34845	0.26342	0.52912	0.67324	0	0.45356
orientation						
f218	0	1.66475	1.78708	1.30423	0.9693	1.43134
f234	1.66475	0	1.78757	1.0067	1.38822	1.46181
f243a	1.78708	1.78757	0	1.84868	1.73722	**1.79014**
f248a	1.30423	1.0067	1.84868	0	0.76636	1.23149
s251v	0.9693	1.38822	1.73722	0.76636	0	1.21528

dissimilarity values.

Discussion of the EXPRESS results

The results obtained by the EXPRESS method on the four tasks are quite disappointing. Only in one of the four tasks, the method is able to detect the odd painting. On the basis of this performance we may conclude that the authenticity of the paintings in our four sets cannot be determined reliably by means of the EXPRESS method.

6.5.2 IMPRESS results

The results obtained by the IMPRESS method on the sets 1 to 4 are shown in the tables 6.10 to 6.13. For each table, the results are grouped in four dissimilarity matrices, one for each scale. Scale 1 is the finest scale of analysis (i.e., the scale of individual hairs or strokes of a brush) and scale 4 is the coarsest scale of analysis (i.e., the scale of multiple strokes). Again, the final column shows the average dissimilarities of the paintings associated with the rows.

Table 6.8: The results obtained with the EXPRESS method on set 3.

area	**f451**	**f482**	**f499**	**f546**	**s225v**	**avg**
f451	0	0.18835	0.43368	0.11317	0.35132	0.27163
f482	0.18835	0	0.26995	0.25837	0.19333	0.2275
f499	0.43368	0.26995	0	0.52157	0.11292	**0.33453**
f546	0.11317	0.25837	0.52157	0	0.44219	0.33383
s225v	0.35132	0.19333	0.11292	0.44219	0	0.27494
eccentricity						
f451	0	0.5233	0.54611	1.86572	0.40863	0.83594
f482	0.5233	0	0.59662	1.7343	0.51714	0.84284
f499	0.54611	0.59662	0	1.71967	0.37399	0.8091
f546	1.86572	1.7343	1.71967	0	1.73402	**1.76343**
s225v	0.40863	0.51714	0.37399	1.73402	0	0.75844
major axis						
f451	0	0.22828	0.44595	0.19301	0.37086	0.30952
f482	0.22828	0	0.2865	0.28628	0.22062	0.25542
f499	0.44595	0.2865	0	0.53962	0.12884	0.35022
f546	0.19301	0.28628	0.53962	0	0.45473	**0.36841**
s225v	0.37086	0.22062	0.12884	0.45473	0	0.29376
minor axis						
f451	0	0.23229	0.47111	0.20882	0.39115	0.32584
f482	0.23229	0	0.31986	0.30679	0.24386	0.2757
f499	0.47111	0.31986	0	0.57572	0.15082	0.37938
f546	0.20882	0.30679	0.57572	0	0.48724	**0.39464**
s225v	0.39115	0.24386	0.15082	0.48724	0	0.31827
orientation						
f451	0	1.777	1.73194	1.84478	1.74084	**1.77364**
f482	1.777	0	0.43627	1.76628	0.46185	1.11035
f499	1.73194	0.43627	0	1.59013	1.33051	1.27221
f546	1.84478	1.76628	1.59013	0	1.75277	1.73849
s225v	1.74084	0.46185	1.33051	1.75277	0	1.32149

Task 1

The results of the IMPRESS method on painting task 1 are shown in table 6.10. As the results show, for all scales the Wacker forgery (f418) has the largest average distance to all other paintings. In all four dissimilarity matrices, the average dissimilarity is largest for this painting. As with the EXPRESS method, this method is capable of detecting the Wacker forgery.

Task 2

The results of the IMPRESS method on painting task 2 are listed in table 6.11. In set 2, the odd painting (s251v by Monticelli) yields the largest average dissimilarity value for all scales. Although somewhat less prominent than in task 1, the Monticelli clearly is distinguished from the other paintings. Therefore, the IMPRESS method is capable of detecting the non-Van Gogh painting in this task.

Table 6.9: The results obtained with the EXPRESS method on set 4.

area	**f292**	**f337**	**f347**	**f369**	**f370**	**s274v**	**avg**
f292	0	0.13483	0.22167	0.16501	0.14771	0.08169	0.15018
f337	0.13483	0	0.19532	0.2029	0.14301	0.09946	0.15511
f347	0.22167	0.19532	0	0.10576	0.09554	0.17213	**0.15808**
f369	0.16501	0.2029	0.10576	0	0.08485	0.15966	0.14364
f370	0.14771	0.14301	0.09554	0.08485	0	0.11312	0.11685
s274v	0.08169	0.09946	0.17213	0.15966	0.11312	0	0.12521
eccentricity							
f292	0	1.91459	0.47919	0.87978	1.30862	1.86127	1.28869
f337	1.91459	0	1.85612	1.87713	1.89084	1.91255	**1.89025**
f347	0.47919	1.85612	0	0.66019	1.35364	1.63157	1.19614
f369	0.87978	1.87713	0.66019	0	1.82008	1.85009	1.41745
f370	1.30862	1.89084	1.35364	1.82008	0	0.74031	1.4227
s274v	1.86127	1.91255	1.63157	1.85009	0.74031	0	1.59916
major axis							
f292	0	0.23088	0.27523	0.18996	0.19655	0.15098	0.20872
f337	0.23088	0	0.24582	0.27244	0.2026	0.18516	**0.22738**
f347	0.27523	0.24582	0	0.17304	0.13008	0.20791	0.20642
f369	0.18996	0.27244	0.17304	0	0.13645	0.21177	0.19673
f370	0.19655	0.2026	0.13008	0.13645	0	0.14253	0.16164
s274v	0.15098	0.18516	0.20791	0.21177	0.14253	0	0.17967
minor axis							
f292	0	0.25729	0.28142	0.21469	0.19887	0.18638	0.22773
f337	0.25729	0	0.2511	0.28514	0.21421	0.1805	**0.23765**
f347	0.28142	0.2511	0	0.1847	0.14136	0.21245	0.21421
f369	0.21469	0.28514	0.1847	0	0.15218	0.22151	0.21165
f370	0.19887	0.21421	0.14136	0.15218	0	0.15222	0.17177
s274v	0.18638	0.1805	0.21245	0.22151	0.15222	0	0.19061
orientation							
f292	0	1.67237	1.72147	1.8525	1.66579	0.71723	**1.52587**
f337	1.67237	0	0.37246	1.05383	0.34324	1.43747	0.97587
f347	1.72147	0.37246	0	0.70681	0.26225	1.61139	0.93488
f369	1.8525	1.05383	0.70681	0	0.77428	1.83619	1.24472
f370	1.66579	0.34324	0.26225	0.77428	0	1.62453	0.93402
s274v	0.71723	1.43747	1.61139	1.83619	1.62453	0	1.44536

Tasks 3 and 4

The results obtained on painting tasks 3 and 4, presented in tables 6.12 and 6.13 are disappointing. In both cases, the odd painting is not detected by the IMPRESS method. For set 3, Van Gogh's f482 is consistently more dissimilar than the other paintings in the set, including Gauguin's s225v. For set 4, Van Gogh's f347 is rated as most dissimilar.

Discussion of the IMPRESS results

The IMPRESS method successfully detected the non-Van Gogh's in the first two sets, but failed to do so in sets 3 and 4. Although the method performs slightly better than its explicit counterpart, the performance is still disappointing. Apparently, the first-order statistics of IMPRESS method do not capture the characteristic features of Van Gogh.

Table 6.10: The results obtained with the IMPRESS method on set 1.

