Genre and Style based Painting Classification

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Abstract

As the size of digitized painting collections increase, it becomes more difficult to organize and retrieve paintings from these collections. To manage search and other similar operations efficiently, it becomes necessary to organize the painting databases into classes and sub-classes. Manual tagging of these ever-increasing databases would become very costly and time consuming. The above challenging problem has motivated researchers to work in the area of painting analysis, genre and style classification, artist classification and automatic annotation of paintings with these tags. These problems are quite difficult as first the expected human performance for this task for non-expert but reasonably knowledgeable individuals is believed to be well below 100% percent. And second, there is a very big databases of paintings with relatively few painters painting in a single genre and style and many who paint in multiple genres and styles. In this paper, we explore the problem of feature extraction on the paintings and focus on classification of paintings into their genres and styles. We worked with 6 genres and 10 styles.We get an an accuracy of 84.56% for genre classification . We achieved an accuracy of 62.37% for classifying the paintings into 10 styles. We include a comparison to existing feature extraction and classification methods as well as an analysis of our own approach across different feature vectors.

1. Introduction

In recent years art [1] has migrated to the web. Virtual galleries like Caterpillar Labs [2], WikiPaintings [8] , Web Gallery of Art [6] , Olga's gallery [4] ,Pintura [5], Web Museum Paris [7] have made it possible for artists, art lovers, art buyers and others interested in art to come together in virtual space to view, buy, sell and more generally do everything that we do in traditional settings. While a direct face-to-face experience with the work itself is very hard or possibly impossible to replicate, many other avenues of engagement become possible when art is 'virtualized'. In particular, it is possible to annotate art with a vast amount of meta-data which can help viewers, buyers, sellers etc. to compare, contrast, understand and do a variety of manipulations on a digital representation that is impossible in the real world.

Generating the meta-data by hand is time consuming and expensive. In this paper, we uses machine learning techniques to generate meta information for paintings which can be used for carrying out different types of searches in large virtual galleries. In particular, in this paper we are concerned with generating genre and style tags for paintings. By genre of a painting we mean its type, for example landscape, portrait, sculpture, still life etc. By style we mean common ways in which groups of painters paint, for example cubism, impressionism, pop, surrealism, abstract expressionism etc.

Many collections of paintings/art works are now available on the web. These collections contain the work of past painters whose works have been classified by human painting experts as well as works (usually current) that have not been classified. The task of classifying paintings into their genres or styles is usually left to the art expert as it is not simple to describe the process by which such classification happens. Recently, several machine learning scientists have made attempts to automate classification of paintings. This task has been informed by the features human experts use to classify paintings. Art genres or styles are often understood in terms of features like brush strokes, line styles, color mixing, shapes, borders, objects etc.

Some artists have specific signature elements which make their art recognizable but genre reflects the common, similar elements which are shared by various artists. So while a genre may have various artists specific to it many artists belong to multiple genres. The hypothesis is that for the most part objective aspects of a painting like colour mixing, shapes, strokes, texture etc. will sufficiently capture

[1] In this paper by art we generally mean paintings.The same ideas can be extended to other types of art like sculpture, photography, prints and other media where a digital image can capture to a large extent the essence of the work.

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what is unique about a genre or style.

To be able to automatically tag paintings we must first build models for each tag category. These models are then used to annotate a work whose tags are not known. As noted above we do this for the tag categories of genre and style. These problems are quite difficult as even human performance for this task is not perfect- witness the disagreements of experts.

2. Background

With the advancement in the machine learning algorithms and image processing techniques, there have been increase in the attempts to tackle the painting related problems. However there have been few attempts made to tackle the problem of classifying the paintings into their genres and styles. Similar problem like painter identification has been researched more than the former one. Research from these similar works have given some insight for tackling the problem.The first question which comes to mind is that whether the image processing techniques can be used for the problems related to the paintings . Feature descriptors should extract the higher level semantics of the paintings in order to have any correlation with the visual features extracted by the brain.

