Color Multi-Fusion Fisher Vector Feature for Fine Art Painting Categorization and Influence Analysis

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Abstract

This paper presents a novel set of image features that encode the local, color, spatial, relative intensity information and gradient orientation of the painting image for painting artist classification, style classification as well as artist and style influence analysis. In particular, a new color DAISY Fisher vector (CD-FV) feature is first created by computing Fisher vectors on densely sampled DAISY features. Second, a color WLD-SIFT Fisher vector (CWS-FV) feature is developed by fusing Weber local descriptors (WLD) with Scale Invariant Feature Transform (SIFT) descriptors and Fisher vectors are computed on the fused WLD-SIFT features. Finally, an innovative color multi-fusion Fisher vector (CMFFV) feature is developed by integrating the Principal Component Analysis (PCA) features of CD-FV, CWS-FV and color SIFT-FV features. The effectiveness of the proposed CMFFV feature is assessed on the challenging Painting-91 dataset. Experimental results show that the proposed CMFFV feature is able to (i) achieve the state-of-the-art performance for painting artist classification, (ii) outperform other popular image descriptors, as well as (iii) discover the artist and style influence to understand their connections and evolution in different art movement periods.

1. Introduction

Computational painting categorization and analysis is an emerging research area in computer vision, which is gaining increasing attention in the recent years. It contains four sub-tasks: artist classification, style classification, artist influence and style influence, which have many potential applications such as museum industries, painting theft investigation, forgery detection, etc. Pioneer works in cognitive psychology [28], [32] believe that the analysis of visual art is a complex cognitive task as different elements of visual art such as color, brush strokes, shapes and boundaries require involvement of multiple centers in the human brain. From the computer vision point of view, unlike conventional image classification tasks, computational painting categorization exhibits two important issues for artist classification and style classification respectively. First, as for the artist classification, there are large variations in appearance, topics and styles within the paintings of the same artist. Second, as for the style classification, the inherent similarity gap between paintings within the same style is much larger compared to the traditional image classification tasks. Besides, the influence analysis of artist and style relies heavily on the information of paintings, which may also be affected by these two issues. As a result, conventional features, such as LBP[12], PHOG [1], GIST [13], SIFT [11], complete LBP [5], CN-SIFT [9] etc., which are applied to conventional image classification, independently cannot capture the key aspects of computational painting categorization. A comparative evaluation of different conventional features by Khan et al. [9] for computational fine art painting categorization clearly suggests the need of designing more powerful visual features specific to painting categorization tasks.

Painting (art) images are different from photographic images as the texture and color patterns of visual classes (ex: sky, mountains, grass etc.) are not consistent in painting images. For example, when we look at a painting, we can find certain visual classes (say, a multicolored face or a disproportionate figure) which are discordant with the real world visual classes captured by photographic images. Therefore, descriptors that achieve robustness to both photometric and geometric transformations are required. Also, some painters have a very distinctive style of using specific colors (for ex: dark shades, light shades etc.) or specific brush strokes. In addition, other important descriptive attributes that discriminate art paintings of different artists are the texture form, color tone, sharpness of edges, brush stroke movement, contrast and pattern [18]. In order to capture these aspects, we have to consider both the relative intensity information and gradient orientation of the painting images, which the conventional features do not incorporate well. Motivated by the observations from both cognitive psychology and computer vision, we present in this paper a new set of features to analyze the paintings from different complementary views corresponding to the multiple centers in the human brain for fine art painting categorization. We particularly look to encode a descriptor that incorporates the local, color, spatial as well as the relative intensity information and its gradient orientation.

To address the issues raised above, we first present a new DAISY Fisher vector (D-FV) feature which enhances the Fisher vector feature by fitting dense DAISY descriptors [29] to a Gaussian Mixture Model (GMM). The D-FV feature is robust against photometric and geometric transformations within the paintings in order to deal with inconsistencies of different visual classes in the painting images. We then develop a novel WLD-SIFT Fisher vector (WS-FV) feature by integrating the Weber local descriptors (WLD) [2] with SIFT descriptors and calculating Fisher vector on the sampled WLD features. The WS-FV feature captures the relative intensity and orientation information for brush strokes in the paintings. Third, we further extend the above features to color images resulting in CD-FV and CWS-FV by incorporating color information in the paintings. Finally, we present an innovative color multi-fusion Fisher vector (CMFFV) by fusing the principal components of CD-FV, CWS-FV and color SIFT-FV (CS-FV) feature. The process of derivation of the CMFFV feature is illustrated in figure 1.

