Artistic Style Characterization of Vincent Van Gogh's Paintings using Extracted Features from Visible Brush Strokes

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Abstract: This paper outlines important methods used for brush stroke region extraction for quantifying artistic style of Vincent Van Gogh's paintings. After performing the region extraction, stroke-related features such as colour and texture features are extracted from the visible brush stroke regions. We then test the features by performing a binary classification between painters from different art movements and painters from the same art movement.

1 INTRODUCTION

Identifying artistic styles in digital paintings have been of great interest for researchers in the field of Computer Vision. It has many applications such as for cultural heritage preservation (Putri and Arymurthy, 2010), differentiating art movement period (Johnson. et al., 2008), building a style-based image retrieval system (Lombardi et al., 2004) and forgery detection (Rosseau, 1968). There are many factors that determine an artistic style. Such factors are the brush stroke characteristics and colour palette used by the artist and the way objects are drawn. From those factors, brush stroke characteristics contribute the most to an artistic style (Zang et al., 2013). For instance, Pointillist-style consists of small, elliptical and repeated brush strokes that are put together in such way that it will form the object when a viewer looks at it from a certain distance (see Fig. 1).

The existence of many painting styles with each of them having several unique brush stroke characteristics has motivated considerable research into brush stroke analysis, which can be done mathematically and statistically with the aid of *stylometry*. The aim of stylometry is to quantify artistic styles with a series of extracted features from the digitized artworks (Hughes et al., 2010). An image will represented as a string of features of statistical, texture, colour or shape, which will be analyzed using machine learning techniques. In this paper, we use stroke-based stylometry as we characterize various paintings by examining the statistical properties of the visible brush strokes.

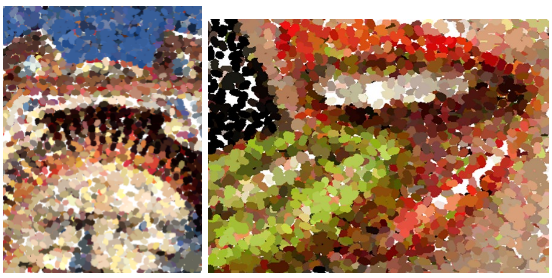

Figure 1: Example of computer-generated Pointillist rendering (Putri, 2012).

This work presents important image processing methods for extracting visible brush strokes from a set V of digital paintings by Vincent Van Gogh. Using extracted brush strokes, we describe feature extraction methods based on their texture and shape. The extracted features can then be compiled into a feature set S which serves as the quantified brush strokes properties. Since brush strokes appearances are closely related to the artistic style of the painting itself (Strassman, 1986), S can be seen as the style representation of V.

This paper is organized as follows: In Section 2, we describe some related work in artistic style characterization and brush stroke extraction. Section 3 gives a detailed description of the datasets and methods used in our work. Then, in Section 4, we provide some results and discussions. Finally, Section 5 concludes this paper and outlines our future research directions.

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2 RELATED WORKS

2.1 Artistic Style Characterization

In a stylistic painterly non-photorealistic (NPR) system, the characterization of artistic style is necessary for capturing, representing, and remapping a particular artistic style to an input image. Every digitized paintings can be seen as a composition of two components: the *style* and the *content* (Gatys et al., 2015). Artistic style characterization process extracts the style component of digitized paintings as a set of features. The features are then used by the NPR system as a heuristic in the painterly rendering process.

Research done by Hughes et al. (2010) investigated the characterization of artworks done by the Flemish painter Pieter Bruegel the Elder using sparse coding analysis. The aim of the research was to distinguish the authentic Bruegel paintings from the imitations by determining their similarity of the sparse model. The sparse model attempts to describe the image space by training a set of orthogonal basis functions that effectively represent the space. Sparse coding is proven to be an effective method for feature modelling in drawings and in other two-dimensional media due to the sparseness of the artworks' statistical structures that are considered to give a high contribution to the perception of similarity.

Sener et al. (2012) extracted various features for identifying children's book illustrators. From illustration samples by authors Alex Scheffler, Debi Gliori, Dr. Seuss and Korky Paul, features such as 4x4x4 bin RGB histograms, *gist* (Oliva and Torralba, 2001), colour dense SIFT (Lowe, 2004) and gradient histograms are extracted. Support Vector Machine with various kernels are then used for classification. From their experimentation, it was found that these features are useful for distinguishing one artist's style from another.