Kammerer *et al*. [21] used an imaging technique called infrared reflectography to reveal underdrawing strokes which are visually hidden. They analyzed the strokes to determine which drawing tool was used to draft that painting. This information helped in the systematization of the styles of painting.They used two classification methods , one on the texture based and the other on the contour based on the segmented strokes to classify the strokes on the basis of the drawing tools which were used to create those strokes.

Abas *et al*. [9] implemented a content based analysis on the cracks of paintings. He used morphological top-hat operator and grid-based automatic threshold to detect cracks. With a chain based code representation, they generated the statistical structure of the global as well as of local features of the cracks. Then they used the fuzzy k-means clustering, an unsupervised approach to cluster the paintings on the basis of the cracks.

Jia Li *et al*. [23] analyzed the painting styles of 5 chinese artists. They used wavelet transformation for feature extraction and used two-dimensional (2-D) multi-resolution hidden Markov model (MHMM) which captures a large region of a image making it likely to capture more properties of the painting strokes to classify the paintings.

Lu *et al*. [26] proposed the content based identification and classification scheme for the Traditional Chinese Paintings (TCP). They used simple colour descriptors and gray-level co-occurrence matrices (GLCM) for textual features. They claimed to distinguish TCP from non TCP and further classify TCP paintings based on painters with an accuracy of 85%. Such simple color descriptors like variance and mean may be insufficient for our task as our database is much diverse than theirs.

Fahad Shahbaz Khan *et al*. [17] used a fusion of global and local features. He used color name descriptor to form color vocabulary and and SIFT to create shape vocabulary using Bag of Words (BoW) Model. His work showed that shape outperform color and both perform better on fusion than their alone performance.

Daec *et al*. [15] assessed the authenticity of the art works by using several features like edge features, gray level co-occurrence matrices (GLCM) , gabor texture features, and color features.They used the paintings of 2 artists - Johan Dijkstra and Jan Wiegers with the database containing 147 images of the former and 160 of the latter for their experiment. They concluded that the texture information which is related to the brush strokes is the most discriminating feature which can be used to separate painters.

Lombardi [24] used several low-level features like light, line, texture, and color to classify paintings into style. He showed that preserving additional spatial and frequency colour information may not improve the classification accuracy. He proposed a palette description algorithm which performed as well as the colour descriptors one but with a less overhead. He used several supervised and unsupervised techniques like k-nearest neighbour (kNN), Hierarchical Clustering, Self-Organizing Maps (SOM), and Multidimensional Scaling (MDS) to analyze, classify, and visualize style relationships.

Shen [28] attempted to classify the western paintings. He used both local texture features as well as global colour and texture features. He used CIE $L \star u \star v$ as a colour feature and gabor features as global textual features. He used gabor wavelets as local textual features. Histogram of edges was used for the shape features and coefficients of DCT (Discrete Cosine Transform) were used for color layout. He used rbf based neural network to classify 1080 paintings into 25 painters with a 69.7% identification precision.

Icoglou *et al*. [20] developed a system for indexing and classifying paintings based on their art movement. They used six dimensional feature set for the representation of painting's content. This six dimensional feature set consists of features like percentage of dark pixels, luminance histogram, the gradient map of the painting etc. They experimented with Bayesian, k-NN and non-linear SVM classifiers for the classification part.

Culjak *et al*. [13] offers an approach to the automatic classification of paintings into their genres. He used 68 features in total which consists of features based on color and texture features like mean values of histogram intervals for RGB and HSV color and luminance,number of local maxima for the HSV color and luminance histograms,positions of the peak for HSV color and luminance histogram, ratio of dark pixels,amount of edges extracted using Canny edge detector, with and without previous blurring/sharpening, estimation of image sharpness, vertical and horizontal symmetry and ratio of sharpened edges and real edges.They classified the paintings into 6 genres with an accuracy of 60.2%.

Our objective is very much the same what Zujovic *et al*. [31] tried to achieve. They used gray level features like edges as well as colour features like HSV along with the steerable pyramid implementation to classify the paintings into genres. They tested their experiment on database containing five styles which are Abstract Expressionism, Cubism, Impressionism, Popart and Realism with 59, 60, 96, 58 and 80 paintings respectively for each style. Various classifiers like Bayes, k-NN (k-nearest neighbour), Support Vector Machine (SVM), Artificial Neural Network (ANN), Adaboost on J48 Decision Tree were used and he achieved an accuracy of 68.3% with Adaboost J48 decision tree classifier for classifying the paintings into their respective genres.

