Report on Digital Image Processing for Art Historians

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Abstract:

As art museums are digitizing their collections, a cross-disciplinary interaction between image analysts, mathematicians and art historians is emerging, putting to use recent advances made in the field of image processing (in acquisition as well as in analysis). An example of this is the *Digital Painting Analysis* (DPA) initiative [2], bringing together several research teams from universities and museums to tackle art related questions such as artist authentication, dating, etc. Some of these questions were formulated by art historians as *challenges* for the research teams. The results, mostly on van Gogh paintings, were presented at two workshops. As part of the Princeton team within the DPA initiative we give an overview of the work that was performed so far.

1. Introduction - Penetrating the art world

Determining the authenticity of a painting can be a daunting task for art historians, requiring extensive art historical research as well as the analysis of pigments, fabrics etc. However much insight chemical analysis yields [4], it requires the destruction of a sample from the painting and is therefore seldom allowed by conservators. Digital image processing for analyzing paintings could thus prove a useful addition to the art experts' toolbox, even beyond the purpose of authentication. We expect that art historians will gradually learn to use and trust these tools; a similar emergence and eventual success took place in the medical world in the mid 80s, with the advent of computed tomography. Subsequently, reconstruction algorithms played a significant role in creating other medical imaging technologies, including MRI, PET and SPECT.

To stimulate the interaction between the art historical world and branches of digital image processing, the *Digital Painting Analysis* (DPA) initiative organized two workshops in Amsterdam (IP4AI or *Image Processing for Artist Identification*) and a symposium (celebrating the inauguration of TiCC, *Tilburg centre for Creative Computing*) to facilitate a dialog between the two communities. The Van Gogh Museum (Amsterdam) and the Kröller Müller Museum (Otterlo) made it possible for participating teams to work with high resolution digital images of paintings (mostly van Goghs) in their collections.

2. Challenges - Convincing the art expert

To jumpstart the IP4AI workshops, art historians formulated *challenges* for the research teams, asking them to provide convincing arguments in favor of digital image processing. These included the following:

- *Authentication:* distinguish an original van Gogh painting from a copy or forgery. This was the main focus of the first workshop; preliminary results of the participating research teams can be found in [7].
- *Dating:* classify works by van Gogh that were either painted in his early Paris phase ($1886 - 1888$) or in his later Arles period. Art historians noticed changes in van Gogh's way of painting throughout his career. Small brushstrokes seem to be more prominent in his Paris period while broader ones prevail in Arles.
- *Identifying distinguishing features:* can an artist's hand be characterized and features be found that distinguish him from other painters?
- *Image enhancement:* fuse information obtained by different modalities (x-ray, infrared, visual, etc.) to (virtually) enhance damaged paintings, or underpaintings. A first challenge here is detailed and precise registration.
- *Inpainting:* digitally reconstruct missing pieces from a painting when only limited data is at hand.

The purpose of this paper is to provide an overview of the tools and general methodology used by the Princeton research team in order to tackle these challenges. Detailed results can be found in [6, 10].

2.1 Classification - Authentication, dating and identifying features

For the analysis of paintings it is crucial to extract distinguishing features/statistics that truly characterize the style of an artist. It is obvious that simple image statistics such as mean or variance of an image will not suffice by themselves. To take an extreme example: reordering by increasing grayscale the pixels in every row of a digital image of a natural scene, and then doing the same in every column, produces an image with same mean and variance as the original, but bereft of (almost) all other information. More complex models that provide additional information are needed. The approach taken for the first three challenges built such models. The analysis consists of *three main steps*: transform, modeling and classification.

Transform. A multiresolution transform is performed on patches of the image. We used the Dual-Tree Complex Wavelet Transform (DTCWT) [9]; it provides approximate shift invariance and directional selectivity (properties standard wavelet transforms lack). The DTCWT uses two parallel filter banks and produces six subbands of coefficients that let us analyze changes in the image in six directions ($\pm 15°$, $\pm 45°$and $\pm$ $75°$) at different scales.