Scale 1	f412	f415	f418	f511	f618	avg
f412	0	0.55768	1.00642	0.08945	0.07094	0.43112
f415	0.55768	0	0.48853	0.54389	0.50436	0.52362
f418	1.00642	0.48853	0	1.00245	0.96153	**0.86473**
f511	0.08945	0.54389	1.00245	0	0.07631	0.42802
f618	0.07094	0.50436	0.96153	0.07631	0	0.40328
Scale 2						
f412	0	0.32348	0.84592	0.06825	0.06861	0.32656
f415	0.32348	0	0.53734	0.28312	0.32785	0.36795
f418	0.84592	0.53734	0	0.81334	0.84297	**0.75989**
f511	0.06825	0.28312	0.81334	0	0.08325	0.31199
f618	0.06861	0.32785	0.84297	0.08325	0	0.33067
Scale 3						
f412	0	0.15593	0.70186	0.08597	0.0843	0.25701
f415	0.15593	0	0.55283	0.14892	0.19473	0.2631
f418	0.70186	0.55283	0	0.63376	0.73027	**0.65468**
f511	0.08597	0.14892	0.63376	0	0.14638	0.25376
f618	0.0843	0.19473	0.73027	0.14638	0	0.28892
Scale 4						
f412	0	0.13515	0.61658	0.1386	0.08316	0.24337
f415	0.13515	0	0.53356	0.17242	0.14524	0.24659
f418	0.61658	0.53356	0	0.49225	0.64559	**0.57199**
f511	0.1386	0.17242	0.49225	0	0.19247	0.24893
f618	0.08316	0.14524	0.64559	0.19247	0	0.26662

Table 6.11: The results obtained with the IMPRESS method on set 2.

Scale 1	f218	f234	f243a	f248a	s251v	avg
f218	0	0.48525	0.2238	0.28402	0.43821	0.35782
f234	0.48525	0	0.27891	0.24038	0.34246	0.33675
f243a	0.2238	0.27891	0	0.10566	0.34456	0.23823
f248a	0.28402	0.24038	0.10566	0	0.3852	0.25382
s251v	0.43821	0.34246	0.34456	0.3852	0	**0.37761**
Scale 2						
f218	0	0.36816	0.17221	0.24234	0.30405	0.27169
f234	0.36816	0	0.26912	0.20812	0.35427	0.29992
f243a	0.17221	0.26912	0	0.10421	0.33677	0.22058
f248a	0.24234	0.20812	0.10421	0	0.36905	0.23093
s251v	0.30405	0.35427	0.33677	0.36905	0	**0.34104**
Scale 3						
f218	0	0.30093	0.16621	0.22304	0.2183	0.22712
f234	0.30093	0	0.25687	0.17252	0.34266	0.26825
f243a	0.16621	0.25687	0	0.10666	0.31639	0.21153
f248a	0.22304	0.17252	0.10666	0	0.33628	0.20962
s251v	0.2183	0.34266	0.31639	0.33628	0	**0.30341**
Scale 4						
f218	0	0.28488	0.18026	0.2231	0.17787	0.21653
f234	0.28488	0	0.25179	0.16159	0.3169	0.25379
f243a	0.18026	0.25179	0	0.1084	0.29265	0.20827
f248a	0.2231	0.16159	0.1084	0	0.30563	0.19968
s251v	0.17787	0.3169	0.29265	0.30563	0	**0.27326**

6.6 The IMPRESS2D method

The conclusion of the research on the EXPRESS and IMPRESS methods, so far is that the IMPRESS method seems to outperform the EXPRESS method, but that the IMPRESS method in itself does not perform satisfactorily. Apparently, the first-order

Table 6.12: The results obtained with the IMPRESS method on set 3.

Scale	**f451**	**f482**	**f499**	**f546**	**s225v**	**avg**
f451	0	1.3201	0.79524	0.19408	1.01582	0.83131
f482	1.3201	0	0.75931	1.41752	0.52944	**1.00659**
f499	0.79524	0.75931	0	0.89383	0.27392	0.68058
f546	0.19408	1.41752	0.89383	0	1.12003	0.90637
s225v	1.01582	0.52944	0.27392	1.12003	0	0.7348
Scale 2						
f451	0	1.11986	0.58212	0.22192	0.81112	0.68376
f482	1.11986	0	0.69502	1.26124	0.48845	**0.89114**
f499	0.58212	0.69502	0	0.71928	0.25764	0.56351
f546	0.22192	1.26124	0.71928	0	0.95656	0.78975
s225v	0.81112	0.48845	0.25764	0.95656	0	0.62844
Scale 3						
f451	0	0.86627	0.4024	0.23702	0.59929	0.52625
f482	0.86627	0	0.55509	1.02133	0.39025	**0.70824**
f499	0.4024	0.55509	0	0.52885	0.21451	0.42522
f546	0.23702	1.02133	0.52885	0	0.73985	0.63176
s225v	0.59929	0.39025	0.21451	0.73985	0	0.48598
Scale 4						
f451	0	0.68989	0.29672	0.24202	0.43393	0.41564
f482	0.68989	0	0.46277	0.82255	0.36307	**0.58457**
f499	0.29672	0.46277	0	0.3847	0.16159	0.32644
f546	0.24202	0.82255	0.3847	0	0.52723	0.49412
s225v	0.43393	0.36307	0.16159	0.52723	0	0.37145

Table 6.13: The results obtained with the IMPRESS method on set 4.

Scale 1	**f292**	**f337**	**f347**	**f369**	**f370**	**s274v**	**avg**
f292	0	0.27445	0.83702	0.24261	0.47585	0.20134	0.40625
f337	0.27445	0	0.99268	0.45293	0.66607	0.23255	0.52373
f347	0.83702	0.99268	0	0.6243	0.39857	0.85017	**0.74055**
f369	0.24261	0.45293	0.6243	0	0.24355	0.2568	0.36404
f370	0.47585	0.66607	0.39857	0.24355	0	0.49047	0.4549
s274v	0.20134	0.23255	0.85017	0.2568	0.49047	0	0.40627
Scale 2							
f292	0	0.23009	0.63581	0.12168	0.38674	0.06321	0.28751
f337	0.23009	0	0.819	0.34418	0.58817	0.25093	0.44647
f347	0.63581	0.819	0	0.52407	0.26118	0.63918	**0.57585**
f369	0.12168	0.34418	0.52407	0	0.27122	0.12385	0.277
f370	0.38674	0.58817	0.26118	0.27122	0	0.38868	0.3792
s274v	0.06321	0.25093	0.63918	0.12385	0.38868	0	0.29317
Scale 3							
f292	0	0.19662	0.50117	0.07333	0.35833	0.08195	0.24228
f337	0.19662	0	0.67091	0.24669	0.53607	0.23934	0.37793
f347	0.50117	0.67091	0	0.45752	0.15216	0.48639	**0.45363**
f369	0.07333	0.24669	0.45752	0	0.31338	0.07066	0.23232
f370	0.35833	0.53607	0.15216	0.31338	0	0.34338	0.34066
s274v	0.08195	0.23934	0.48639	0.07066	0.34338	0	0.24434
Scale 4							
f292	0	0.19889	0.4125	0.11749	0.31365	0.1277	0.23404
f337	0.19889	0	0.59328	0.18175	0.50039	0.1917	0.3332
f347	0.4125	0.59328	0	0.44111	0.11339	0.45151	**0.40236**
f369	0.11749	0.18175	0.44111	0	0.34183	0.07823	0.23208
f370	0.31365	0.50039	0.11339	0.34183	0	0.35027	0.32391
s274v	0.1277	0.1917	0.45151	0.07823	0.35027	0	0.23988

statistics computed by the IMPRESS method did not capture Van Gogh's characteristic features. So, a potential solution to this problem is to investigate to what extent using second-order statistics do improve the IMPRESS method. We call the new method IMPRESS2D. In subsection 6.6.1 we describe the second-order analysis with the IMPRESS2D method and in subsection 6.6.2 we provide the IMPRESS2D results.

6.6.1 Second-order analysis with the IMPRESS2D method

Below we extend the IMPRESS method to perform a second-order analysis of paintings. In second-order analysis, pair-wise combinations of orientations are considered, rather than individual orientations. The second-order extension of the IMPRESS method, henceforth referred to as the IMPRESS2D method, takes the results of the multi-scale Gabor transform, described in subsection 6.2.1, but differs from the standard IMPRESS method in the definition of the histograms. In contrast to the histogram representation described in subsection 6.2.2, the extended method defines two-dimensional (2D) spatial histograms of all the energy values of all combinations of orientations within a single painting. In our analysis we confine ourselves to the finest spatial scale (i.e., scale 1). The 2D histograms are centered at locations of energy values exceeding a predefined threshold value E_τ.

