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Pandora: Description of a Painting Database for Art Movement Recognition with Baselines and Perspectives

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Abstract

To facilitate computer analysis of visual art, in the form of paintings, we introduce Pandora (Paintings Dataset for Recognizing the Art movement) database, a collection of digitized paintings labelled with respect to the artistic movement. Noting that the set of databases available as benchmarks for evaluation is highly reduced and most existing ones are limited in variability and number of images, we propose a novel large scale dataset of digital paintings. The database consists of more than 7700 images from 12 art movements. Each genre is illustrated by a number of images varying from 250 to nearly 1000. We investigate how local and global features and classification systems are able to recognize the art movement. Our experimental results suggest that accurate recognition is achievable by a combination of various categories.

1 Introduction

The remarkable expansion of the digital data during the last period favored a much easier access to works of art for the general public. Great efforts were put lately into creating automatic image processing solutions that facilitate a better understanding of art [8]. These solutions may aim at obtaining high-quality and high-fidelity digital versions of paintings [12] or may address various aspects such as: image diagnostics, virtual restoration, color rejuvenation etc. as discussed in the review of Stork et al. [13]. Another more appropriate to the ultimate goal of computers is the context recognition. One of the broadest possible implementation of context recognition is the automatic art movement identification.

According to Artyfactory [10], *art movements* are “collective titles that are given to artworks which share the same artistic ideals, style, technical approach or timeframe”. While some works are clearly set into a single art movement, others are in the transition period, as painters loved to experiment new ideas, leading to creation of a new movement. Also while the actual characteristics place a work in some art movement, its author, for personal reasons, refused to be categorized in such a way, giving birth to disputes.

In this paper, we look into the problem of computational categorization of digitized paintings into artistic genres (or art movements). In contrast to other directions of image classification, such as scene or object recognition, where large databases and evaluation protocols do exist, such an aspect is less emphasized for digitized paintings. Typically, the evaluation of a new method is carried on a small database with few paintings belonging to few genres. Given the latest advances of machine learning, two aspects should be noted: (1) deep networks with the many parameters easily overfit on small databases and (2) to have progress, we need larger databases.

In this paper we start by reviewing painting collections introduced in prior art and we follow by describing the proposed database. Next, to form a baseline, we continue by reporting the performance of various popular image descriptors and machine learning systems on the introduced database. The paper ends with discussions and conclusions.

2 Related work

In the last period multiple solutions issued automatic analysis of visual art and especially paintings using computer vision techniques. However, most of the research is based on medium-to-small databases. A summary of such methods is presented in table 1. One may easily note the size of the databases (and implicitly the number of art movements investigated) increased with time, while the reported performance decreased until it stabilized in the range of 50-70% for correct art movement recognition. Some of the most representative databases used for art movement identification are:

- Artistic genre dataset [11]. Images, gathered from Web Museum-Paris, were set in the following art movements: Classicism, Cubism, Impressionism, Surrealism, Expressionism.
- Artistic genre dataset [12]. Images from various Internet sources were categorized into 5 genres : Abstract, Impressionism, Cubism, Pop Art and Realism.
- Painting genre dataset [13]: Images collected from the Internet were grouped into: Abstract expressionist, Baroque, Cubist, Graffiti, Impressionist and Renaissance.
- Artistic style dataset [14]: Paintings from 9 painters were grouped into three art movements: Impressionism, Abstract expressionism and Surrealism.
- Artistic genre dataset [9] with images collected from Artchive fine-art dataset and grouped into: fine-art genres: Renaissance, Baroque, Impressionism, Cubism, Abstract, Expressionism and Pop art.
- Paintings-91 dataset [15] with images collected from the Internet. While the database is larger than the previous ones, only paintings corresponding to painters that have the majority of works into one art movement got a genre label. It resulted in a smaller

Table 1: Art movement recognition solutions with the size of used databases. The database size refers only to the database used for art movement recognition, as in some cases larger databases have been implied for other purposes. The value for recognition rate (RR) is the one reported by the respective work while the “test ratio” is the percentage used for testing from the overall database (CV-stands for cross validation). We kindly ask the reader to retrieve all the details from the respective work.