3. FEATURE EXTRACTION

The performance of the system would hugely depend on the selection of the features. So, it becomes very important to choose suitable features which can capture the desired link between the tag and the features. For addressing the salient aspects like objects, gist of painting, edges, texture and color of paintings, we decided to use five features namely SIFT, GIST, HoG combined with LBP, GLCM and color.

3.1. SIFT

Motivated by the better performance of SIFT in Image Categorization and the usage of SIFT feature successfully by Fahad Shahbaz Khan *et al*. [17] to predict the painter and Bressan *et al*. [10] in calculating the similarity between painters and paintings we decided to use SIFT as one of our features for our task. Fei fei *et al*. [18] showed that dense local features perform better on scene classification. So we extracted dense sift features [25] on each painting. Then we build a visual vocabulary of 400 visual words by using the K-means implementation of VLFEAT [29]. Then we constructed a spatial pyramid [22] as proposed by Lazebnik *et al*. We partitioned the image till level 2 which gives us 21 sub-regions for each painting (1 sub-region for level 0, 4 sub-region for level 1 and 16 sub-region for level 2). Now we represented each sub-region by a histogram of these visual words on the dictionary. Then we represented the image by concatenating the vector formed for all 21 sub-regions. Thus each painting is represented by a vector of size 8400 dimensions.

3.2. GIST

Douze *et al*. [16] have shown that GIST performed efficiently on images in their web-scale search system which shows that it can be a useful descriptor for painting classification. So to categorize the spatial character or shape of the painting we decided to use GIST as one of the features for our system.We use the GIST [27] implementation available online on the project site [1] to extract the GIST features. First we re-scaled the paintings to have the height of maximum 360 pixels keeping the aspect ratio same . Then the painting is decomposed by 32 filters (tuned to 8 orientations and 4 scales). Output magnitudes of all filters are downscale to same size 4×4 matrix. Then the painting is represented by the weighted combination of all the downscaled output magnitudes of all filters resulting into a 1×512 dimensional vector for each painting.

3.3. HoG and LBP

Histogram of Oriented Gradients (HoG) is one of the most widely used descriptors for object recognition in Computer Vision.Wang *et al*. [30] showed that Local Binary Pattern (LBP) combined with HoG improves the object detection rate. It has been determined that HoG performs poorly when the images are cluttered with noisy edges. LBP is complementary to HoG in this aspect as it filters out the noisy edges using the uniform pattern. Santana *et al*. [11] have also shown that HoG and LBP combined perform much better than the individual features. So inspired by the above works, we decided to use LBP and HoG combined for our task.

We used the VLFEAT [29] library to extract HoG features [14] . First we re-scaled the paintings to have the width of maximum 360 pixels keeping the aspect ratio same.Then we extracted the UoCTTI variant HoG on each painting using the VLFEAT [29] library. This variant computes both directed and undirected gradients as well as a four dimensional texture-energy feature on a cell size of 16*16 and as a result we get a 31 dimensional HoG vector for each cell. We extracted LBP feature using VLFEAT library. We use 3*3 neighbourhood for calculating LBP. Thus the LBP feature here is a 8 bit long string vector.These 256 possibilities are further quantized into a smaller number of patterns using uniform quantization which yields a total of 58 quantized patterns. Finally we concatenate both the HoG and LBP vector descriptors which yields a combined vector of 89 dimensions. Now we apply a bag of words approach on this 89 dimensional combined HoG-LBP vector. We form a visual dictionary of 4000 words for this vector by using the K-means implementation of VLFEAT and then we combine the histogram on this dictionary for each vector which gives us a vector of 4000 dimensions for each painting.

We experimented with different cell sizes: 2, 4, 8, 16 and 32 and with variable dictionary size: 500, 1000, 2000, 4000 and 8000 on which we found that in our case the HOG-LBP descriptor was giving better result for cell size 16 and on dictionary size of 4000. So we have used feature vector with size of 4000 words.