Our proposed features are evaluated on the challenging Painting-91 dataset [9] for all the four subtasks: artist classification, style classification, artist influence and style influence. Experimental results show that our new features achieve the state-of-the-art performance for fine art painting categorization, and discover the artist influence and style influence.

Our contributions are summarized as follows: (i) We present a new D-FV feature and a novel WS-FV feature which capture different aspects of the paintings. (ii) We further extend our new features to color D-FV (CD-FV) and color WS-FV (CWS-FV) features by incorporating color information in the paintings. (iii) We then develop an innovative CMFFV feature by fusing the principal components of CD-FV, CWS-FV and color SIFT-FV (CS-FV) feature. (iv) We achieve the state-of-the-art performance for the artist classification task of Painting-91 dataset and compute the artist influence and style influence graphs.

2. Related Work

Recently, several research efforts have been invested for painting classification using computer vision techniques. Shamir et al. [20] described a method for automated recognition of painters and schools of art based on their signature styles. Sablating et al. [19] examined the structural signature of a painting based on the brush strokes in potrait miniatures. The work of Zujovic et al. [33] described an approach to automatically classify digital pictures of paintings by using the salient aspects of a painting such as color, texture and edges. Shamir and Tarakhovsky [21] showed that automatic computer analysis can group artists by their artistic movements, and provide a map of similarities and influential links that is largely in agreement with the analysis of art historians. Siddique et al. [24] presented an efficient approach for learning a mixture of kernels by greedily selecting exemplar data instances corresponding to each kernel using AdaBoost for painting dataset classification. A multiple visual feature based framework was proposed by Shen [23] for automatic classification of western painting image collection. The work of Culjak et al. [3] offered an approach to automatically classify paintings into their genres by extracting features based on color and texture of the painting.

Local, color, spatial, intensity information, and gradient orientation information are the cues based on which human beings can distinguish between images, and hence they contribute significantly to painting artist and style classification. Van de Weijer et al. [31] showed the effectiveness of color names learned from images for texture classification and action recognition. The work of van de Sande [30] showed that SIFT descriptor incorporated with color information result in a robust local descriptor for classification purposes. Guo et al. [5] proposed the complete LBP descriptor wherein a region in an image is represented by its center pixel and a local difference sign-magnitude transform. Shechtman et al. [22] proposed the self-similarity descriptor which measures similarity of visual entities based on matching internal layout of the image.

3. Novel Fused Fisher Vector Features

3.1. Fisher Vector

Fisher vector is widely applied for visual recognition problems such as face detection and recognition [25], object recognition [8, 17], etc. Particularly, let $\mathbf{X} = \{\mathbf{d}_t, t = 1, 2, ..., T\}$ be the set of T local descriptors extracted from the image. Let μ_λ be the probability density function of $\mathbf{X}$ with parameter λ, then the Fisher kernel [8] is defined as follows: $K(\mathbf{X}, \mathbf{Y}) = (\mathbf{G}_\lambda^X)^T \mathbf{F}_\lambda^{-1} \mathbf{G}_\lambda^Y$ where $\mathbf{G}_\lambda^X = \frac{1}{T} \bigtriangledown_\lambda \log_{\mu_\lambda}(\mathbf{X})$, which is the gradient vector of the log-likelihood that describes the contribution of the parameters to the generation process. And $\mathbf{F}_\lambda$ is the Fisher information matrix of μ_λ.

Since $\mathbf{F}_\lambda^{-1}$ is symmetric and positive definite, it has a Cholesky decomposition as $\mathbf{F}_\lambda^{-1} = \mathbf{L}_\lambda^T \mathbf{L}_\lambda$. Therefore, the kernel $K(\mathbf{X}, \mathbf{Y})$ can be written as a dot product between normalized vectors $\mathbf{G}_\lambda$, obtained as $\mathbf{G}_\lambda^X = \mathbf{L}_\lambda \mathbf{G}_\lambda^X$ where $\mathbf{G}_\lambda^X$ is the Fisher vector of $\mathbf{X}$.