Method	Move-ments	Db. size	RR.	Test ratio
Gunsel et al. [11]	3	107	91.66%	53.5%
Zujovic et al. [26]	5	353	68.3%	10% CV
Siddiquie et al. [21]	6	498	82.4%	20% CV
Shamir et al. [20]	3	517	91%	29.8%
Arora&ElGammal[9]	7	490	65.4%	20% CV
Khan et al. [13]	13	2338	62.2%	46.53% CV
Condorovici et al.[7]	8	4119	72.24%	10% CV
Agarwal et al. [8]	10	3000	62.37%	10% CV
<i>Proposed</i>	<i>12</i>	<i>7724</i>	<i>54.7%</i>	<i>25% CV</i>

database illustrating Abstract expressionism, Baroque, Constructivism, Cubism, Impressionism, Neo-classical, Pop art, Post-impressionism, Realism, Renaissance, Romanticism, Surrealism and Symbolism. Probably this is the most structured database previously proposed.

- Artistic genre dataset [8] is the basis of the proposed database. We increased that dataset by adding more images to illustrate the existing art movements and added 4 new ones.
- Artistic genre dataset [9] contains images collected from WikiArt and grouped into: Abstract-expressionism, Baroque, Cubism, Impressionism, Expressionism, Pop Art, Rococo, Realism, Renaissance and Surrealism.

Concluding, many of the databases previously used, are small and contain non-standard evaluation protocols allowing overfitting. Thus, a larger scale database with fixed evaluation protocol should be beneficial for further development on the topic.

3 Pandora database

Our main contribution is the creation of a new and extensive dataset of art images¹. While we follow the Paintings-91 database [13], our dataset is significantly larger, it was build around art movements and not painters and we tried to span wider time periods from antiquity to current periods. The later property should help the automatic study of style evolution, of thematic evolution and cross-time relationship identifications.

The Pandora (Paintings Dataset for Recognizing the Art movement) dataset consists of 7724 images from 12 movements: old Greek pottery, iconoclasm, high renaissance, baroque,

¹The up-to-date database with pre-computed features data reported here is available at http://imag.pub.ro/pandora/pandora_download.html

Table 2: The structure of the Pandora database.

Art movement	No. of paintings	Historical period
Old Greek pottery	350	Antiquity
Iconoclasm	665	Middle age
High renaissance	812	1490 - 1527
Baroque	960	1590 - 1725
Rococo	844	1650 - 1850
Romanticism	874	1770 - 1850
Impressionism	984	1860 - 1925
Realism	307	1848 - present
Cubism	920	1900 - present
Abstract-expressionism	340	1920 - present
Fauvism	426	1900 - 1950
Surrealism	242	1900 - present

rococo, romanticism, impressionism, realism, cubism, fauvism, abstract-expressionism and surrealism. The precise database structure is shown in table 2 and some examples representative for the art movements are in figure 1. We kindly ask the reader to note some of difficulties in distinguishing between genres: the main difference between Abstract and Fauvism is the less *natural order* in the structure of the Abstract works, while the Fauvism tends “to use color to express joy”. Baroque has a darker tone with respect to Romanticism while the later depicts “exotism or extraordinary things”. The difference between Realism and Surrealism is that the later illustrate “irrational juxtaposition of images” [10] (e.g. such as wings attached to the girl). Yet thinking in computer terms, to detect the *irrational* of *joy* in an image is extremely hard. Thus we consider that to achieve such goals, one needs, first, an appropriate database of considerable size and variability.

4 Art movement recognition performance

4.1 Training and testing

To separate the database training and testing parts, a 4-fold cross validation scheme was implemented. The division into 4 folds exists at the level of each art movement, thus each image being uniquely allocated into a fold. The same division was used for all further tests and it is part of the database.

4.2 Features and classifiers

As “there is no fixed rule that determines what constitutes an art movement” and “the artists associated with one movement may adhere to strict guiding principles, whereas those who belong to another may have little in common” [10], there cannot be a single set of descriptors that are able to separate any two art movements.