The extension of the work of Sener et al. (2012) by Vieira et al. (2015) uses a set of 93 different features extracted from various digital paintings by 12 artists. Among those features are image energy and entropy along with their statistical properties. Relevant features were selected by measuring the cluster dispersion using scatter matrices. Image energy and entropy are proven to be more representative of style than any other colour-based features. This research successfully identifies the correlation between several Baroque painters based on their works.

2.2 Brush Stroke Extraction

Brush strokes are the medium used by painters to communicate what they want to convey in their paintings. The way they are drawn can also provide some information related to the painter, for instance the painter's art movement and his/her emotional state (Callen, 1982). Because of this, brush stroke extraction has an important role in the area of digital painting analysis since brush strokes contain a lot of information that can be used as features to represent a painting.

Li et al. (2012) described a brush stroke extraction method for distinguishing Van Gogh's paintings from his contemporaries. Their method was used for distinguishing Van Gogh's paintings from two different periods, which are Paris and Arles-St.Remy period. Their work consists of developing statistical framework for the assessment of the distinction level of different painting categories, brush stroke extraction algorithm, and numerical features for brush stroke characterization. They used the EDISON edge detection algorithm developed by Meer and Georgescu (2001). After edges are detected, edge linking algorithm and enclosing operation are performed in order to close the gaps between edge segments. Then, the processed edges are extracted using the connected component labelling. Finally, brush stroke conditions are defined as: the brush skeleton not severely branched; the ratio of broadness to length is within the range of [0.05, 1.0]; and the ratio of the brush size to two times length times width span is within [0.5, 2.0]. The brush skeleton is produced by the thinning operation of the extracted connected components.

Johnson. et al. (2008) did a mathematical analysis for the classification of Van Gogh paintings. They examined high resolution grayscale scans of 101 paintings, which consist of: 82 paintings by Van Gogh, 6 paintings by other painters and 13 others which are loosely classified to be Van Gogh or non-Van Gogh by art experts. In their research, they combined two kinds of features that are extracted from the paintings, which are texture-based feature obtained by wavelets and stroke-based geometric features obtained by edge detection. They argue that it is extremely challenging to locate strokes accurately from grayscale images in a fully automated manner.

Berezhnoy et al. (2009) elaborated a method called as *prevailing orientation extraction technique* (POET). This method focuses on brush stroke texture orientation extraction for segmenting individual brush strokes in Van Gogh's painting. The method consists of two stages: the filtering stage and the orientation extraction stage. In the filtering stage, a rotation invariant circular filter with good response for band-passing is applied. The orientation extraction stage extracted the principal orientation of brush strokes from the filtered images. The filtered images were transformed into binary images using multilevel thresholding before the orientations were extracted. The evaluation of POET is based on the cross comparison between the judgments of POET and human subjects.

3 CHARACTERIZING ARTISTIC STYLE

3.1 Brush Stroke Extraction

In this paper, the term *brush stroke* refers to the trails of paints in the canvas that are produced by the painter during the painting process. A brush stroke can be placed on a canvas using other tools that are not necessarily in the form of brushes. The brush strokes that we are interested in are the ones who are visible enough to the viewers (i.e. not concealed behind other brush strokes). We employed three methods for brush stroke extraction as detailed below.

3.1.1 Iterative Brush Region Extraction

The method by Putri and Mukundan (2015) employed colour-based method that extracts brush area with the assumption of colour homogeneity inside the brush regions. The extraction is done by using a brush template called *blob*, which is a circular region that will move through the input image and detect regions with uniform colour. The formal definition of a blob of radius R with centre at pixel location P_0 is given by:

$$B_R(P_0) = \{P \in I \mid \|P - P_0\| \leq R\} \tag{1}$$

The colour constraint for the blob defined in Eq. (1) is the subset:

$$S_R(P_0) = \{P \in B_R(P_0) \mid \|v(P) - v(P_0)\| < \Delta E\} \tag{2}$$

with the condition of:

$$\#S_R(P_0) > 0.9(\#B_R(P_0)) \tag{3}$$

The definitions of variables in the above equations are listed in Table 1.

The extraction is done sequentially from left-to-right and top-to-bottom with the largest possible brush stroke radius R. The region that is detected to be inside the blob, which satisfies the conditions given in Eq. (1), (2) and (3), is considered to be a part of a brush stroke.

Table 1: Notations for Eq. (1), (2), and (3).