The matching of two two-dimensional histograms H_A and H_B is performed using an extension of equation 6.1:

$$D2(A,B) = \sum_{i,j=1}^{N_{bins},N_{bins}} \left| \frac{H_A(i,j)}{\sum_{p,q=1}^{N_{bins}} H_A(p,q)} - \frac{H_B(i,j)}{\sum_{p,q=1}^{N_{bins}} H_B(p,q)} \right|, \tag{6.3}$$

where $D2(A,B)$ is a measure of the distance between both histograms. Moreover, N_{bins} represents the number of bins per dimension (the histogram contains N_{bins}^2 bins). The parameter settings for the IMPRESS2D method are listed in table 6.14.

Table 6.14: Parameter settings for the evaluation of the IMPRESS2D method.

Method	Parameter	Description	Value
IMPRESS2D	E_τ	energy threshold	0.1
IMPRESS2D	N_{bins}	number of bins	201^2

The 2D histograms allow for the analysis of combinations of oriented visual structures at specific scales. In terms of paintings, the extended IMPRESS method is able to quantify the presence of spatially adjacent brush strokes of different orientations. The flowchart of the IMPRESS2D method can be found in Appendix B-5.

6.6.2 IMPRESS2D results

The failure of the standard IMPRESS method may be caused by the fact that it collects first-order Gabor statistics only. Van Gogh's style may very well reflect itself in second-order statistics, i.e., in the combinations of orientations and scales of brush strokes. To determine whether this is the case, we submitted the IMPRESS2D method to the four tasks. Below, we present the results obtained on the four tasks.

Results on all tasks

Figure 6.7 illustrates the second-order histograms obtained for set 1 at scale 1. The 6×6 histograms are visualized as images in which larger bin values correspond to brighter pixels. The rows and columns correspond to the six Gabor filter orientations. The prominent presence of a particular combination of oriented visual structure in a painting is reflected in the associated second-order histogram provided that (1) they give rise to an energy $E > E_{\tau}$ and (2) are separated by no more than $(N_{bins} - 1)/2$ pixels.

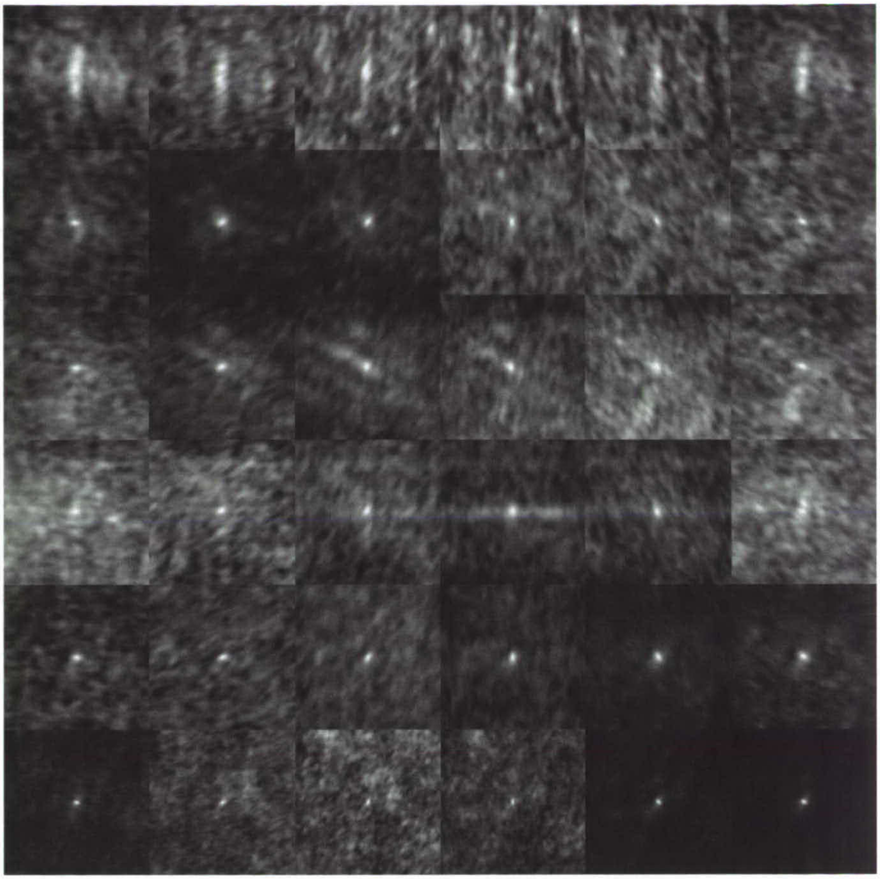


Figure 6.7: Illustration of the second-order histograms computed for painting f412. The rows and columns represent orientations of the Gabor filters and each histogram (square image) is a combination of two orientations. The intensities reflect the height of the histogram bins, larger bins correspond to brighter regions. To enhance visibility, all images are rescaled on the interval of gray values from black (0) to white (maximum bin value).

To evaluate the effectiveness of the IMPRESS2D method, we define an aggregate measure ρ_{NN} that summarizes the degree to which the dissimilarity value of the odd paintings exceeds above those of all other paintings. The measure, originally proposed by Tax and Duin (2000) (see also Tax (2001)), compares the local density of a sample point (the painting/histogram under consideration) to the density of the other points (paintings) using the nearest-neighbor method. For a painting p, the dissimilarity measure $\rho_{NN}(p)$ is defined as follows:

$$\rho_{NN}(p) = \frac{||p - NN(p)||}{||NN(p) - NN(NN(p))||}, \tag{6.4}$$

where $NN(p)$ denotes the nearest neighbor of painting p. When $\rho_{NN}(p) \approx 1$ the local density of the sample point corresponds to that of the nearest neighboring point indicating that the painting p does not differ from the other paintings. Odd paintings give rise to a value $\rho_{NN}(p) > 1$.

We found values of $\rho > 1$ for scale 1 only. Within scale 1, for each task there was a single combination of orientations for which a value of $\rho > 1$ was obtained. Table 6.15 lists these combinations and the associated values of ρ. The table shows that for tasks 1, 2, and 3, the combination of orientations 0^o and 120^o is diagnostic for the odd painting, whereas for task 4 this is the case for the combination of orientations 0^o and 30^o.

Table 6.15: The results obtained with the IMPRESS2D method on the four tasks for scale 1. The Combinations of orientations for which $\rho > 1$ are shown in the second column. The third column specifies the value of ρ.

Task	combination of orientations (orientation 1 - orientation 2)	ρ
1	0^o - 120^o	2.122
2	0^o - 120^o	1.854
3	0^o - 120^o	2.451
4	0^o - 30^o	2.817

Clearly, the second-order extension of the IMPRESS method provides a suitable basis for detecting the odd paintings in all sets.

6.7 Chapter discussion

Our examination of explicit and implicit methods revealed that digital analyses based on first-order explicit or implicit features fail to detect all odd paintings considered. In order to be able to perform successfully on the four tasks considered, second-order features (combinations of oriented filters) are required.

Our results show that, on the restricted sets of paintings, the odd-one-out can be reliably detected using second-order features. Of course, the main challenge is to determine in advance which second-order feature (combination of orientations and scales) is diagnostic for determining the authenticity of a painting. Our results on the first three tasks suggest that the combination of orientations 0^o and 120^o is an important second-order feature that may very well generalize to other tasks. However, on the fourth task, this combination of orientations is not indicative for authenticity. We expect, therefore, that the determination of the set of critical second-order features will grow with the number of sets (tasks) examined. Once a sufficient number of sets has been examined, a stable set of diagnostic second-order features may be obtained. The definition of appropriate sets or tasks and the interpretation of the second-order features in art-historian terms is an interdisciplinary endeavor that requires a close collaboration between computer scientists and art historians.