Modeling. A large number of pixels, and thus also of transform coefficients, combined with noise on the pixel values (due to the acquisition process) impose robust dimensionality reduction and feature extraction techniques. We used Hidden Markov Trees (HMT) [3]. It is possible to describe the wavelet coefficients for a large class of images in terms of two key properties [11]:

- *2Population:* smooth image regions are represented by wavelet coefficients with a narrow probability distribution function (pdf); edges, ridges or other singularities by wavelet coefficients with a wide pdf.
- *Persistence:* the classification into narrow/wide pdf-coefficients tends to propagate across scales.

These two properties are used to design a statistical model to represent images. Due to the multiresolution nature of the wavelet transform, the wavelet coefficients can be arranged into a quadtree (one coefficient from a coarser scale corresponds to four wavelet coefficients at the next finer scale). At each scale, hidden variables control the wavelet coefficients. They can have two states: L (large, for edge-like structures) and S (small, for smooth regions). The wavelet coefficients are modeled as samples from a mixture of two Gaussian distributions, one with a large variance for the coefficients corresponding to an edge and one with a small variance for coefficients from a smooth region. HMT model the statistical dependencies between wavelet coefficients at different scales. The parameters of the HMT we used as features are:

- α_T: a 2×2 transition probability matrix, that depicts the probabilities that a child node is in a particular state, given the state of the parent node.
- μ_i: the means of the narrow and wide Gaussian distribution ($i = 1, 2$) for each subband.
- σ_i: variance of the narrow and wide Gaussian distribution ($i = 1, 2$) for each subband.

For example, if we apply a 4-level DTCWT transform on a patch of an image, then the features extracted from that patch would be the following: $6 \times 4 \times 2$ means, $6 \times 4 \times 2$ variances and $6 \times 4 \times (2 \times 2)$ probabilities, adding up to a total of 192 features. These HMT features are grouped into a model parameter vector and are determined using the *expectation maximization* algorithm.

Classification. The model parameters vectors extracted in the previous step are used as the input for classification algorithms. We used several types of machine learning algorithms: Support Vector Machines, Adaboost, Decision Stump and Random Forest. All experiments were performed with WEKA [1], a collection of machine learning algorithms for data mining tasks.

2.1.1 Authentication challenge results

The authentication challenge was the main research topic for the first IP4AI workshop [7]. To validate their earlier results the Princeton team asked Dutch art conservation student Charlotte Caspers to make original paintings on different materials, with different kinds of paint and brushes, and to create a faithful copy for each of these originals. The dataset provided ground truth: we knew which paintings were original and which ones were copies. We considered both HMT features and *thresholding features* [10]. The aim was to recognize the difference between a fluid and a more hesitant (copying) stroke through machine learning. For this kind of classification problem the *SVM with polynomial kernel* machine learning algorithm was the best classifier.
The images were subdivided into patches, some of which were used for training the machine learning algorithm. The best results were obtained by using only patches from the painting under investigation and its copy (see Figure 1). The results can be found in Table 1; they show that when both soft and hard brushes are used, the algorithm achieves a succes rate similar to that obtained by state-of-the-art authentication algorithms for handwriting.

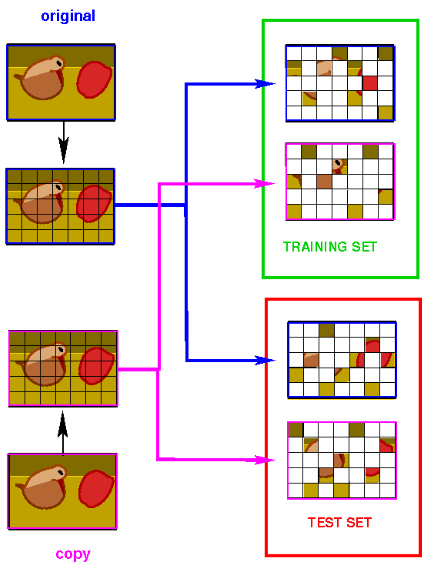

Figure 1: Four sets of patches without overlap.