B_R	Set of pixels with a radius of R referred as a *blob*
S_R	Subset of B_R
P_0	Pixel location of the centre of B_R
$P \in I$	Pixel in an image I
$v(P)$	Colour component of P
$\|x-y\|$	Distance value between two object x and y
ΔE	Error threshold for colour comparison
$\#A$	Number of elements in set A

3.1.2 Texture Boundary Detection

This method detects brush strokes by identifying different textures in the painting image. A brush stroke can have a very different texture from other neighbouring brush strokes. This happens due to various factors, such as artist preferences, paint concentration, stroke orientation, and so forth. This method used image entropy to measure the randomness of the pixel information stored in every visible brush stroke. In this method, local entropy value of the neighbourhood is calculated for each pixel in the extracted visible brush strokes. To obtain the visible brush strokes area from the image I, we perform these steps:

1. Convert I to grayscale image I_{gray}.
2. Adjust the contrast of I_{gray} using histogram equalization.
3. Perform binary thresholding with Otsu's method (Otsu, 1975) to cluster the area with visible brush strokes.
4. The visible brush strokes is the area in I_{gray} that have the binary value 1. This area is called as $I_{grayvis}$.

After obtaining $I_{grayvis}$, we then extract the entropy value for each of its pixels. The entropy value in a pixel P is given as follows:

$$E_P = -\sum(n_P \, log_2 \, n_P) \tag{4}$$

where n_P is histogram counts of the neighbourhood of P. In this method, an 8x8 neighbourhood is used.

3.1.3 Gabor Filters

In this method, a filter bank of Gabor filters with various scales and rotations is applied in order to evaluate the distribution of intensity level. Gabor filters are proven to be a robust method for analysing oil painting images which have textured brush strokes (Putri and Arymurthy, 2010).

The two-dimensional Gabor filter is defined as:

$$g_{\lambda,\theta,\sigma,\phi}(s,t) = e^{-(\frac{s'^2}{\sigma_s^2}+\frac{t'^2}{\sigma_t^2})} cos(\frac{s'}{\lambda}+\phi) \tag{5}$$

From Eq. (5), a filter response of signal f is defined as:

$$R_{\lambda,\theta,\sigma,\phi}(x,y) = \iint_W f(x-s,y-t)g_{\lambda,\theta,\sigma,\phi}(s,t)\,ds\,dt \tag{6}$$

For every pixel in the painting, the Gabor energy is defined as:

$$e_{\lambda,\theta}(x,y) = \sqrt{R_{\lambda,\theta,1,0}(x,y)^2 + R_{\lambda,\theta,1,\frac{\pi}{2}}(x,y)^2} \tag{7}$$

The definitions of variables in the above equations are listed in Table 2.

The Gabor energies given in Eq. (7) are computed for $\lambda_i, i = 1,...,6$ and $\theta_i = \frac{i\pi}{8}, i = 0,...,7$. Each pair of Gabor filters with the combination of λ_i and θ_i detects the image intensity transition via convolution. Every convolution will produce energy values for each pixel. The total energy from every convolution is the number of contours (or light-dark transition), thus will detect regions with different textures (Johnson. et al., 2008).

Table 2: Notations for Eq. (5), (6), and (7).

$g_{\lambda,\theta,\sigma,\phi}$	Gabor filter with parameters λ, θ, σ, and ϕ
(s,t)	Two-dimensional position of the impulse
λ	Filter scale, also known as spatial frequency
θ	Filter orientation
σ_s and σ_t	Standard deviation of circular Gaussian envelope $\sigma_s = 1$ and $\sigma_t = 1$
ϕ	Phase offset of the filter response $\phi = 0$ for the real component $\phi = \frac{\pi}{2}$ for the imaginary component
s'	$s\,cos\,\theta + t\,sin\,\theta$
t'	$s\,sin\,\theta + t\,cos\,\theta$
$R_{\lambda,\theta,\sigma,\phi}$	Gabor filter response with parameters λ, θ, σ, and ϕ
f	Signal which response is to be calculated using $R_{\lambda,\theta,\sigma,\phi}$
W	Filter window
$e_{\lambda,\theta}$	Gabor energy on scale λ and orientation θ

3.2 Feature Extraction

From the three aforementioned methods, we extract features that are related to the texture and shape of the brush strokes from every painting patch from the dataset. Shape features are extracted from the results of iterative brush region extraction and texture boundary detection, while Gabor energy features are extracted from the results of Gabor filters method. The dataset and the generation of patches will be explained further in Subsection 3.3.