6.8 Chapter conclusion

The results obtained in our experimental investigation of digital brush-stroke analysis methods suggest that an implicit approach is slightly more sensitive to differences in brush-stroke texture than an explicit approach. More importantly, our results show that second-order Gabor features (i.e., combinations of brush-stroke orientations) are diagnostic for the authenticity of paintings in the selected sets examined. Therefore, we may answer RQ3 as follows. Second-order filters are able to capture painter-specific features that may serve as a fingerprint or signature of the painting by Van Gogh. We remark that the implicit second-order features at a fine spatial scale reveal his identity independent of his style or of the painted scene.

Chapter 7

Conclusions and future research

In this chapter we complete our digital painting-analysis research by answering the three research questions and the problem statement. In addition, we briefly describe future research. The answers to the three research questions stated in chapter 1 are presented in subsection 7.1. Then, in subsection 7.2 we give an answer to the problem statement. Finally, subsection 7.3 presents three directions of future research.

7.1 Answers to the research questions

Our research addressed three research questions. In this section, we answer each of these research questions separately by referring to the results and conclusions of the associated chapters.

RQ1: *How and to what extent can color analysis of the digitalized reproductions facilitate the authentication process?*

The results obtained by MECOCO, described in chapter 4, indicate that the automatic analysis of complementary colors can be performed by means of multi-scale Gabor filters defined in the spatial domain and opponent-color domain. Provided that the digital reproductions are supplied with color reference cards for calibration, the analysis of complementary (opponent) colors can facilitate the authentication process by detecting and quantifying the presence of complementary color transitions in paintings. This answer provides a clue to the *to what extent*-part of RQ1. A quantitative answer can be derived from the investigations concerning RQ3 (see chapter 6).

RQ2: *Which features of the brush work can be extracted effectively from the digital reproduction of a painting?*

In chapter 5, we developed a method, called the POET that is capable of determining the prevailing orientation of brush strokes in patches of digitized paintings.

The performances obtained by the POET are indistinguishable from those obtained by human observers. This leads us to answering RQ2 as follows. The prevailing orientation of brush work can be extracted effectively from the digital reproductions of paintings.

RQ3: *Are there visual features which could serve as a fingerprint of the master and reveal his identity independent of his style or the scene of his work?*

We performed an extensive study of explicit and implicit visual analysis using the EXPRESS and IMPRESS methods in chapter 6. An experienced art historian of the Van Gogh museum defined four tasks, each of which consists of a set of genuine Van Gogh paintings and a single painting not painted by Van Gogh. The results of the EXPRESS and IMPRESS methods revealed that second-order filters are required to detect the visual features that are diagnostic for the authenticity in the four tasks. Therefore, we answer RQ3 by stating that combinations of brush stroke orientation could serve as a fingerprint and may reveal a painter's identity.

7.2 Answer to the problem statement

The answers to the three research questions allow us to answer our problem statement, stated in chapter 1.

PS: *To what extent can recent advances in image processing and image analysis supplement art historians in their task of painting authentication?*

From our results we may conclude that image processing and image analysis are able to supplement art historians in their task of painting authentication. The methods presented in this thesis show that image processing and analysis techniques can (i) confirm established knowledge (cf. chapter 4), (ii) perform on a par with human observers (cf. chapter 5), and (iii) detect visual features that are diagnostic for the authenticity of paintings (cf. chapter 6).

7.3 Future research

Our work on the automatic analysis of (digitized) paintings represents an initial step towards the development of a full-fledged software environment to support art historians in their examination of paintings.

The results presented in this thesis are based on a carefully collected set of digital reproductions of Ektachromes. The reproductions obtained have a relatively high resolution and were all digitized using the same scanner, but still exhibit considerable variation in color (cf. chapter 4). In addition, the Ektachromes were acquired in different time periods, presumably with different cameras, and even in two different museums (i.e., the Van Gogh museum and the Kröller-Müller museum). Such variations during acquisition may lead to "fingerprints" in the digital reproductions (i.e., false characteristics) that are diagnostic for the acquisition procedure, rather than for the author of the painting.

We identify three lines of future research that build upon the results achieved in this thesis. These lines pertain (i) to the quality of the digital reproductions, (ii) the identification of the full set of diagnostic features for Van Gogh, and (iii) the development of software for supporting art historians.

First, future research should address the quality of the reproduction, i.e., future research should be performed on calibrated reproductions, preferably based on multi-spectral digital scans. The initial steps towards creating a high-resolution multi-spectral dataset have been made. Lumiere Technology[1] has been implemented in creating a set of multi-spectral digital reproductions using a dedicated high-resolution camera. These reproductions are freely available for digital analysis to a selected set of research groups[2] and are expected to boost the quality of digital painting analysis considerably.

The second line of future research is the identification of the complete set of diagnostic second-order features. In chapter 5, we have performed an initial analysis revealing the importance of second-order features for distinguishing between paintings created by Van Gogh and those created by other painters. Since we considered four sets only, the second-order features established to be diagnostic are quite limited. To identify the complete set of second-order features requires (i) the second-order analysis of all available digital reproductions of paintings by Van Gogh and his contemporaries, and (ii) the careful examination of the results in close conjunction with art-historian experts.

The third line of future research is crucial for the introduction of computer science and artificial intelligence in the cultural heritage domain of painting analysis. It is the development of dedicated software that incorporates the techniques described in this thesis and elsewhere (Johnson *et al.*, 2008).

[1] See http://www.lumiere-technology.com

[2] See http://www.digitalpaintinganalysis.org

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Appendix A: List of Van Gogh paintings digitized

Number	Catalogue code	Title
1	f724	Mountainous landscape seen over the wall of the asylum
2	f219	Still life with meat and vegetables
3	f418	Seascape at Saintes Maries de la Mer
4	f278	Flower still life
5	s218v	View from Montmartre
6	s205v	Portrait of Bernards grandmother
7	s206v	Self-portrait with portrait of Gauguin
8	s274v	Young woman at a table, Poudre de Ritz
9	s251v	Vase with flowers
10	s251v	Portrait of Vincent van Gogh painting sunflowers
11	f101	Basket of Apples
12	f109v	Self-Portrait
13	f122	Avenue of Poplars in Autumn
14	f130	Head of a Woman
15	f160	Head of a Woman
16	f174	Head of an Old Woman with White Cap (The Midwife)
17	f177a	Flying Fox
18	f179v	Self-Portrait with Straw Hat and Pipe
19	f180	Self-Portrait with Pipe
20	f181	Self-Portrait with Dark Felt Hat at the Easel
21	f205	Portrait of an Old Man with Beard
22	f206	Head of a Woman with her Hair Loose
23	f207a	Portrait of Woman in Blue
24	f208	Self-Portrait with Pipe
25	f208a	Self-Portrait with Dark Felt Hat
26	f212	Skull with Burning Cigarette
27	f215	Nude Study of a Little Girl, Seated
28	f215b	Portrait of a woman
29	f215c	Portrait of a woman
30	f215d	Portrait of a seated woman
31	f216a	Plaster Statuette of a Female Torso
32	f216b	Plaster Statuette of a Female Torso
33	f216c	Plaster Statuette of a Horse
34	f216d	Plaster Statuette of a Female Torso
35	f216e	Plaster Statuette of a Male Torso
36	f216f	Plaster Statuette of a Kneeling Man
37	f216g	Plaster Statuette of a Female Torso
38	f216h	Plaster Statuette of a Female Torso
39	f216i	Plaster Statuette of a Female Torso
40	f216j	Plaster Statuette of a Female Torso
41	f218	Glass with yellow Roses
42	f229	Montmartre: Quarry, the Mills
43	f230	The Hill of Montmartre with Quarry
44	f231	View of Roofs and Backs of Houses
45	f232	Sloping Path in Montmartre
46	f233	The hill of Montmartre with stone quarry
47	f234	Vase with Asters and Phlox
48	f243a	Vase with Myosotis and Peonies
49	f244	Tambourine with Pansies
50	f248a	Vase with Gladioli
51	f25	Congregation Leaving the Reformed Church in Nuenen
52	f253	Still life with wine, bread and cheese
53	f253a	A Plate of Rolls
54	f254	Still Life with Apples
55	f255	A Pair of Shoes
56	f256	Still Life with Mussels and Shrimps
57	f260	Backyards of Old Houses in Antwerp in the Snow
58	f261	View of the Roofs of Paris
59	f263a	Self-Portrait with Pipe and Glass
60	f266a	Factories Seen from a Hillside in Moonlight
61	f267	Self-Portrait