Following the observations from prior works [8], [13], multiple categories of feature descriptors should be used. For instance, to differentiate between impressionism and previous styles, one of the main difference is the brush stroke, thus *texture*. Old Pottery and Orthodox



Old Greek Pottery



Orthodox Iconoclasm



High Renaissance



Baroque



Rococo



Romanticism



Impressionism



Realism



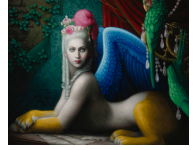
Cubism



Fauvism



Abstract



Surrealism

Figure 1: The 12 art movements illustrated in the proposed database.

Iconoclasm are older and use a limited *color palette*. Also, one needs to understand the content of the painting to distinguish between realism and surrealism (for instance); thus, global *composition* descriptor should be used.

To provide a baseline for further evaluation, we have tested various combinations of popular feature extractors and classification algorithms.

The texture feature extractors used are :

- **Histogram of oriented gradients (HOG)** [9] which computes the oriented gradient in each pixel and accumulates the weight of each orientation into a histogram. It has been previously used in painting analysis [13], [8].
- **Pyramidal HOG (pHOG)** the above mentioned HOG is implemented on 4 levels of a Gaussian pyramid.
- **Color HOG** - the above mentioned HOG descriptor applied on each color plane of the RGB color space.
- **Local Binary Pattern (LPB)** [18] is a histogram of quantized binary patterns pooled in a local image neighborhood of 3×3 and restrained to a total of 58 quantized non-uniform patterns. The LPB was used in painting description [13], [8].
- **Pyramidal LBP (pLBP)** - the above mentioned descriptor computed over 4 levels of a Gaussian pyramid.
- **Local Invariant Order Pattern** [23] - assume the order after sorting in the increasing intensity local samples.

For HOG, LBP and LIOP we have relied on the implementation from the VLFeat library [23].

- **Edge Histogram Descriptor (EHD)** is part of the MPEG-7 standard. It accounts for the distribution of four basic gradient orientations within regular image parts. The implementation is based on BilVideo-7 library [9].
- **The spatial envelope, GIST** [19] describes the spatial character or shape of the painting and was previously used for painting categorization [9].

The color descriptors tested are:

- **Discriminative Color Names (DCN)** [24] - represents the dominant color retrieved through an information oriented approach. Here, we have used author provided code. The baseline form (Color Name) was successfully used to determine the style and the painter [13].
- **Color Structure Descriptor (CSD)** [16], which is based on color structure histogram, a generalization of the color histogram. The CSD accounts for some spatial coherence in the gross distribution of quantized colors within the image and it has been shown that is able to differentiate between various art movements [16]. We computed a 64 long CSD vector using the BilVideo-7 library [9].

Machine learning classification systems tested are:

- **Support Vector Machine.** We have relied for its implementation on the Lib-SVM [8]. We used on the radial basis function c-SVM and followed, for each case, the optimization (i.e. exhaustive search in (cost, gamma) space) recommended by the LibSVM creators.
- **Random forest** [5]. We have used 100 trees and unlimited depth. At each node we randomly look for a split in $N_1 = \sqrt{N}$ dimensions where N is the input feature dimension.

Let us note that before the development of the deep networks the random forests and support vector machines have been found to be the most robust families of classifiers [16]. Also, for small and diverse databases SVM and RF out-compete deep networks.

- **k-Nearest neighbor (kNN).** We have implemented 1-NN, 3-NN and 7-NN based on Euclidean distance. While we report the results in terms of correct recognition rate, the nearest neighbor results will give an indication about the retrieval performance as it may be translated in terms of precision–recall.

Furthermore we have tested several systems that were previously used for art movement recognition. Inspired from previous work [9], we have run the Bag of Words (BoW) over SIFT keypoint detector with a vocabulary of 500. We have also tested a combination of color description, texture analysis based on Gabor filters and scene composition based on Gestalt frameworks [9].

Additionally, while the database is small for such a purpose and thus not really suited for deep learning, to have an indication of baseline performance, we have trained and evaluated a version of Deep Convolutional Neural Network (CNN). Our implementation is based on the MatConvNet [24] library and LeNet architecture [13].

Table 3: Recognition rates when various combinations of features and classifiers are used on the Pandora database. We marked with bold the best performance.

