Identifying the painter using texture features and machine learning algorithms

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ABSTRACT

Every artist has their own unique style of painting. The quantitative analysis of artworks is therefore essential to better understand the statistical differences between the paintings of different artists. In this study, we test if we can distinguish the works of Juan Luna from other Filipino painters using features derived from different sections of their paintings - foreground, background, foreground and background. We extracted texture features from the Gray Level Co-occurrence Matrix (GLCM) of the patches obtained from these sections and apply neural networks and Support Vector Machine (SVM) on duplets and triplets of features. From k-fold validation, the SVM on duplet of features from the background section of the paintings gave the highest accuracy of 83% for 375 dpi and 82% for 100 dpi. We have therefore shown that our approach can distinguish the works of Juan Luna from other Filipino painters.

CCS Concepts

• **Applied computing → Arts and humanities → Fine arts**

Keywords

visual stylometry; image classification; texture; GLCM; Neural Networks; SVM; Juan Luna; Filipino artists

1. INTRODUCTION

Identifying the authorship of a given painting can be done by skilled art connoisseurs through their expert visual examination and historical knowledge. However, an analytic characterization of the stylometry of the artist can offer a more objective way for art classification and authentication.

With the advent of physics-inspired approaches for image processing applied on wide range of discipline particularly on art and science, deeper understanding on the characteristic of paintings, and the style of the artists as well, are drawn by analyzing various features of the paintings. In an article by Sigaki et.al [1], they showed the evolution of paintings spanning a period on the order of a millennium by mapping two features of the paintings - entropy and complexity. Many other features can also be extracted from paintings including texture, color combinations, direction of brushstrokes, etc. To date, convolutional neural networks (CNN) is now used for feature extraction and is well-favored given its promising performance. In 2015, Jangtjik et.al. [2] successfully classified paintings from 13 different artists using CNN with 88% recall rate. Sun et.al [3] also used CNN to classify Chinese ink-wash paintings with 85% recall rate.

However, building upon CNN requires large scale training dataset because of the complexity of the model in terms of the number of parameters in the architecture [4]. In cases where the availability of digitized paintings of the artists are limited, CNN might not be a good approach.

In this paper, we propose a textural analysis on the brushstrokes from different sections of paintings as an approach in classifying paintings based on artists with limited dataset only. In an article by Qi and Hughes [5], they showed that features extracted on patches obtained from background sections of the painting only is more successful than patches from the whole painting. However, they did not account for the foreground section.

No research study has yet considered extracting features from foreground section of the paintings alone. In this study, we consider the foreground section. From the three different sections of a painting – background only, foreground only, and whole painting, we checked which of these sections will provide the most separable features by two different machine learning algorithm – neural network and SVM.

In addition, most studies prefer feeding high dimensional features to machine learning algorithms. In this study, we were able to extract six different texture features. But instead of feeding all these features to neural network and SVM which requires high computational power, we test if combination of two and three features can already provide a satisfactory performance. This approach in return provides a more efficient way of classifying paintings since low dimensional features does not require high computational power.

2. MACHINE LEARNING ALGORITHMS

Machine learning (ML) is data analytics technique that teaches computers to learn from experience by finding natural patterns in data. ML algorithms use computational methods to learn information directly from data without relying on a predetermined equation as a mode. ML has two types of technique – supervised and unsupervised learning. Unsupervised learning group and interpret data based only on input data while supervised learning developed predictive model based on both input and output data

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[6]. In this paper, two supervised ML algorithms are used to classify the extracted features from the paintings namely neural network and support vector machine (SVM).

2.1 Neural Network

Neural network consists of many simple, connected processors called neuron, each producing a sequence of real-valued activations. The neural network model usually consists of multiple hidden layers depending on the type of data set to be trained, with certain activation function applied on each layer. The learning part in this algorithm is about finding the weights that yield episodes with small total error with the hope that the network will generalized well in later episodes, causing only small errors on previously unseen sequences of input features [7]. The training involves optimization of the weight parameters by using empirical risk minimization which stops training once learning error is within a specified margin. This leads to non-optimal model and the solution is often plagued by local minimum problems [8].