Continued on next page

Table 1 – continued from previous page

Number	Catalogue code	Title
62	f269v	Self-Portrait
63	f270a	Chestnut Tree in Blossom
64	f275	Lane in Voyer d'Argenson Park at Asnieres
65	f28	The Kingfisher
66	f281	Coleus Plant in a Flowerpot
67	f289	Portrait of a Man with a Skull Cap, Portrait of a restaurant owner, possibly Lucien Martin
68	f292	Boulevard de Clichy
69	f293	The Banks of the Seine
70	f294	Self-Portrait with Straw Hat
71	f296	Self-Portrait with Grey Felt Hat
72	f297	Skull
73	f297a	Skull
74	f299	Walk Along the Banks of the Seine Near Asnieres
75	f304	The Seine with the Pont de la Grande Jette
76	f307	Trees and Undergrowth
77	f308	Undergrowth
78	f309	Path in the Woods
79	f309a	Trees and Undergrowth
80	f310	Wheat Field with a Lark
81	f314	Couples in the Voyer d'Argenson Park at Asnieres
82	f316	Vegetable Gardens at Montmartre
83	f321	Exterior of a Restaurant at Asnieres
84	f331	A Pair of Shoes
85	f334	Still Life with a Basket of Crocuses
86	f335	Still Life with Three Books (oval)
87	f336	Basket of Sprouting Bulbs (oval)
88	f337	Flowerpot with Chives
89	f338	Still Life with Lemons on a Plate
90	f339	Still Life with Absinthe
91	f340	Still Life with Decanter and Lemons on a Plate
92	f341	View of Paris from Vincent's Room in the Rue Lepic
93	f342	Interior of a Restaurant
94	f344	Self-Portrait with Grey Felt Hat
95	f346	Vegetable Garden in Montmartre
96	f347	Street Scene in Montmartre: Le Moulin a Poivre
97	f356	Self-Portrait
98	f358	Still Life: French Novels
99	f369	Woman Sitting by a Cradle
100	f370	Agostina Segatori Sitting in the Cafe du Tambourin
101	f371	Japonaiserie: Flowering Plum Tree (after Hiroshige)
102	f372	Japonaiserie: Bridge in the Rain (after Hiroshige)
103	f373	Japonaiserie: Oiran (after Kesa Eisen)
104	f374	Still Life with Red Cabbages and Onions
105	f377	Two Cut Sunflowers
106	f383	Still Life with Grapes, Pears and Lemons
107	f388v	Garden with Sunflowers
108	f389	A Pork-Butcher's Shop Seen from a Window
109	f390	An Old Woman of Arles
110	f392	Blossoming Almond Branch in a Glass
111	f400	The Langlois Bridge at Arles with Road Alongside the Canal
112	f402	Two White Butterflies
113	f403	The White Orchard
114	f404	Peach Tree in Blossom
115	f405	Blossoming Pear Tree
116	f408	Farmhouse in a Wheat Field
117	f409	View of Arles with Irises in the Foreground
118	f411	Wheat Field with the Alpilles Foothills in the Background
119	f412	Harvest at La Crau, with Montmajour in the Background
120	f413	Fishing Boats on the Beach at Saintes-Maries
121	f415	Seascape at Saintes-Maries
122	f423	The Zouave (Half Length)
123	f441	The Baby Marcelle Roulin
124	f451	The Sower
125	f458	Still Life: Vase with Fifteen Sunflowers
126	f464	Vincent's House in Arles (The Yellow House)
127	f469	Self-Portrait with Straw Hat
128	f482	Vincent's Bedroom in Arles
129	f486	Les Alyscamps: Falling Autumn Leaves
130	f499	Paul Gauguin's Armchair
131	f511	Orchard in Blossom
132	f515	View of Arles with Trees in Blossom
133	f522	Self-Portrait in Front of the Easel
134	f524	Self-Portrait with Pipe and Straw Hat
135	f532	Portrait of a One-Eyed Man
136	f538	Portrait of Camille Roulin
137	f546	Paul Gauguin (Man in a Red Beret)
138	f555	Orchard with Blossoming Apricot Trees
139	f557	Almond Tree in Blossom
140	f572	Willows at Sunset
141	f574	Ploughed Field
142	f576	Farmhouses in a Wheat Field Near Arles
143	f597	Wild Roses
144	f603	Still Life with Grapes
145	f605	Crab on Its Back
146	f607	Pair of Leather Clogs, A
147	f610	Great Peacock Moth
148	f618	Wheat Fields with Reaper at Sunrise
149	f61r	Still Life with Bottles and Earthenware
150	f61v	Self-Portrait with Straw Hat

Continued on next page

Table 1 – continued from previous page

Number	Catalogue code	Title
151	f621	Cypresses and Two Women
152	f630	The Piet (after Delacroix)
153	f632	The Plough and the Harrow (after Millet)
154	f634	The Sheep-Shearers (after Millet)
155	f645	Les Peiroulets Ravine
156	f647	Evening: The Watch (after Millet)
157	f651	The Walk: Falling Leaves
158	f652	Pine Trees against a Red Sky with Setting Sun
159	f659	The Garden of Saint-Paul Hospital
160	f670	The Woodcutter (after Millet)
161	f671	Blossoming Almond Tree
162	f675	Cottages and Cypresses: Reminiscence of the North
163	f677	The Raising of Lazarus (after Rembrandt)
164	f678	Still Life: Vase with Irises Against a Yellow Background
165	f687	Reaper with Sickle (after Millet)
166	f692	The Thresher (after Millet)
167	f693	The Sheaf-Binder (after Millet)
168	f697	Peasant Woman Cutting Straw (after Millet)
169	f700	Peasant Woman Binding Sheaves (after Millet)
170	f703	Portrait of a Patient in Saint-Paul Hospital
171	f707	Olive Grove
172	f709	Olive Grove: Bright Blue Sky
173	f716	Olive Trees against a Slope of a Hill
174	f723	At the Foot of the Mountains
175	f733	The Garden of Saint-Paul Hospital with Figure
176	f734	The Garden of Saint-Paul Hospital
177	f739	Field with Two Rabbits
178	f742	Study of Pine Trees
179	f744	Entrance to a Quarry
180	f745	Undergrowth with Ivy
181	f746	Tree Trunks with Ivy
182	f748	Poppies and Butterflies
183	f749	Roses and Beetle
184	f76	Vase with Honesty
185	f764a	Still Life: Vase with Rose-Mallows
186	f765	Daubigny's Garden
187	f767	Ears of Wheat
188	f770	Landscape with the Chateau of Auvers at Sunset
189	f778	Wheat Field Under Clouded Sky
190	f779	Wheat Field with Crows
191	f77v	Self-Portrait
192	f799	View of Auvers
193	f806	Farmhouse with Two Figures
194	f816	Tree Roots and Trunks
195	f82	The Potato Eaters