The shape features consist of the region properties of a brush stroke, such as:

1. Major axis length: The length of major axis of the ellipse that has the same normalized second central moments as the region.
2. Minor axis length: The length of minor axis of the ellipse that has the same normalized second central moments as the region.
3. Eccentricity: The eccentricity of the ellipse that has the same normalized second central moments as the region.
4. Perimeter: The distance around the region boundary.
5. Orientation: The angle between the x-axis and the major axis.

For every detected brush stroke, the shape features mentioned above along with their mean and standard deviation are computed, giving 10 features for every patch.

The Gabor energies given in Eq. (7) are calculated for every pixel in the patches with 6 different scales and 8 different orientations. For each patch, the mean and standard deviation of the energies for each scale and orientation are obtained, thus giving us 96 features for every patch.

Consequently, each patch in the corpora can be seen as a row of data which consists of a total of 106 features. The features then got selected to improve the accuracy and decrease the training time of the classification. The feature selection is done by Weka's *AttributeSelection*[1] filter which evaluates subset of features by examining each of their individual ability to predict the correct class.

3.3 The Datasets

3.3.1 The Van Gogh Corpus

Table 3: The Van Gogh Corpus.

Title	Resolution
Le Moulin de la Galette	3840x3082
Self-Portrait with Grey Felt Hat	2606x3163
Self-Portrait with Straw Hat	2452x3068
Cabbages and Onions	3840x2975
A Pair of Leather Clogs	3840x3034
The Garden of Saint-Paul Hospital	3840x3039
Landscape at Twilight	3507x1719
Tree Roots	3840x1879
View of Auvers	3840x3694
Wheat Fields	3840x3153
Wheat Field under Thunderclouds	3840x1885
Wheat Field with Crows	3840x1939

In our work, we choose several paintings by Vincent van Gogh from his different art periods. Van

[1]The *AttributeSelection* filter can be found on Weka Explorer GUI in Weka → Filters → Supervised → Attribute → AttributeSelection.

Gogh's works are chosen due to their distinguishable brush stroke characteristics which are bold, wide, repetitive and have the ability to convey objects with a certain level of abstraction such that the object appears to be fleeting in the viewer's eyes (Callen, 1982). The corpus is made of 12 paintings with high-resolution obtained from The Van Gogh Museum via Google Art Project. Table 3 provides the complete list of paintings in the corpus.

3.3.2 The Testing Corpora

Two kinds of testing corpora are used to validate the extracted features proposed in this work. Both corpora consist of images by painters other than Van Gogh. Those corpora are called as the Rembrandt corpus and the Impressionists corpus.

The Rembrandt corpus consist of the works by Rembrandt Harmenszoon van Rijn, a Realist painter whose brush stroke properties are very different to Van Gogh's. Table 4 provides the complete list of paintings in this corpus. This dataset is used for a classification benchmark to validate the representability of features extracted from the Van Gogh corpus.

The Impressionists corpus consist of the works of other Impressionists such as Claude Monet, Paul Cézanne and Auguste Renoir. The complete list of paintings in this corpus can be seen in Table 5. Van Gogh has a unique way to create Impressionistic brush stroke, thus differentiating his works from other Impressionists can be a useful performance measurement for his brush stroke analysis.

In all corpora, each painting is divided into a set of 500x500 patches. After dividing the images into patches, any remaining blocks that are less than 500x500 pixels are omitted. Each painting consists of approximately 30-50 patches.

We use the L*a*b (CIELAB) colour space since it can simulate colour perception in a way that is close to the human visual system (Reinhard et al., 2008). Since all the images in all corpora are in RGB format, we convert all of the pixel values of them to CIELAB space before we process them to extract features.

3.4 Artistic Style Characterization Pipeline

The artistic style characterization in this work is done by these following processes:

1. Divide each painting in the Van Gogh corpus into 500x500 patches.
2. Extract visible brush strokes from every patches using the three proposed brush stroke extraction methods. The *visible* brush strokes are brush strokes that have identifiable form, i.e. the obvious brush strokes that are not located behind any other brush strokes.
3. Extract features $f_1, ..., f_n$ from the visible brush strokes. For every patch p, the features are then grouped into a set $S_p = \{f_1, ..., f_n\}$.
4. Repeat process number 1-3 for the testing corpora. The obtained feature set is $T_p = \{g_1, ..., g_n\}$.
5. Do a classification-based test from both S_p and T_p. The feature set obtained from the Van Gogh corpus is then tested by a classification-based test with the testing feature sets obtained from the testing corpora.