2.2 Support Vector Machine

SVM on the other hand, are the so-called “nonparametric” models. Although it does not mean that the model does not have parameters at all, the parameters are not predefined and their number depends on the training data used. These data-driven parameters matches the model capacity to data complexity [9]. Due to this, SVM achieves better generalization due to structural risk minimization (SRM). SVM formulation approximates SRM principle by maximizing the margin of separation. Basic SVM is linear but it can be used for non-linear data by using kernel function [10]. Moreover, SVM delivers a unique solution since the optimality problem is convex. This is an advantage compared to Neural Networks, which have multiple solutions associated with local minima and for this reason may not be robust over different samples.

3. ARTISTS OF INTEREST

In this study, we choose to study several works of Juan Luna. Like his colleague Felix Resurreccion Hidalgo, Luna was the first Filipino artist to gain international fame in late 18th century. In his entity at the Madrid Exposition of 1884, his now famous painting – the Spoliarium, with dimension 4 x 7 meters, won not only the highest possible honor, the first of three Gold Medals, but also enthusiastic notice in the newspaper columns of Madrid, Barcelona, and Paris. He is a well-known and respected painter in the Philippines up to this date [11].

To distinguish the works of Juan Luna, the paintings of other Filipino artists are investigated as well. These artists are Isidro Saavedra, Elvira Lagdameo-Royeca, Wenceslao Garcia y Sicat, Amado de la Cruz, Macario Ligaya, Fermin Sanchez, Constancio Ma. Bernardo, Marcelino Rivera, Manuel Dante Fabie, Fermin Sanchez Vergara, Zozimo Dimaano, and Roman Faustino y Topacia.

4. METHODS

4.1 Data

We work on 13 high resolution digitized images of paintings of Juan Luna obtained from the National Museum of the Philippines and another 13 high resolution digitized images of paintings from various Filipino artists obtained from Vargas Museum. The resolution of the images ranges from 393-521 dpi. In this study, all images were gray scaled first and were reduced to 375 dpi (high res) and 100 dpi (low res). Shown in Figure 1 and 2 are the paintings used in this study. A flowchart of the Methods is shown in Figure 3.

Figure 1. Thirteen (13) Luna paintings

Figure 2. Thirteen (13) non-Luna paintings

4.2 Patch selection

Features are extracted from three different sections of the paintings – from foreground section only, background section only, and whole section of the paintings. To do this, the paintings were first manually segmented into foreground and background sections and for each segmented section, multiple patches were cropped with size 1x1 inches and stride of 0.2 inches. Multiple patches were also cropped from the unsegmented (whole) paintings. Given that the paintings have different dimensions and different background and foreground areas, different number of patches were cropped per section of each painting.

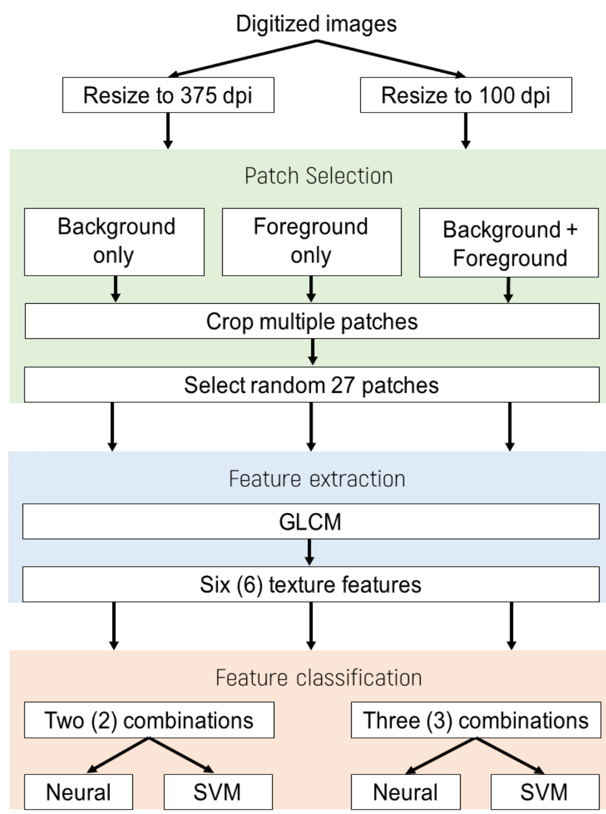

Figure 3. Overall flowchart of Methods

Since the number of available patches per section of each painting are uneven, twenty-seven (27) patches were randomly selected for each of the three sections. Having 26 paintings, 3 sections per painting, and 27 patches per section, a total of 2,106 patches are subject to feature extraction per trial per dpi. Ten (10) trials were done in this experiment. Visual representation of this process can be seen in the green section of Figure 3.