Appendix B: Flowcharts of the methods

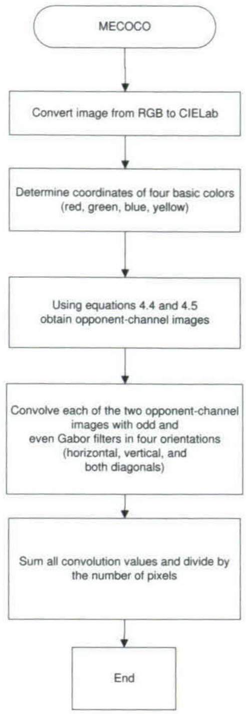

Figure B-1: Flowchart of MECOCO

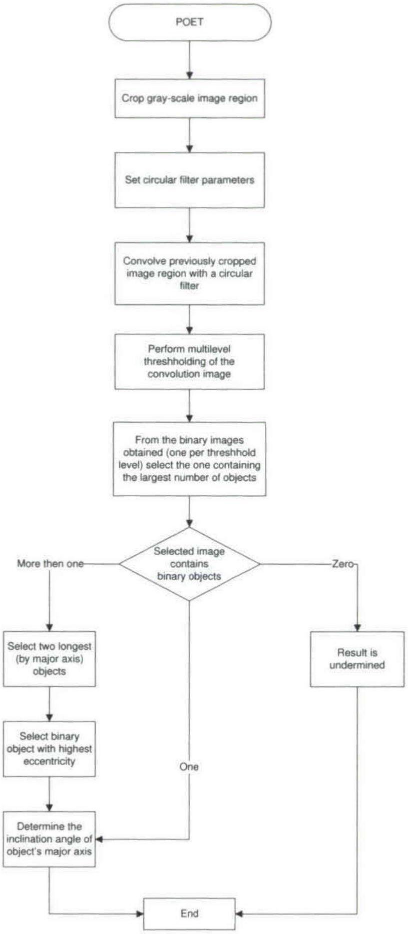

Figure B-2: Flowchart of the POET

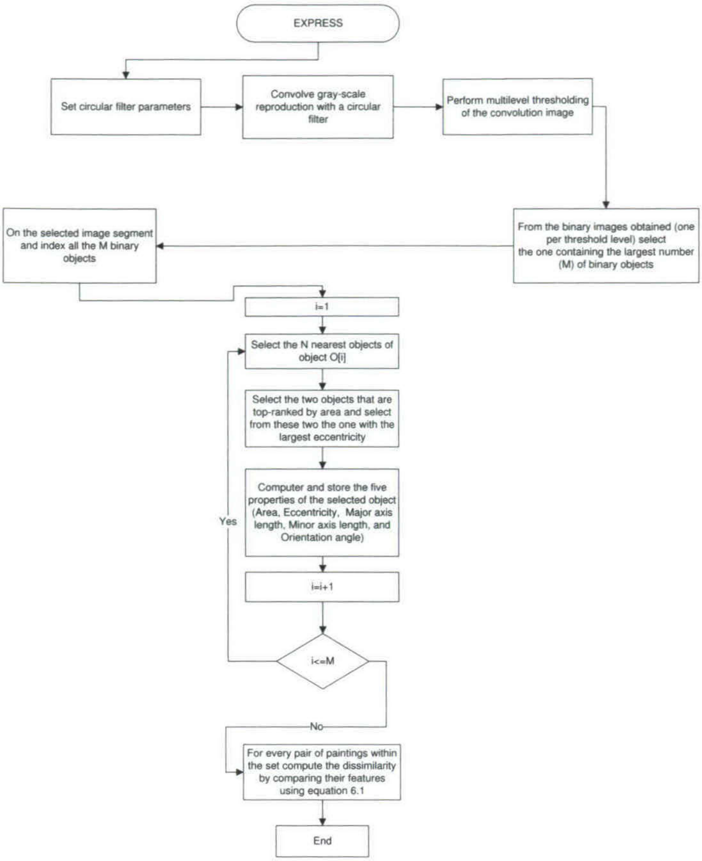

Figure B-3: Flowchart of EXPRESS

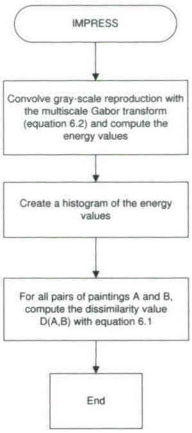

Figure B-4: Flowchart of IMPRESS

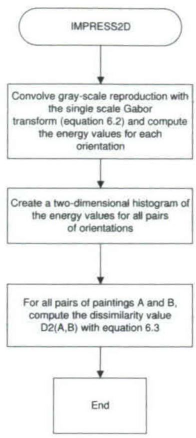

Figure B-5: Flowchart of IMPRESS2D

List of Abbreviations

CATCH	Continuous Access To Cultural Heritage; NWO research programme
CBIR	Content-Based Image Retrieval
CCD	Charge Coupled Device
CF	Circular Filter
CS	Computer Science
CH	Cultural Heritage
CIELab	Commision Internationale de LÉclairage Luminance-a-b color space
dpi	dots per inch
express	explicit representation of strokes
FastICA	Fast method to perform Independent Component Analysis
FFT	Fast Fourier Transform
HSI	Hue Saturation Intensity color space
ICA	Independent Component Analysis
impress	implicit representation of strokes
IR	Infrared
MDS	Multi Dimensional Scaling
MECOCO	Method for the Extraction of COmplementary COlours
MHMM	Multi-resolution Hidden Markov Model
MSAD	Mean Squared Angular Distance
MS-PCA	Multi-Scale Principal Component Analysis
n.s.	not significant
NWO	The Netherlands Organization for Scientific Research
POET	Prevailing Orientation Extraction Technique
PCA	Principal Component Analysis
PS	Problem Statement
RGB	Red Green Blue color space
RQ	Research Question
SF	Steerable Filters
ToKeN	NWO research programme
XYZ	XYZ color space
2D	two-dimensional

List of Symbols

	MECOCO
L	Luminance coordinate of CIELab color representation (L^*)
a	red-green coordinate of CIELab color representation (a^*)
b	yellow-blue coordinate of CIELab color representation (b^*)
X	"red" coordinate of the XYZ color representation
Y	"green" coordinate of the XYZ color representation
Z	"blue" coordinate of the XYZ color representation
F_{rg}	red-green opponency value
F_{yb}	yellow-blue opponency value
$G(A, B, a, b, \sigma_{att})$	two-dimensional Gaussian attenuation function
I_{rg}	red-green opponent-channel image
I_{yb}	yellow-blue opponent-channel image
$Gabor_{even}(x, y, \sigma, \alpha, \omega)$	even Gabor function
$Gabor_{odd}(x, y, \sigma, \alpha, \omega)$	odd Gabor function
x	x-coordinate (horizontal image location)
y	y-coordinate (vertical image location)
σ	standard deviation of the Gaussian envelope of the Gabor function
α	orientation of the Gabor function
ω	spatial frequency of the Gabor function
s	scale of the Gabor function
p	p value (for expressing statistical significance)

	POET
W	pass-band width of the circular filter
R	central spatial-frequency of the circular filter
k	index for the threshold level in the POET
K	number of threshold levels in the POET
α_i	angular orientation of brush stroke i
$D_\alpha(i, j)$	angular distance between the brush strokes i and j

	EXPRESS
N_{nb}	number of neighboring objects taken into account
S	area occupied by the object
E	eccentricity of the object
A	major axis length of the ellipse circumscribing the object
B	minor axis length of the ellipse circumscribing the object
α	orientation of the object (angle between A and the horizontal axis)
$H(i)$	histogram of the i-th feature
$D_i(A, B)$	distance between histograms A and B of the i-th feature
N_{bins}	number of bins in histogram H

	IMPRESS
$G_{s,t}(\rho, \theta)$	two-dimensional Gaussian function at scale s and orientation t
n_s	number of scales
n_t	number of orientations in the IMPRESS method
$E(x, y)$	log-Gabor energy centered at spatial image coordinates (x, y)
$D2(A, B)$	distance between histograms A and B in the IMPRESS method
E_τ	log-Gabor energy threshold value in the IMPRESS method
$\rho_{NN}(p)$	dissimilarity measure of painting p

Summary

The subject of this thesis is the development of computer algorithms to support art historians and other art experts in their visual assessment of paintings. Chapter 1 provides an introduction to the world of visual art and artificial intelligence. The entrance of computers in the cultural heritage domain of art has started later than in other disciplines, such as medicine and law. Yet, the cultural heritage offers challenging research questions for computer science and artificial intelligence. In the first chapter a brief historical overview is given of previous attempts to apply computer-based techniques to analyze visual art. The overview gives rise to the following problem statement: *To what extent can recent advances in image processing and image analysis supplement art historians in their task of painting authentication?* To address this problem statement, the following three research questions are formulated. RQ1 *How and to what extent can color analysis of the digitalized reproductions facilitate the authentication process?*. RQ2 *Which features of the brush work can be extracted effectively from the digital reproduction of a painting?*. RQ3 *Are there visual features which could serve as a fingerprint of the master and reveal his identity independent of his style or the scene of his work?* These three questions will be addressed in chapters 4, 5, and 6, respectively.