Table 4: The Rembrandt Corpus.

Title	Resolution
Parable of the Hidden Treasure	3703x2864
The Entombment of Christ	2024x1604
Judas Returning the Thirty Pieces of Silver	2048x1585
The Apostle Paul in Prison	3168x3727
David with the Head of Goliath before Saul	2048x1412
Balaam and the Ass	2252x3000
Man in a Gorget and a Cap	2358x3208
The Spectacle-Pedlar	2793x3284
The Operation	1410x1724
The Abduction of Europa	3000x2342
The Raising of Lazarus	4113x4905
The Parable of Rich Fool	2998x2228
Tobit Accusing Anna of Stealing the Kid	2058x2724
Family Portrait	3000x2264
Descent from the Cross	2789x3840
The Stoning of Saint Stephen	2024x1458

Table 5: The Impressionists Corpus.

Title	Painter	Resolution
At the Water's Edge	Paul Cézanne	4000x3146
Bazille and Camille	Claude Monet	2975x4000
Flowers in a Rococo Vase	Paul Cézanne	2452x3068
Oarsmen at Chatou	Auguste Renoir	4000x3255
Sainte-Adresse	Claude Monet	4000x2786
The Japanese Footbridge	Claude Monet	4000x3219
Woman with a Parasol	Claude Monet	3220x4000

From the result of process number 5, if S_p are separable for every Van Gogh painting patch p then the features f_1, ..., f_n are considered representative for quantifying Van Gogh's painting style.

4 EXPERIMENTAL RESULTS

4.1 Brush Stroke Extraction

The extraction results can be seen in Fig. 2. Texture boundary detection and Gabor filter give good

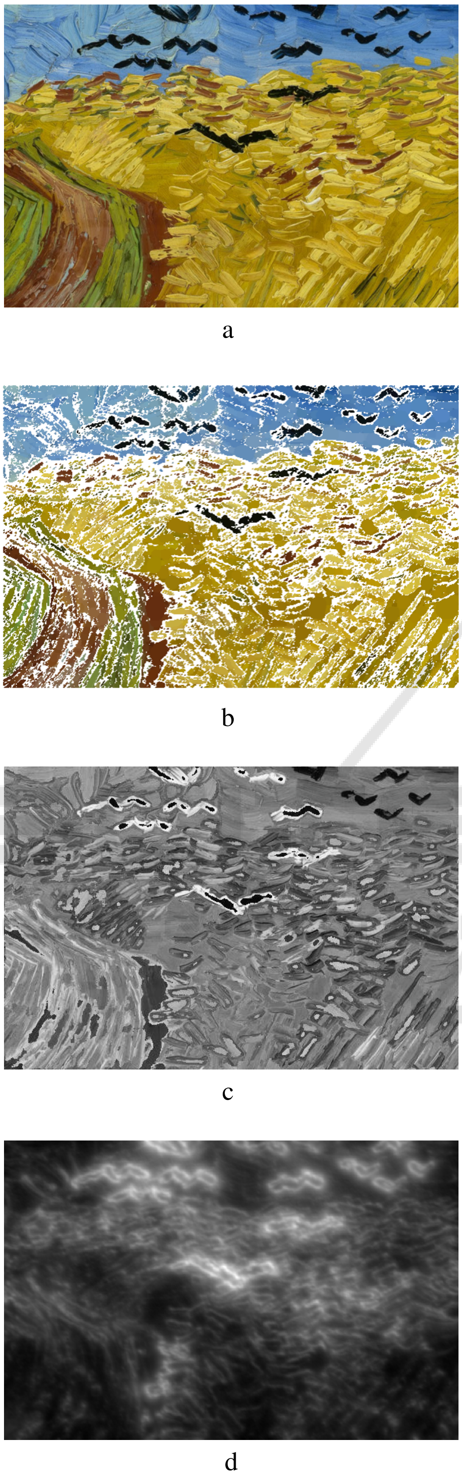

Figure 2: (a) The input image and the brush extraction result using: (b) iterative brush region extraction, (c) texture boundary detection and (d) Gabor filters.

result in capturing visible brush strokes due to their ability to detect regions based on the texture within them. Iterative brush region extraction is fast in the implementation but unsuccessful in detecting small textured brush strokes that are placed in the same area. For instance, it misses smaller strokes in the sky area of Fig. 2b.

