# Tracing the Colors of Clothing in Paintings with Image Analysis

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## Introduction

The history of color is full of instances of how and why certain colors come to be associated with certain concepts, ideas, politics, status and power. Sometimes the connotations occur arbitrarily, like in the instance when pink was assigned to baby girls, and blue started to be associated with baby boys at the turn of 19th Century [Paoletti, 1987]. Sometimes though, color associations have very tangible reasons, such as in the case of Marian blue, reserved only for painting Virgin Mary over the centuries. The reason is found in the scarcity of the rock lapis lazuli -even more valuable than goldfrom which the blue pigments were extracted. Individual colors have convoluted and contested histories, since they have been attached to many symbols at any given time. John Gage, an art historian who has devoted 30 years of research on the topic of color, explains the conundrum of what he terms "politics of color" in a simple fashion: "The same colors, or combinations of colors can, for example, be shown to have held quite antithetical connotations in different periods and cultures, and even at the same time and in the same place."[Gage, 1990].

The purpose of the present study is to introduce a method for automatically extracting color distributions and main colors of paintings, as well as color schemes of people in paintings. By visualizing these over time for cross-referencing with historical data, this study will reveal changes in how particular colors were used in a given time period and culture. In this study, we will look at artworks to find out whether certain colors or tones are associated with a specific sex, and if these connotations change over time. To that end, we apply algorithmic tools to process very large datasets automatically, and information visualization tools to depict the findings.

#### **Related Work**

Today, major cultural heritage collections are available online. Digitization and preservation of artworks is an important occupation of museums and cultural heritage institutions, as well as many Digital Humanities projects. Portions of of such digitized collections are made available to further computer vision research in order to scrutinize art historical questions. Such collections are usually enriched with meticulously tagged metadata describing the origins of each artwork. However, these datasets do not provide comprehensive gender annotations. For example, Rijksmuseum's arts database has a wide selection of categories with rich metadata that is primarily about the art objects themselves (see Table 1 - the quantity of meta information and context vary between different art samples), but without any reference to what these artworks hold [Mensink and Van Gemert, 2014]. Automatically determining whether a sitter of a portrait is female or male in a painting is not an easy task.

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Title	Date	Subject
Rortret van Jan	1660	Valckenburgh, Jan
Rortret van een jonge man	1675 -	Alphen, Simon van
Carel Hendrik Ver Huell	1804	Ver Huell, Carel
Portret van een meisje	1623	<u> </u>
Portret van een man	1540 -	-

#### Table 1: Sample from Rijksmuseum meta data

Several publications have appeared in recent years with the aim of automatic gender recognition. The survey by Ng et al. described a variety of approaches to gender recognition in natural images [Ng et al., 2012]. Xiong and De la Torre (2013) proposed a practical and effective method for automatically detecting faces in natural or man-made images. Once the face is detected, a supervised classifier is used to determine whether it belongs to a male or female. This requires the ground truth annotation of a large number of face images, from which the automatic classifier learns the visual boundary between these two classes.

There has been focused studies to address face recognition tasks on artistic images [Srinivasan et al., 2015]. For the purposes of face detection, mainstream algorithms perform sufficiently well on paintings that are of interest for this study. Automatic male/female classification is not perfect, it will occasionally get confused and produce an incorrect label. However, over thousands of images, a small number of individual errors will not prevent us from seeing the general patterns of color usage with males and females.

# **Methodology**

In this study, the aim is to analyze the trends of clothing color in different periods, separately for males and females. For this purpose, we work on a database of paintings, for which the era (or date) is provided, and we seek to annotate each image with the gender of the depicted person, as well as a rough segmentation of the area of the clothing. The general workflow of the proposed approach is depicted in Figure 1.



Figure 1. The workflow of the proposed approach.

#### Database

The Rijksmuseum is a Dutch national museum dedicated to arts and history in Amsterdam. The Rijksmuseum database contains 112.039 high-resolution images with extended meta data [Mensink and Van Gemert, 2014]. However, as mentioned previously in Section 2, the Rijksmuseum database has neither gender nor clothing color information embedded into its metadata. We describe briefly how we determine the missing information.

# **Gender Classification**

We have performed classification of the perceived sex from the face images. This process is commonly called Gender classification in computer vision – not to be mixed with characteristics of masculinity, femininity or sex organs, but what is perceived solely from the face crops on the paintings.