Chapters 2 and 3 examine previous work on image processing in the cultural-heritage domain of visual art. Chapter 2 reviews studies in which digital analysis techniques are used in relation to paintings. Many ideas of the studies reviewed will be of relevance for supporting the art expert. We distinguish three main types of studies: (1) content-based painting retrieval, (2) digital restoration of paintings, and (3) digital painting analysis. Chapter 3 focuses on the review of previous work that may support art historians in their authentication of paintings. We show that early approaches to the digital analysis of paintings can be subdivided into two categories: implicit approaches and explicit approaches. Implicit approaches do not attempt to extract brush strokes or other meaningful objects, but measure the (statistical) properties of the image regions under consideration. Explicit approaches do attempt to segment brush strokes or other objects and measure the properties of the segmented objects. More recent work is reviewed by discussing color-analysis and texture-analysis approaches. For the texture-analysis approaches a distinction is made between local and global texture analysis. Local analysis is restricted to small regions (patches) of paintings, whereas global analysis applies to the entire painting.

Chapter 4 addresses the first research question, RQ1: How and to what extent

can color analysis of the digitalized reproductions facilitate the authentication process? Our aim here is (1) to determine how successful the usage of complementary colors has been in Vincent van Gogh's oeuvre and (2) whether this characteristic has made his paintings identifiable in time. It is commonly acknowledged that, especially in his French period, Van Gogh started employing complementary colors to emphasize contours of objects or parts of scenes. In this chapter we propose a new method called MECOCO (Method for the Extraction of COmplementary COlours) to measure complementary-color usage in a painting by combining an opponent-color space representation with Gabor filtering. To achieve the aim, (1) we define a novel measure called the opponency value that quantifies the usage of complementary-color transitions in a painting, and (2) we study Van Gogh's painting style. MECOCO's analysis of a dataset of 145 digitized and color-calibrated oil-on-canvas paintings confirms the global transition pattern of complementary colors in Van Gogh's paintings as generally acknowledged by art experts. In addition, MECOCO also provides an objective and quantifiable way to support the analysis of colors in individual paintings.

Chapter 5 addresses the second research question, RQ2: Which features of the brush work can be extracted effectively from the digital reproduction of a painting? In this chapter we show that spatial characteristics play a major role in the human analysis of paintings. One of the main spatial characteristics is the pattern of brush work. The orientation, shape, and distribution of brush strokes are important clues for the analysis. This chapter focuses on the automatic extraction of the orientation of brush strokes from digital reproductions of paintings. We present a novel technique called the POET (Prevailing Orientation Extraction Technique). The technique is based on two stages: a circular filter stage and an orientation-extraction stage. Experimental evaluation of the POET reveals that it performs on a level indistinguishable from that of humans. From our results we may conclude that the POET supports the automatic extraction of the spatial distribution of oriented brush strokes. Such an automatic extraction will aid art experts in their analysis of paintings.

Chapter 6 addresses the third research question, RQ3: Are there visual features which could serve as a fingerprint of the master and reveal his identity independent of his style or the scene of his work? In this chapter we present two different methods for extracting brush-stroke features from paintings: the EXPRESS method and the IMPRESS method. The EXPRESS (EXPlicit REpresentation of StrokeS) method employs the circular filter described in chapter 5 to extract objects from a painting. The objects are assumed to correspond to (parts of) the brush strokes. Hence, they form an explicit representation of the strokes. The IMPRESS (IMPlicit REpresentation of StrokeS) method employs a filter-based approach that transforms a region containing brush strokes into a vector of filter coefficients that constitute a feature-space representation. The coefficients contain information on the brush strokes and surrounding texture and therefore form an implicit representation of the brush strokes. Both methods are evaluated on four painting-classification tasks requiring the identification of the single painting not created by Van Gogh in a set of 5 to 6 paintings. The EXPRESS method succeeds on one task only and the IMPRESS method succeeds on two out of the four tasks. To improve the performance of the IMPRESS method, the

IMPRESS2D method is presented. The IMPRESS2D method relies on the second-order statistics of filter responses and succeeds on all four tasks. Here we may conclude that second-order features offer a viable basis for identifying Van Gogh's specific visual features.

Chapter 7 answers the three research questions and the problem statement. The *to what extent* part of RQ1 is answered as follows: provided that color-calibrated digital representations are available, the analysis of complementary colors by MECOCO can facilitate the authentication process. (The *how* part of RQ1 is contained in the answer to RQ3, below.) The answer to RQ2 is that the prevailing orientation of brush work can be extracted effectively from the digital reproductions of paintings using the POET. The third research question, RQ3, is answered as follows: combinations of brush-stroke orientations as used by IMPRESS2D are able to serve as a fingerprint and may reveal a painter's identity. Finally, the problem statement is answered as follows. From our results we may conclude that image processing and image analysis are able to supplement art historians in their task of painting authentication. The methods presented in this thesis show that image processing and analysis techniques can (i) confirm established knowledge (cf. chapter 4), (ii) perform on a par with human observers (cf. chapter 5), and (iii) detect visual features that are diagnostic for the authenticity of paintings (cf. chapter 6).

The thesis concludes with a review of future research in which three lines of future research are identified: (1) improving the quality of the digital reproductions of paintings, (2) the identification of the full set of diagnostic Van Gogh features in addition to combinations of brush stroke orientations, and (3) the development of multifaceted software incorporating the methods described in the thesis for supporting art historians.

Samenvatting

Dit proefschrift handelt over de ontwikkeling van computeralgorithmen ter ondersteuning van de visuele beoordeling van schilderijen door kunsthistorici en andere kunstexperts. Hoofdstuk 1 geeft een introductie in de wereld van visuele kunst en kunstmatige intelligentie. In vergelijking met het medische en juridische domein is de introductie van de computer in het cultureel erfgoed relatief laat te noemen. Als toepassingsdomein voor de informatica en de kunstmatige intelligentie biedt het cultureel erfgoed uitdagende onderzoeksvragen. In het eerste hoofdstuk van dit proefschrift wordt een beknopt historisch overzicht gegeven van eerdere pogingen om computertechnieken toe te passen op de analyse van visuele kunst. Het overzicht leidt tot de volgende probleemstelling: *In hoeverre kunnen kunsthistorici worden ondersteund door recente ontwikkelingen in de beeldverwerking en beeldanalyse?* Vanuit deze probleemstelling zijn drie onderzoeksvragen geformuleerd: RQ1 *Hoe en in hoeverre kan kleuranalyse van digitale reproducties van schilderijen het authenticatieproces bevorderen?* RQ2 *Welke kenmerken van de penseelstreken kunnen effectief worden geëxtraheerd van de digitale reproductie van een schilderij?* RQ3 *Bestaan er visuele kenmerken die als een vingerafdruk fungeren van de auteur en zijn identiteit kunnen onthullen onafhankelijk van zijn stijl of het geschilderde onderwerp?* Deze drie vragen worden behandeld in de hoofdstukken 4, 5, en 6, respectievelijk.

Hoofdstukken 2 en 3 geven een overzicht van eerdere studies op het grensvlak van de beeldverwerking en het domein van de visuele kunst.

Hoofdstuk 2 geeft een overzicht van studies waarin beeldanalyse en schilderijen een rol spelen. We onderscheiden drie typen van studies: (1) *content-based painting retrieval*, (2) digitale restoratie van schilderijen, en (3) digitale schilderijen analyse. Hoofdstuk 3 beschouwt eerder werk dat de kunsthistoricus kan ondersteunen bij het bepalen van de authenticiteit van schilderijen. De benaderingen uit dit eerder werk kunnen worden onderverdeeld in twee typen: expliciete en impliciete benaderingen. Expliciete benaderingen proberen de penseelstroken (of andere objecten) te isoleren en vervolgens de eigenschappen van deze objecten te bepalen. Impliciete benaderingen proberen niet om de penseelstreken te isoleren, maar bepalen de (statistische) eigenschappen van de penseelstreken en hun achtergrond. Voorts wordt recent onderzoek naar kleuranalyse en textuuranalyse beschreven. In de benaderingen voor textuuranalyse wordt een onderscheid gemaakt tussen locale en globale textuuranalyse. Locale analyse beperkt zich tot kleine gedeelten (*patches*) van het schilderij, terwijl globale analyse het gehele schilderij bestrijkt.