4.2 Distinguishing Van Gogh from other Painters

The features from the extracted brush strokes are then classified according to their respective class. There are three classes, which are Van Gogh (VG), other Impressionists (NVG) and Rembrandt (R). The purpose of the classification is to validate the representability of the extracted features, i.e. how effective are the features in quantifying the artistic style of Van Gogh.

The classifications are done in Weka in two ways: first as binary classifications between the classes VG and R, and second as binary classifications between the classes VG and NVG. The experiments are done using 10-fold cross validation (CV) with 70/30 percentage split, in which 70% of the data are used for training and the rest 30% are used for testing. Multilayer Perceptron (MLP) and J48 classifiers are used to their reliability and capability to learn the data adaptively (Su et al., 1996) (Bhargava et al., 2013). The configurations for the classifiers are given in Table 6 and 7.

In Table 8, it can be seen that the results of the classification between the works of Van Gogh and Rembrandt are high in accuracy and F-measure value. This is expected since those two painters come from different art movement periods thus have a very different style to depict an object. While as an Impressionist, Van Gogh tends to use bold strokes to convey only the most essential part of the objects; Rembrandt use very tiny strokes to depict his objects as real as possible, thus making him a Realist.

Table 6: Weka J48 Classifier Configurations.

Parameters	Value
Binary splits	False
Option for collapsing the tree	True
Pruning confidence	0.25
Option for making split point actual value	False
Minimum number of instances	2
Number of folds for reduced error pruning	3
Option for reduced error pruning	False
Seed for random data shuffling	1
Option to perform subtree raising	True

The classification results between Van Gogh and his fellow Impressionists show less accuracy levels than the results between Van Gogh and Rembrandt, but are still satisfactory. Being under the same in-

Table 8: The Classification Results of Van Gogh's Brush Stroke Features.

Class	Classifier	Testing Mode	Accuracy	F-Measure
VG & R	MLP	10-fold CV	99.56%	0.996
VG & R	MLP	30/70	99.53%	0.995
VG & R	J48	10-fold CV	97.79%	0.978
VG & R	J48	30/70	98.57%	0.986
VG & NVG	MLP	10-fold CV	97.74%	0.977
VG & NVG	MLP	30/70 split	98.76%	0.988
VG & NVG	J48	10-fold CV	87.57%	0.876
VG & NVG	J48	30/70	87.58%	0.875

Table 7: Weka MLP Classifier Configurations.

Parameters	Value
Option to autocreate the network connections	True
Option to allow learning rate decay	False
Learning rate for the backpropagation	0.3
Momentum rate for the backpropagation	0.2
Option to filter nominal to binary	True
Option to normalize attributes	True
Option to normalize numeric class	True
Number of epochs	500
Threshold for number of consecutive errors	20
Percentage of validation set	0
Value to seed the random number generator	0

fluence of Impressionism art movement, the painters in the Impressionists class have similar style to Van Gogh in terms of object representation. Nevertheless, Van Gogh has different way to portray light and use curvy and expressive brush strokes to create visual effect that will make his paintings more engaging to the viewers. This makes him as a Neo-Impressionist painter who employs the techniques of the Impressionists in unconventional ways (Callen, 1982).

5 CONCLUSION AND FUTURE WORK

5.1 Conclusion

In this paper, three methods are used for quantifying artistic style by analysing the visible brush strokes. Those three methods are iterative brush region extraction, texture boundary detection and Gabor filters. Then, based on their shape and texture, the properties of extracted strokes are encapsulated in a set of features. The features are then classified to test their representability of quantifying a particular artistic style. The experiment results show that the proposed methods give satisfactory results in producing features that are able to differentiate the works by Van Gogh from the works by another Impressionists painters.

5.2 Future Work

The immediate extension of this work is NPR parametrization based on the extracted features for painterly stroke-based rendering of photograph images. The parameters will be used for guiding the digital brush which will be modelled as a group of coordinated particles that travels across the digital canvas. After the rendering results are produced, their aesthetics will then be assessed using Convolutional Neural Network to eliminate the biases that will be introduced by artist-based assessment.

Another possible extension of this work is to build a robust style-based painting retrieval system which can be used for retrieving artworks based on their artistic style, painter or art movement era. This system will be beneficial for art education and appreciation in museums or art galleries.

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