4.3 Feature extraction

The Gray-Level Co-occurrence Matrix (GLCM) of each 2,106 patches were constructed. GLCM is a statistical method of examining texture that considers the spatial relationship of pixels [12]. Figure 4 shows an example of how GLCM is constructed from a 3x3 gray-scaled input image (left side of the figure).

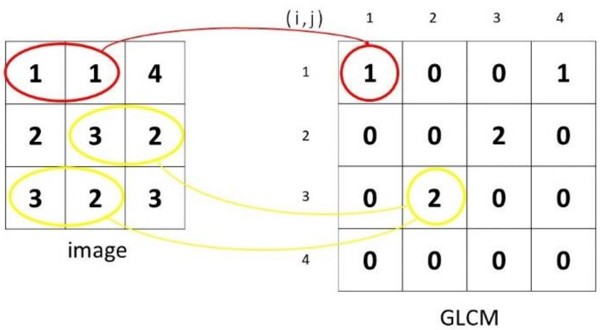

Figure 4. Construction of GLCM from an image

The right side of the figure is the constructed GLCM. The matrix element $GLCM(i,j)$ is the relative frequency with which two pixels in the input image, separated by 1-pixel offset to the right, occur within the neighborhood, one with intensity *i* and the other with intensity *j*. For example, in the GLCM matrix, $GLCM(1,1)$ contains the value 1 because there is only one case in the input image where two horizontally adjacent pixels have the values 1 and 1 whereas $GLCM(3,2)$ contains the value 2 because there are two cases where two horizontally adjacent pixels have the values 3 and 2. The same procedure is done for other pixel pairs $GLCM(i\,,j)$ [13]. In this study, the GLCM is constructed for pixels pairs separated with 5-pixel offset to the right. From the GLCM, six texture features namely contrast, dissimilarity, homogeneity, ASM, energy, and correlation, were then computed using equations 1 to 6. Visual representation of this process can be seen in the blue section of Figure 3.

$$\text{contrast} = \sum_{ij=0}^{levels-1} P_{i,j}(i-j)^2 \tag{1}$$

$$\text{dissimilarity} = \sum_{i,j=0}^{levels-1} P_{i,j}|i-j| \tag{2}$$

$$\text{homogeneity} = \sum_{i,j=0}^{levels-1} \frac{P_{i,j}}{1+(i-j)^2} \tag{3}$$

$$\text{ASM} = \sum_{i,j=0}^{levels-1} P_{i,j}^2 \tag{4}$$

$$\text{energy} = \sqrt{ASM} \tag{5}$$

$$\text{correlation} = \sum_{i,j=0}^{levels-1} P_{i,j}\left[\frac{(i-\mu_i)(j-\mu_j)}{\sqrt{(\sigma_i^2)(\sigma_j^2)}}\right] \tag{6}$$

4.4 Feature classification

Two machine learning classifiers namely neural network and support vector machine were used for predicting the authorship of the paintings. The machine learning algorithms are implemented by using functions of the Python scikit-learn library. We used k-fold cross validation procedure to estimate the performance of the classifiers. For each fold, features of one painting are tested while the features of 25 others were trained. This yields to a total of 26-fold cross validation. In training and testing the extracted features, instead of feeding all the six texture features to the classifiers, only two and three combinations were used for training and testing. The reason for this is because modeling with a machine learning algorithm should be a balance between performance and computational simplicity. Lesser features mean lesser weights to learn and therefore lesser computational complexity. This is the reason why only 2 and 3 input units were considered in this paper. If it is found to acceptably work on 2 features better than 3, then it is sufficient to use only 2 input units.

With that being said, for the neural network, since the order of the features matters, 30 permutations of the duplet of features and 120 permutations of the triplet of features from the six available texture features were trained and tested. While for SVM, since the order of the features does not matter, only 15 and 20 combinations of duplet and triplet of features respectively, were trained and tested. Visual representation of this process can be seen in the red section of Figure 3. Note that our concern is to check if certain combinations of texture features can be separated by the classifiers. That is, only the combination with the highest accuracy are presented in Results and Discussion.