Hoofdstuk 4 richt zich op de eerste onderzoeksvraag, RQ1: *Hoe en in hoeverre*

kan kleuranalyse van digitale reproducties van schilderijen het authenticatieproces bevorderen?

Het doel is (1) te bepalen hoe succesvol Van Gogh was in het gebruik van complementaire kleuren in zijn oeuvre en (2) vast te stellen in hoeverre complementaire kleuren gebruikt kunnen worden voor de datering van zijn schilderijen. Het is algemeen bekend dat Van Gogh, vooral in zijn Franse periode, complementaire kleuren ging gebruiken om contouren van objecten of delen van landschappen te accentueren. In dit hoofdstuk presenteren we een nieuwe methode, genaamd MECOCO (Method for the Extraction of COmplementary COlours), ter bepaling van de complementaire kleuren door middel van de combinatie van opponente kleurruimterepresentaties en Gabor filters. Vervolgens wordt een nieuwe maat gedefinieerd en wordt Van Gogh's schilderstijl bestudeerd. MECOCO's analyse van een verzameling van 145 gedigitaliseerde kleur-gekalibreerde olie-op-canvas-schilderijen bevestigt het globale patroon van complementaire kleuren in Van Gogh's schilderijen. Bovendien biedt MECOCO een objectieve en kwantificeerbare methode ter ondersteuning van de bepaling van kleuren in een schilderij.

Hoofdstuk 5 richt zich op de tweede onderzoeksvraag, RQ2: *Welke kenmerken van de penseelstreken kunnen effectief worden geëxtraheerd van de digitale reproductie van een schilderij?* In dit hoofdstuk laten we zien dat spatiele eigenschappen een voorname rol spelen bij de menselijke analyse van schilderijen. Een van de belangrijkste eigenschappen betreft het patroon van penseelstreken. Dit hoofdstuk richt zich op de automatische extractie van de oriëntatie van penseelstreken. We presenteren een nieuwe techniek genaamd de POET (Prevailing Orientation Extraction Technique). De techniek is gebaseerd op twee stadia: een circulair filter-stadium en een oriëntatie extractie-stadium. Experimentele evaluatie van de POET laat zien dat deze techniek qua prestaties niet te onderscheiden is van de prestaties van menselijke waarnemers. Uit de resultaten kunnen we concluderen dat de POET de automatische extractie van georiënteerde penseelstreken ondersteunt. Een dergelijke automatische extractie zal kunstexperts ondersteunen bij de analyse van schilderijen.

Hoofdstuk 6 richt zich op de derde onderzoeksvraag, RQ3: *Bestaan er visuele kenmerken die als een vingerafdruk fungeren van de auteur en zijn identiteit kunnen onthullen onafhankelijk van zijn stijl of het geschilderde onderwerp?* In dit hoofdstuk worden twee verschillende methoden gepresenteerd voor de extractie van penseelstreekkenmerken van schilderijen: de EXPRESS-methode en de IMPRESS-methode. De EXPRESS (EXPlicit REpresentation of StrokeS) methode is gebaseerd op het circulair filter dat is beschreven in hoofdstuk 5. Van de door het filter geëxtraheerde objecten wordt aangenomen dat ze overeenstemmen met de (delen van) penseelstreken. In die zin vormen ze een expliciete representatie van de penseelstreken. De IMPRESS (IMPlicit REpresentation of Strokes) methode is gebaseerd op een filter dat een deel van het schilderij vertaalt in een vector van filtercoëfficienten, een zogenaamde *feature space*-representatie. De coëfficienten bevatten informatie over de penseelstreken en de aangrenzende textuur. De *feature space*-representatie vormt daarom een impliciete representatie van de penseelstreken. Beide methoden worden geëvalueerd op vier taken, elk bestaande uit het detecteren van het schilderij dat niet door Van Gogh is geschilderd uit een verzameling van 5 tot 6 schilderijen. De EXPRESS-methode is enkel succesvol op een van de vier taken en de IMPRESS-methode op twee van de vier taken. Om de prestaties van de IMPRESS methode te verbeteren, presenteren we de IMPRESS2D-methode. Deze methode maakt gebruik van de tweede orde-statistieken van de filters en is succesvol op alle vier de taken. Op basis hiervan mogen we concluderen dat tweede orde-kenmerken een goede basis vormen voor het identificeren van Van Gogh's specifieke visuele kenmerken.

Hoofdstuk 7 beantwoordt de drie onderzoeksvragen en de probleemstelling. Het *in hoeverre* gedeelte van RQ1 wordt als volgt beantwoord: mits kleurgekalibreerde reproducties beschikbaar zijn, kan MECOCO het authenticatieproces faciliteren. (Het *hoe* gedeelte van RQ1 is onderdeel van het antwoord op RQ3, hieronder.) Het antwoord op RQ2 luidt dat de voornaamste oriëntatie van penseelstreken automatisch kan worden geëxtraheerd van digitale reproducties met behulp van de POET. De derde onderzoeksvraag, RQ3, wordt als volgt beantwoord: combinaties van oriëntaties van penseelstreken, zoals gebruikt door IMPRESS2D, kunnen fungeren als een vingerafdruk van de schilder en als zodanig zijn identiteit onthullen.

Uit onze resultaten kunnen we concluderen dat beeldverwerking en beeldanalyse kunsthistorici kunnen ondersteunen in de bepaling van de authenticiteit van een schilderij. De in dit proefschrift gepresenteerde methoden tonen aan dat beeldverwerking en analysetechnieken (i) bestaande kennis kunnen bevestigen (cf. hoofdstuk 4), (ii) op menselijk niveau kunnen presteren (cf. hoofdstuk 5), en (iii) visuele kenmerken kunnen detecteren die diagnostisch zijn voor de authenticiteit van een schilderij (cf. hoofdstuk 6).

Het proefschrift eindigt met een overzicht van toekomstig onderzoek waarbij drie lijnen van onderzoek worden geïdentificeerd: (1) verbetering van de kwaliteit van digitale reproducties van schilderijen, (2) de identificatie van de volledige verzameling van diagnostische visuele kenmerken, en (3) de ontwikkeling van software ter ondersteuning van kunsthistorici.

Curriculum Vitae

Igor Berezhnoy was born in Lozovaya town, Soviet Union, on the 23^{th} of January 1975. Because of his father's military service Igor attended secondary school at various cities of the USSR. In 1987, his family moved to Kiev where he obtained his secondary school diploma in 1992. Subsequently, he started his studies at the Department of Applied Mathematics and Computer Science at the National University of Technology of Ukraine. In 1998, he obtained his M.Sc. degree with a major in decision-making systems. His M.Sc. thesis was a study on the application of machine learning to the short-term forecasting of stock-exchange rates. After obtaining his M.Sc. degree and several years of working for various companies in Kiev, in 2000 Igor joined the User System Interaction (USI) program at the Department for User Centered Engineering of Eindhoven University of Technology in the Netherlands. In 2002 he graduated as Master of Technological Design. Shortly thereafter, he accepted a position as a Ph.D. student at Maastricht University under the supervision of professor Eric Postma and professor Jaap van den Herik. Funded by the ToKeN research programme of the Netherlands Organization for Scientific Research (NWO), he became a member of the AUTHENTIC project in which he performed research on the development and application of image-processing and machine-learning algorithms to the authentication of paintings. In the project he collaborated with the Van Gogh Museum and the Kröller-Müller Museum. In February 2007 he joined the Philips Research Laboratories at the High Tech Campus in Eindhoven, where he currently is appointed as a Senior Scientist at the User Experience (UX) Group.

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