2.1.2 Dating challenge results

For the dating challenge a set of 66 high resolution paintings (90 pixels per linear inch) were put at the disposal of all teams. All the classifiers listed above were trained with 256×256 patches using 10-fold cross validation. As can be seen in Table 2, the Random Forest (RF) classifier was the most accurate. Three paintings for which art historians are not sure when they were painted needed to be attributed to one of two periods. Figure 2 shows the resulting classification success rate for patches of paintings from the training set. The RF algorithm was then used on the patches of the three paintings to be attributed, and a majority vote of the patches was determined.

Pair	Ground	Paint	Brushes	Style	Total	Copy	Original
1	CP Canvas	Oils	Soft&Hard		78%	67%	89%
2	CP Canvas	Acrylics	Soft&Hard		72%	55%	89%
3	Smooth CP Board	Oils	Soft&Hard		78%	78%	78%
4	Bare linen canvas	Oils	Soft	TI	75%	50%	100%
5	Chalk and Glue	Oils	Soft	TI	50%	0%	100%
6	CP Canvas	Acrylics	Soft	TI	38%	75%	0%
7	Smooth CP Board	Oils	Soft	Sm,Bl	55%	22%	88%

Table 1: Accuracy for each test on the Caspers data set. Abbreviations: Sm=Smooth, Bl=Blended, TI=Thick Impasto.

SVM	AB	DS	RF
61.2%	63.2%	63.1%	70.5%

Table 2: Accuracy of different classifiers.
Abbreviations: SVM=Support Vector Machines, AB= AdaBoost, DS=Decision Stump, RF=Random Forest.

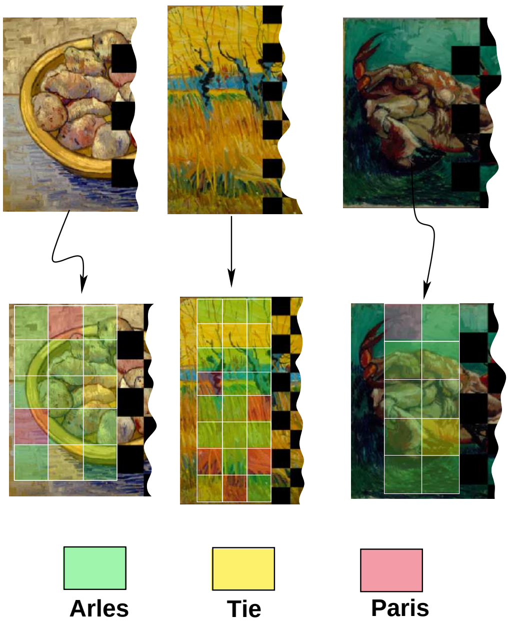

Figure 2: Classification results for three paintings.

2.1.3 Extracting Distinguishing Features results

The test set consisted of floral still lifes painted by van Gogh, Monticelli and other contemporary artists. The goal was to quantify to what extent van Gogh and Monticelli share features, in their brushwork and color schemes, absent in the style of the others. The purpose here was thus to distinguish styles instead of painters (as in authentication). The same methodology described above was used. Results show that wavelet coefficients in direction $-45°$, scale 6 characterize the style of van Gogh and Monticelli whereas wavelet coefficients in the $15°$, scale 4 subband are more prominent in the other paintings. Examples of these distinguishing features are highlighted in Figure 3. More detailed results are in [6].

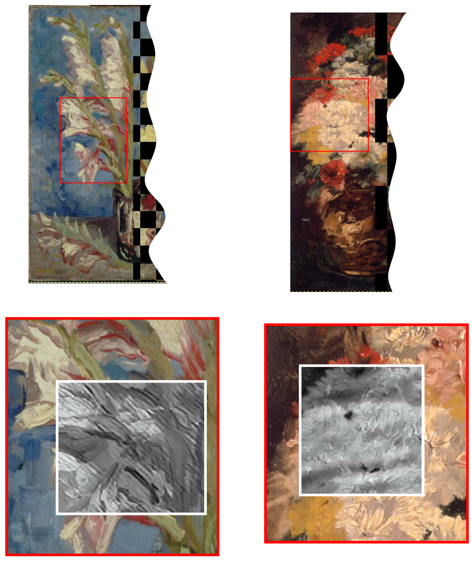

Figure 3: Distinguishing feature challenge.
Left: "Still Life: Vase with Gladioli" by V. van Gogh.
Right: "Vase with Flowers" by G. Jeannin.