3.4. GLCM

Lines, shapes, brushwork can be seen as the texture of a painting. In layman's language, texture can be understood as the measure of relative smoothness and roughness of a painting. As brushwork can be captured by texture features, texture becomes an important feature to distinguish painting styles. Lu *et al*. [26] have successfully used GLCM (gray level co-occurrence matrices) for chinese painting classification and Daec *et al*. [15] used GLCM as features to assess the authenticity of the art works. Daec further concluded that the texture information which is related to brush strokes is the most discriminating feature and can be used to separate painters. Inspired by the above works we decided to use GLCM [19] to extract the texture of paintings.
GLCM is based on the estimation of the second-order joint conditional probability density functions between two pixels with distance d specified distance d. In this paper we considered 4 directions { $0^0, 90^0, 45^0$ and 135^0.} with distance d = 1. In our approach, we chose 8 as a tone number which gives a matrix of 8×8 for 1 direction which resulted in a 64 dimensional vector for each direction. Since we have 4 directions, the total vector length will be 256 for each image.

In this paper , we chose 8 as a tone number because we found that increasing the gray levels was decreasing the accuracy but reducing the number of gray levels further may not capture the texture sufficiently

3.5. COLOR

We decided to use the CIELAB color model as it is device independent unlike RGB and CMYK. First we convert the RGB values to CIELAB values. Then we calculate color histogram on these values. We partitioned each image into 16 patches. For each dimension of CIELAB space i.e. L*, a*,b* we partitioned that dimension into 4 bins which in result yield us a vector of 64 bins for each patch. Now since we have 16 patches in total, we get a vector of 1×1024 dimension for each image.

We experimented with different bin sizes for each component in CIELAB color space and found that having extra number of bins does not improve the accuracy immensely but unnecessary increases the memory space and computation time. So we decided to partition each component of CIELAB color space into 4 bins.

4. Experimentation Setup

We downloaded the paintings from wikipaintings [8] . For our experimentation we chose 6 genres -Abstract Paintings(AP), Interiors(INT), Landscapes(LS), Portraits(POR), Sculpture(SP) and Wildlife(WL) and 10 styles - Abstract-Expressionism(AE), Baroque(BQ), Cubism(Cub), Impressionism(IMP), Expressionism(EXP), Pop-art(PA), Rococo(ROC), Realism(REA), Renaissance(REN) and Surrealism(SUR). . We created separate databases for genre and style. We downloaded 300 paintings for each genre and similarly we downloaded 300 paintings for each style. Thus in total we have 1800 images in genre database and 3000 images in style database. The size and the quality of the paintings we downloaded are not uniform. This can lead to bad classification results but this can be a blessing in disguise as it will make our system more robust to such changes making it more suitable for handling larger databases which may not be have data having fixed size and resolution.

We experimented with various classifiers like random forest , MLP (multilayer perceptron) , libsvm[12] with various kernels (like linear, rbf kernel, χ^2 , histogram intersection kernel) and found out that libsvm with χ^2 kernel gave us the best accuracy. So, we use libsvm [12] with χ^2 kernel [3] classifier for classifying the paintings into genres and styles. All the reported accuracies are 10-fold cross validation accuracies.

We use individual features as well as all the features combine for the classification task. For using all the features together we used a ensembled model. We divided our dataset into three parts , training set (80%) , testing set (10%) and validation set(10%). That is for each style or genre , we have 240 paintings in training set, 30 images in validation set and 30 images in testing set.

4.1. Ensembling

We have calculated the accuracies of each individual feature using the libsvm with χ^2 kernel. We tried to combine these features to form an ensembled model using the weighted combination of each feature . Following are the steps to find the weights for each features.

- Divide the dataset into three partitions - training, validation and testing set.
- Train libsvm with χ^2 kernel on training set
- Learn weights of different classifiers on validation set by minimizing the error on it.
- Use these learnt weights for each feature to classify the test set.

For ensembled model we have calculated 10-fold cross validation accuracy. We followed the above algorithm and learnt different weights for each feature in every fold of cross validation. The final accuracy is average of accuracy for each fold.