For this purpose we have prepared a test dataset of face images from Rijksmuseum paintings and three

training datasets of face images: 10k US Adult Faces[Bainbridge et al., 2013], Labeled faces in the wild[Huang et al., 2007] and in an approach similar to Jia's work [Jia and Cristianini, 2015], we have gen- erated our own IMDB dataset. IMDB dataset images are collected using the Google Image search, using actor and actress names as queries. In total, 5600 male and 5300 female faces were downloaded.

None of the datasets have gender annotations, and hence we have performed face detection and facial landmark extraction methods in [Xiong and De la Torre, 2013], first, then hand-clean face detection and landmark extraction results against false positives and validate gender information (for all 10k US Adult Faces dataset and LFW dataset we had to manually annotate each image, but also Google Image search results for IMDB dataset are not perfectly robust, hence the IMDB dataset also had to be verified). Then we have aligned the faces to a mean shape [Gower, 1975], and extract features that are resistant to illumi- nation effects [Ojala et al., 2002]. We then train a classifier using the sequential minimal optimization (SMO) method [Platt et al., 1998].

The biggest challenge for evaluating gender recognition performance on the paintings is to make sure the ground-truth gender data are actually correct [Mathias et al., 2014]. From our experience, this demanding task requires a full view of the painting, rather than just the detected face. Results of some combinations of the datasets are given in Table 2. We could reach above 75% accuracy on paintings, just by using photographs of actors and actresses in the training of the system. Some of misclassification examples are given in figure 2.

	IMDB	IMDB and 10k	IMDB, 10k and LFW
Female	62.16%	62.32%	57.11%
Male	84.51%	83.40%	85.79%
Total	77.21%	76.41%	76.28%

Table 2. Gender recognition performance on Rijksmuseum. All results are com- parable and best (by small margin) is acquired when only the IMDB dataset is used.



(b) Male Sitters, classified as Female

Figure 2. Misclassified paintings

#### Clothing color information

Portrait paintings that are completely focused on the sitter's face have still a lot of background noise that disrupt the color representation of the paintings (see Figure 3). Our hypothesis is that color representation, when focused on the clothing of the model, will still reflect the color scheme that is associated with the gender of the sitter.







(a) Portrait of Margaret of Austria, Consort of Philip III, Frans II Pourbus, c. 1600







Maria Machteld van Sypesteyn, 1748

(b) Willem IV (1711-51), prins van Oranje-Nassau





(c) Portrait of Ambrogio Spinola, Michiel Jansz can Mierevelt, 1609

 (d) Portret van Margaretha van de Eeckhout,echtgenote van Pieter van de Poel,
Arnold Boonen, 1690 - 1729

Figure 3. Four paintings from the Rijksmuseum collection, classified and segmented in terms of colors.

In order to extract the color information of an outfit we need to do a coarse segmentation of the clothing. We used the GrabCut approach [Rother et al., 2004]. In this method, a user defines an area of interest, as well as foreground and background seeds for the segmentation. In our study, background and foreground seeds are initialized based on the detected face landmarks.

Figure 4 provides an initial visualization of the dominant color distributions for each era, for males and females. Concentric circles have thickness associated with the frequency of the color. Bright colors are relatively rare, as the paintings in our tagged collection are generally dark, with the occasional shaft of light illuminating part of the painting. But a very distinct pattern can be observed in that females wear lighter colors compared to males, and show higher variance over the years. Some painting examples are given in Figure 5.



Figure 4. Clothing colors over time. Females wear significantly lighter colors than males. Best viewed in color.



(b) Sample male paintings between 1700 - 1850

Figure 5. Paintings of males and females from the Rijksmuseum database over time. Best viewed in color.

#### Conclusions

Every period and location has certain dominant color associations and symbolism. To investigate hundreds of thousands paintings in a single sweep requires automatic analysis tools. Our main objective in this work in progress is to perform an analysis on the usage of color for different genders along the centuries, and to develop tools for establishing semantic associations of colors for each particular period of study. With the increased popularity of open-art, this study can be extended significantly by introducing more databases alongside Rijksmuseum, for example, drawing on the Europeana collection [Doerr et al., 2010].

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