Feat. / Class.	Random Forest	SVM	1-NN	3-NN	7-NN
HOG	0.266	0.248	0.200	0.214	0.233
pHOG	0.342	0.364	0.262	0.266	0.267
colorHOG	0.268	0.277	0.213	0.221	0.236
LBP	0.386	0.395	0.303	0.298	0.320
pLBP	0.459	0.525	0.368	0.362	0.377
LIOP	0.344	0.362	0.246	0.252	0.260
EHD	0.319	0.287	0.270	0.267	0.286
GIST	0.379	0.337	0.297	0.280	0.282
DCN	0.298	0.264	0.192	0.201	0.215
CSD	0.435	0.489	0.337	0.3357	0.363
pLBP + DCN	0.488	0.521	0.278	0.282	0.297
pLBP + CSD	0.540	0.547	0.377	0.282	0.297

4.3 Results

We report first the results achieved when various combinations of features and classifiers are used (to be followed in table 3). We also report, in tables 4, 5, the confusion matrices for the best combination in each category: pLPB+SVM, GIST+RF, CSD+SVM and respectively pLBP+CSD+SVM.

Secondly we report comparatively the best performance of aggregated systems in table 6. We note that for this particular database, the best performance is achieved by a standard combination of features (pyramidal LBP + Color Structure Descriptor) with a Support Vector Machine.

While one may find disappointing the performance of various established systems, this is perfectly explainable. For the Bag of Words there is too much variability between key-points to find a common ground; instead of the baseline version tested here, one should opt for much larger vocabularies with accurate compression to keep memory requirements low. Regarding the performance of the DeepCNN, the reported value should be perceived as a lower boundary, as the database is too small for directly training nets with tens of thousands of variables, since no data augmentation was implemented and the images being resized at 32×32 lost some of the defining characteristics.

5 Discussion and conclusions

The best achieved performance was by a combination of pyramidal LBP and Color Structure Descriptor. One may expect the addition of GIST to further increase the performance, but this does not happen, probably due to the curse of dimensionality (the features dimension reaching 800); in such a case a feature selection method should be used, but we consider it outside the scope of the current paper.

The next important observation is that different descriptors do a good job separating some currents and not so good on identifying others. For instance, the CSD separates excellently the Orthodox Iconoclasm which has a unique color palette (due to degradation in time and reduced colors available at creation), but it is not able to separate Fauvism from

Table 4: Confusion Matrices for the best performers on each category. The art movement used acronyms are: old Greek pottery–*Gre*, iconoclasm–*Ico*, high renaissance–*Ren*, baroque–*Bar*, rococo–*Roc*, romanticism–*Rom*, impressionism–*Impr*, realism–*Real*, cubism–*cub*, fauvism–*Fauv*, abstract-expressionism–*Abs* and surrealism–*Sur*.

	Gre	Ren	Icon	Roc	Rom	Bar	Impr	Cub	Abs	Fauv	Real	Sur
Gre	200	20	28	2	3	5	35	51	3	1	0	2
Ren	5	360	24	54	47	153	95	70	1	2	0	1
Icon	7	21	559	7	1	15	23	30	2	0	0	0
Roc	4	90	21	272	129	214	73	38	1	0	0	2
Rom	9	106	16	165	219	183	107	55	2	5	3	4
Bar	4	173	21	186	121	292	87	65	2	3	0	6
Impr	10	97	47	66	106	95	429	109	8	6	2	9
Cub	14	93	65	42	55	76	167	361	12	12	2	21
Abs	11	43	43	5	18	11	66	67	46	2	0	28
Fauv	7	53	20	15	35	43	118	89	6	18	1	21
Real	2	10	16	22	25	17	39	16	1	3	135	21
Surr	2	13	16	7	16	7	43	37	14	7	2	78