4.5 Architecture of the classifier

Given that two and three texture features were taken, we have two network models differing only on the number of input units in the architecture. The network architecture for the two combinations has two input units (+1 bias) while the network architecture for the three combinations has three input unit (+1 bias). Both of which has two hidden layers with five and two hidden nodes, respectively, and one output unit (either 0 or 1). A rectified linear unit (ReLU) was used as the activation function for every layer. SVM on the other hand has radial basis function (rbf) as its kernel. Gholami et.al. [14] concluded in their recent paper that the RBF (Gaussian) kernel function is the best kernel to have an efficient SVM.

5. RESULTS AND DISCUSSION

The performance of our method is summarized in Figure 5. Accuracy is used as the performance measure of our model since the class distribution in the confusion matrix is balanced. Shown in the figure is the histogram of the accuracy of the neural network and SVM for two and three combinations which features are derived from three different patch origins (background section, foreground section, whole painting). The represented accuracy is the average accuracy for the 10 trials. To note, we refer to neural network with two combinations as Neural 2 and three combinations as Neural 3. The same applies for SVM.

For 100 dpi, features derived from background section only outperformed those derived from other two patch origins with accuracy higher than the rest for all cases of classifiers. On the other hand, SVM 2 has significantly higher accuracy than the rest of the classifiers for all the three patch origins.

For 375 dpi, features derived from foreground sections has higher accuracy for neural 2 and 3. However, background section once again has higher accuracy for SVM 2 and 3. SVM 2 on the other hand has significantly higher accuracy than the rest of the classifier.

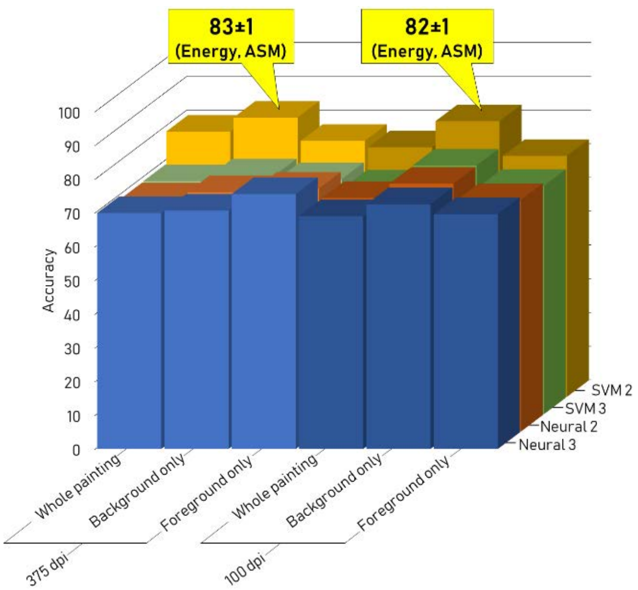

Figure 5. Accuracy for different classifiers and patch origin

Overall, SVM 2 from the background section has the highest accuracy of 83% for 375 dpi and 82% for 100 dpi. This suggests that features derived from background section of paintings are significantly distinguishable by the neural network and SVM which also proves the claim that this section bear the unconscious and unique habitual movements of an artist as suggested by art experts [5]. The significantly higher accuracy of SVM 2 also suggests that duplet of features is enough to produce a satisfactory performance without proceeding through higher dimensional features which requires higher computing power. It is also observed that the same feature combination, ASM and energy, gave the highest accuracy for the two dpi. In choosing which resolution is better than the other, our results show that low resolution (100 dpi) is enough to produce a satisfactory performance.

On the other hand, we can also see that there 6 cases where features from foreground section is more distinguishable by Neural 2, Neural 3, and SVM 3 for the two dpi, when compared to features from the whole painting. It is even the most distinguishable in Neural 2 and 3 for 375 dpi. It can be concluded that segmenting the paintings into foreground and background sections should be considered in painting classification, rather than solely relying to features extracted from the whole section of the painting.