4.2. Experiment 1 on genre dataset

SIFT	AP	INT	LS	POR	SP	WL
AP	**0.84**	0.05	0.01	0.02	0.05	0.04
INT	0.04	**0.85**	0.04	0.01	0.02	0.04
LS	0.01	0.01	**0.87**	0.02	0.01	0.08
POR	0.01	0.03	0.02	**0.87**	0.04	0.03
SP	0.08	0.05	0.01	0.03	**0.81**	0.02
WL	0.05	0.05	0.10	0.02	0.04	**0.74**

Table 1: Confusion Matrix for vector SIFT on GENRE

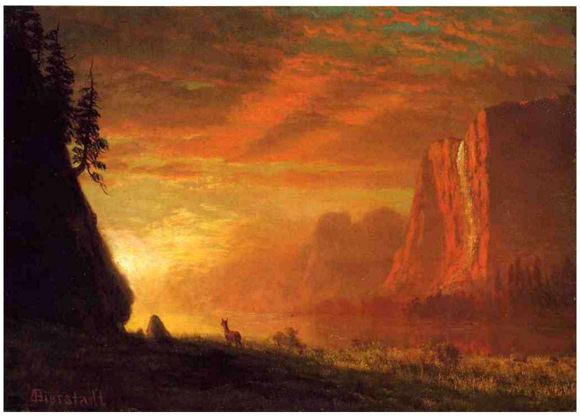

Figure 1: Wildlife painting misclassified as landscape

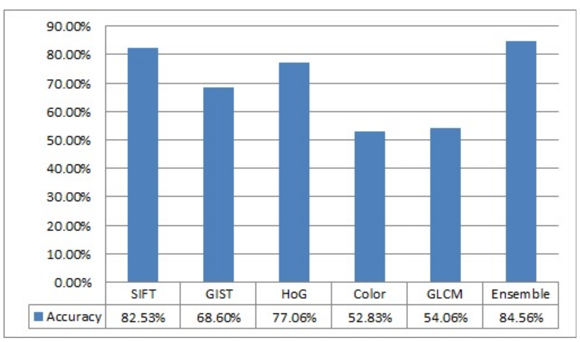

Figure 2: Overall accuracy on Genre Dataset

4.2.1 Analysis of results

SIFT is classifying landscape and portrait paintings with the most accuracy. High performance of SIFT in portrait can be attributed to the fact that all the portrait paintings have the similar structures , for instance all have eyes, nose , etc . As SIFT easily detects objects, so it performed well in the portrait paintings. Landscapes painting also nearly have the similar structures. This may be the reason why SIFT performed well in classifying the paintings of both genres. Most of the wildlife paintings have the landscape background . This may be the reason why most of the misclassified landscape paintings by every feature are classified as the landscapes one. SIFT is performing best among features used individually. We achieved an accuracy of 84.56% in classifying the paintings into 6 genres using all the features together. Figure 2 shows that ensembling all the features yield better results than obtained by using individual features.

4.3. Experiment 2 on Style dataset

SIFT	AE	BQ	CUB	IMP	EXP	PA	REA	REN	ROC	SUR
AE	**0.55**	0.02	0.06	0.08	0.02	0.17	0.00	0.02	0.00	0.08
BQ	0.01	**0.63**	0.03	0.03	0.03	0.00	0.05	0.11	0.08	0.03
CUB	0.07	0.02	**0.57**	0.12	0.06	0.09	0.01	0.02	0.00	0.05
IMP	0.05	0.03	0.15	**0.52**	0.08	0.05	0.03	0.04	0.01	0.06
EXP	0.01	0.02	0.05	0.07	**0.58**	0.01	0.15	0.03	0.02	0.06
PA	0.11	0.01	0.05	0.02	0.02	**0.70**	0.00	0.00	0.00	0.08
REA	0.01	0.09	0.03	0.04	0.08	0.01	**0.63**	0.06	0.05	0.01
REN	0.03	0.11	0.03	0.06	0.03	0.01	0.08	**0.61**	0.02	0.03
ROC	0.00	0.11	0.01	0.04	0.03	0.00	0.03	0.04	**0.72**	0.02
SUR	0.10	0.07	0.09	0.08	0.04	0.09	0.04	0.04	0.05	**0.41**