2.2 Using Different Image Acquisitions

Art museums typically have x-ray and infrared photographs in their collections, which can reveal much about what is below the visible surface of a painting. These can also be digitized (or acquired digitally, in the future), and be studied with digital image processing tools. In order to combine the different modes of image acquisition, the first task is to register the images (we used x-ray, infrared and color images of the same painting) to enhance and detect hidden features. Figure 4 shows a woman's face emerging (horizontally) from underneath the grass in the painting "Patch of Grass". Because x-rays and photographs are acquired by different modalities, the matching is not as straightforward as it seems initially. Both images were divided into patches and reference points in both images were picked in order to define a smooth warping that gave acceptable results. Another example is the counting of threads/inch in the canvas, visible on x-rays, to determine a painting's authenticity and date [8].

2.3 Inpainting

An important aspect for art historians and conservators is the preservation of works of art. When paintings become damaged, all the available information (grayscale photographs, low resolution color photographs, ektachromes,

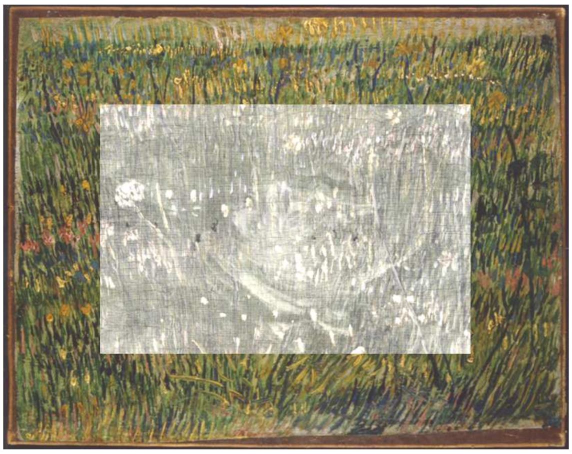

Figure 4: Registered x-ray on “Patch of Grass”.

. . .) is called upon to help art conservators in their reconstruction or restoration. In [5] techniques were proposed to *mathematically* reconstruct the original colors of frescoes (reduced to rubble in a wartime bombing) by making use of the information given by preserved fresco fragments and gray level pictures of the intact frescoes taken before the damage occurred.
We investigated whether such techniques would also work on van Gogh pictures. With the help of M. Fornasier, one of the authors of [5], we applied these algorithms to a high resolution color image of the “Lemons on a Plate” painting. A patch of 200×200 pixels was digitally removed; Figure 5 shows its mathematical reconstruction, using only a low resolution color image (with faithful colors) and a high resolution grayscale image of that painting. The results are quite satisfying and prove that these techniques could be used for restoration purposes.

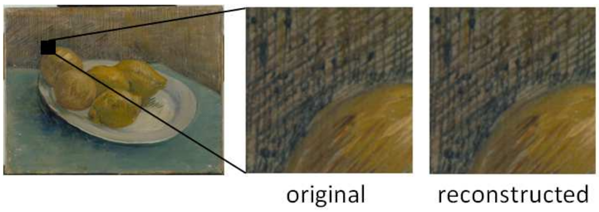

Figure 5: Inpainting.

3. Conclusions

The results obtained for the first and second IP4AI workshop in Amsterdam were promising. It is clear however, that these digital techniques on their own are not sufficient to provide conclusive answers to questions of interest to art historians. Nevertheless, they will likely be a worthy addition to the toolbox of art historians and conservators; they have the great advantage of not being invasive. There is also still room for improvement in the different steps of the analysis of paintings. It is worth pointing out, however, that in order to apply such techniques, the quality of the acquired dataset (i.e. high resolution images) is of utmost importance. Only images of equal quality can be compared with each other.

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