GIST + RF

	Gre	Ren	Icon	Roc	Rom	Bar	Impr	Cub	Abs	Fauv	Real	Sur
Gre	339	4	1	1	0	3	0	1	0	0	1	0
Ren	0	404	16	49	66	219	24	31	0	2	1	0
Icon	0	8	576	3	0	6	30	31	0	11	0	0
Roc	0	118	2	230	153	262	51	18	0	1	8	1
Rom	0	91	4	113	322	228	74	31	0	1	10	0
Bar	0	178	8	152	150	405	42	18	0	1	5	1
Impr	0	24	58	33	35	66	584	133	13	29	9	0
Cub	2	43	42	38	21	32	168	508	16	30	5	15
Abs	0	3	11	1	7	2	55	83	125	45	0	8
Fauv	0	9	15	8	8	11	104	85	34	145	3	4
Real	1	18	14	30	29	42	69	38	4	7	50	5
Surr	0	3	5	8	16	5	44	65	15	19	5	57

CSD + SVM

Impressionism as both use the same colors but distributed differently. The Surrealism is hard to separate by everything else except GIST as it is the only tested feature able to describe the scene composition. Yet the GIST is not able to distinguish the Fauvism from Impressionism as local texture makes the difference. In contrast, the pLBP confusion between Fauvism and Impressionism is much reduced.

Overall, the confusion between Abstract and Cubism is large. As Cubism is defined by the extraordinary apparition of straight lines, to address it, one should try to introduce features appropriate to describe rectilinear objects.

Concluding we propose a new painting database annotated with art movements labels and divided in 4 folds to prepare it for rigorous evaluation. The database is significantly larger than the ones previously used. We have tested a multitude of popular features and classifiers and we have identified the weak and strong points of each of them. We also suggest some directions for future research that we anticipate to be beneficial for progress in the field.

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Table 5: Confusion Matrices for the best performers on each category. The art movement used acronyms are: old Greek pottery–*Gre*, iconoclasm–*Ico*, high renaissance–*Ren*, baroque–*Bar*, rococo–*Roc*, romanticism–*Rom*, impressionism–*Impr*, realism–*Real*, cubism–*cub*, fauvism–*Fauv*, abstract-expressionism–*Abs* and surrealism–*Sur*.

	Gre	Ren	Icon	Roc	Rom	Bar	Impr	Cub	Abs	Fauv	Real	Sur
Gre	271	4	2	1	5	1	11	27	5	18	2	3
Ren	4	444	1	40	60	166	36	58	1	0	1	1
Icon	42	1	598	1	0	3	3	10	3	4	0	0
Roco	0	48	3	324	136	232	63	36	0	0	1	1
Rom	3	94	4	139	339	182	80	27	1	3	0	2
Bar	1	126	3	165	136	441	47	37	0	2	0	2
Impr	9	29	10	49	92	43	618	112	6	14	1	1
Cub	63	29	23	17	29	28	128	570	8	17	0	8
Abs	20	11	21	7	22	17	56	91	59	23	2	11
Fauv	33	5	5	1	18	9	111	58	11	163	2	10
Real	15	11	4	7	17	17	33	23	13	18	141	8
Surr	18	13	10	4	23	19	17	40	13	13	4	68

pLBP + SVM

	Gre	Ren	Icon	Roc	Rom	Bar	Impr	Cub	Abs	Fauv	Real	Sur
Gre	307	0	0	0	0	0	2	40	0	0	1	0
Ren	0	473	2	49	63	159	24	41	0	1	0	0
Icon	0	1	616	1	1	2	10	31	1	2	0	0
Roc	0	83	1	301	163	214	59	23	0	0	0	0
Rom	0	77	0	104	372	184	74	63	0	0	0	0
Bar	0	132	0	169	148	437	50	24	0	0	0	0
Impr	0	17	7	31	43	36	696	143	0	10	1	0
Cub	2	21	13	11	21	17	119	706	1	9	0	0
Abs	0	0	4	1	6	1	53	200	62	13	0	0
Fauv	0	2	2	2	6	1	126	190	3	93	1	0
Real	0	3	0	9	13	11	56	79	0	4	131	1
Surr	0	1	3	4	7	2	33	159	4	6	0	23

pLBP + CSD + SVM

Table 6: Recognition rates when various systems are used.

System	Performance
pLBP + CSD +SVM	0.547
BoW	0.352
Condorovici et al. [14]	0.379
Deep CNN	0.486