Table 2: Confusion Matrix for vector SIFT on Style

4.3.1 Analysis of results

Art Movement	Style
Renaissance	Renaissance
Post-Renaissance	Baroque, Rococo and Realism
Modern Art	Abstract-Expressionism, Cubism, Popart, Expressionism, Impressionism and Surrealism

Table 3: Art-Movement associated with styles

Interesting pattern can be infered from the confusion matrix Table 2. Most of the paintings are confused with the paintings of the style of same art movement. For *e.g.* the paintings of rococo are getting most misclassified as the baroque. Clearly both styles are Post-Renaissance art movement. None of the rococo paintings are getting misclassified as Popart paintings . Similarly most of the pop-art paintings are getting misclassified as abstract-expressionism paintings. Both pop-art and abstract-expressionism are associated with modern art movement. It is also observed that none of the pop-art paintings are getting misclassified as realism, renaissance and rococo paintings. Thus it can be concluded that generally paintings of one style gets confused with the style associated with same art movement. From the confusion matrix it is observed that paintings of art-movement renaissance and post-renaissance movement gets confused among themselves and paintings of style associated with modern art movement gets confused with the paintings of style associated with the same art movement. Only exception for the above observation is the confusion between paintings of realism and expressionism even though both styles are associated with different art-movements. Most of the misclassified paintings of expressionism style are getting classified as paintings of realism, which shows that there must be a similarity between the paintings of the expressionism style and realism style. Again SIFT is performing best among features used individually. We achieved an accuracy of 62.37% in classifying the paintings into 10 styles using all the features together. Figure 4 shows that ensembling all the features yield better results than obtained by using individual features.

Figure 3: Surrealism painting misclassified as popart paintings

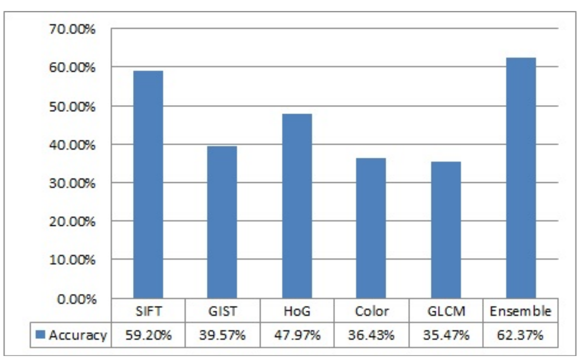

Figure 4: Overall accuracy on Style Dataset

4.3.2 Comparision with previos work

Zujovic *et al.* [31] classify the paintings into 5 styles- Abstract Expressionism, Cubism , Impressionism, Popart and Realism with 59, 60, 96, 58 and 80 paintings respectively for each style. They used gray level features like edges as well as colour features like HSV along with the steerable pyramid implementation for the above task. They achieved an highest accuracy of 68.3%. by using Adaboost J48 decision tree. Our objective is same as of him to classify the paintings into styles.

So we downloaded 300 paintings of the 5 styles used by Zujovic and then tested our features. We then fused all the features and learnt their optimized weights on the validation set . Then we used the optimized linear combination of weights of classifiers of different features learnt on validation set on the testing set to classify the paintings of the testing set into their styles. We got an accuracy of 87.47% on 10-fold cross validation ,thus outperforming the existing results.

The main difficulty for comparing our results with theirs is that it is impossible to use the same database used by them . But it should be noted that our database is much bigger than used by them and we classified the paintings into the same styles as classified by Zujovic with much higher accuracy.

5. Conclusion

We presented a simple and efficient way of feature extraction for the purpose of classification of paintings into genres and styles. To the best of our knowledge no work has been done to classify the paintings into these 6 genres. So these genres are tested for the first time. Our proposed features address the salient aspects of a painting - subject , objects, edges, texture and color. Our database is scraped from wikipaintings [8] and the paintings are of varied size, this provides a good model if the system is brought into the real world scenario. The future work may include using more suitable features which will improve the performance of our system. There is still a lot of scope in improvement even though we outperform the related past work.

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