Furthermore, shown in Figure 6 is the plot of energy versus ASM of all the Luna and non-Luna paintings. The energy and ASM values of the plot are from 27 random patches (done for 10 trials) from the background section of the paintings for 375 dpi. ASM and energy depicts the uniformity of the pixel intensities - the higher the value the more similar the pixel intensities [12]. Energy is 1 for a constant image [15]. It can be seen from the plot that the texture features of Luna's paintings on the background section are spread out on a wider range compared to other Filipino artists. This suggests that gray scaled background patches on Juan Luna's paintings ranges from random/rough to a more uniform/soft texture as compared to other Filipino artists. Shown in Figure 7 is an example of patch with high and low value of ASM and energy.

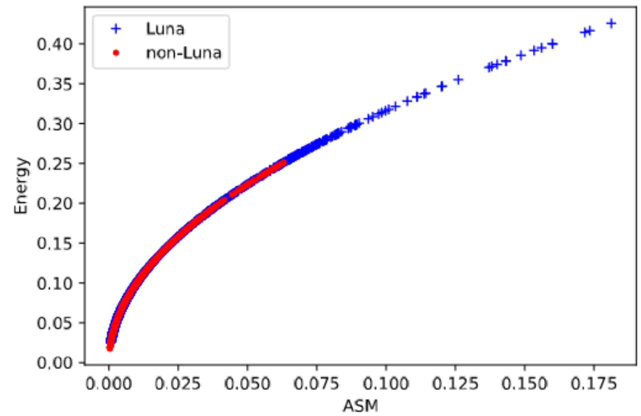

Figure 6. Characterizing the background sections of the paintings of Juan Luna vs non-Luna in energy-ASM plane

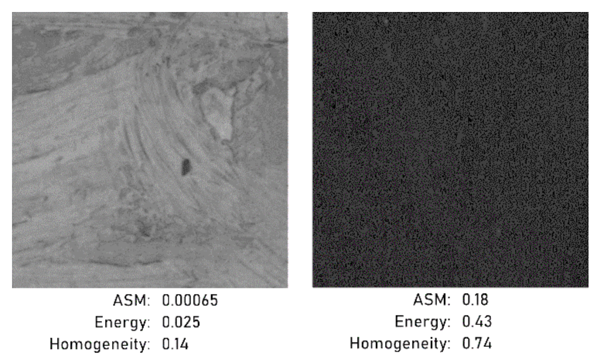

Figure 7. Sample background patches for 375 dpi of Luna paintings with low (left) and high (right) values of ASM, energy, and homogeneity

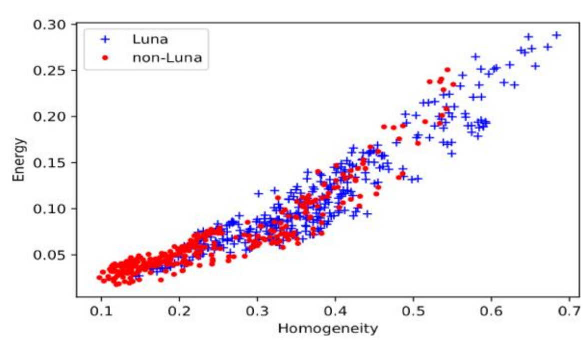

Figure 8. Characterizing the background sections of the paintings of Juan Luna vs non-Luna in energy-homogeneity plane.

Two other feature combinations that gave satisfactory performance are Homogeneity-Energy (79%) and Homogeneity-ASM (78%). Both features are derived from background section with SVM as classifier, and for 100 dpi. Figure 8 shows the plot of homogeneity vs energy. Homogeneity measures the closeness of the distribution of elements in the GLCM to the GLCM diagonal [15].

From the plot, the homogeneity of Luna's paintings has a wider range than non-Luna. This suggests that some background patches on Luna's paintings exhibit a more repetitive structure than other Filipino artists. Figure 7 shows an example of patch with high and low value of homogeneity.

6. CONCLUSION

In this study, we propose a method of extracting features from background, foreground, and whole section of paintings. Six texture features were extracted but instead of feeding all features at once in the machine learning classifiers, only duplet and triplet of feature combinations were trained and tested for lesser computational complexity. Our results have shown that our method can distinguish between paintings of Juan Luna and non-Juan Luna paintings to an accuracy of 83% for 375 dpi and 82% for 100 dpi from background sections alone.

Moreover, we have shown that texture features produce a satisfactory performance without building upon convolutional neural networks for automatic feature extraction which requires large set of data.

7. ACKNOWLEDGEMENT

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