Theoretical analysis [8] shows that Fisher vector de-

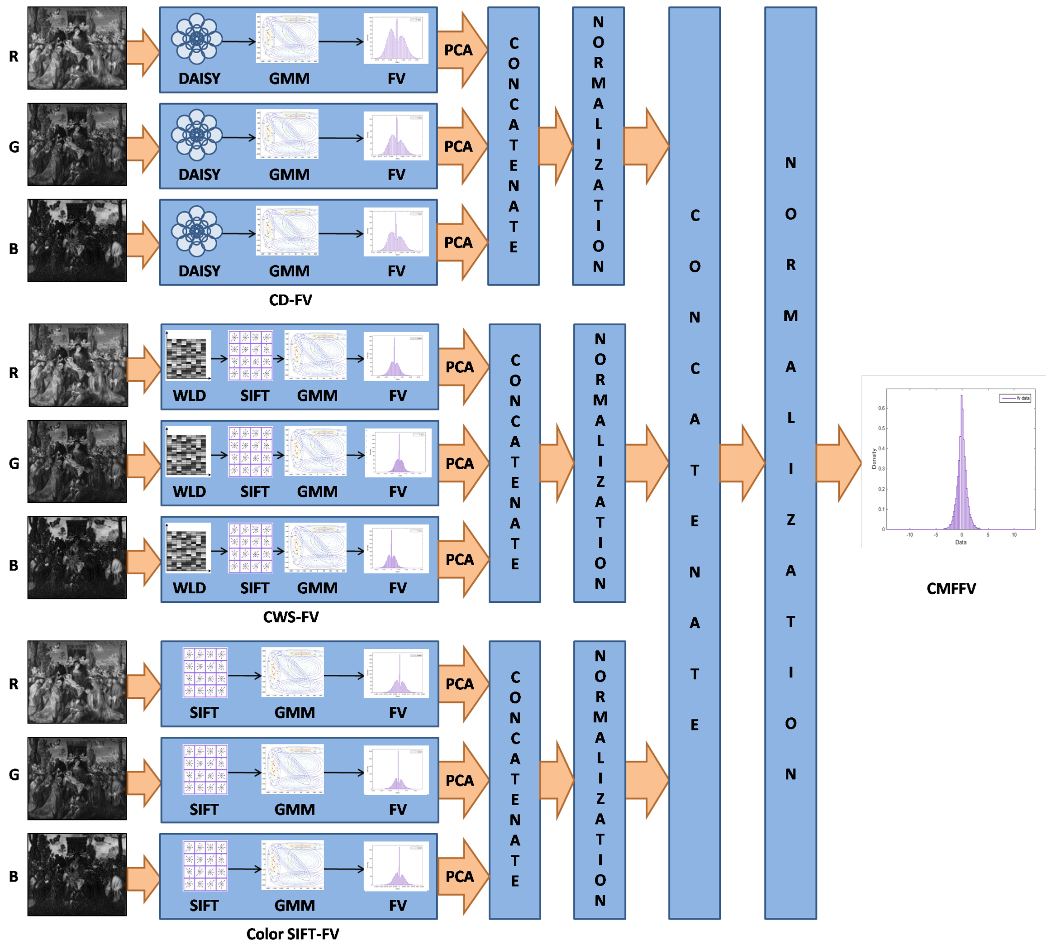

Figure 1. The component images, the process of computation of CD-FV, CWS-FV and the color SIFT-FV features, the PCA process and the CMFFV feature derived from the concatenation and subsequent normalization of the computed features

scribes an image by what makes it different from other images. It focuses only on the image specific features and discards the image independent background features leading to better accuracy in classification.

3.2. Color DAISY Fisher Vector (CD-FV)

In this section, we present a new innovative DAISY Fisher vector (D-FV) feature where Fisher vectors are computed on densely sampled DAISY descriptors. DAISY descriptors consists of values computed from the convolved orientation maps located on concentric circles centered on each pixel location. The DAISY descriptor [29] $\mathcal{D}(u_0, v_0)$ for location (u_0, v_0) is defined as follows:

$$\begin{aligned}
&\mathcal{D}(u_0, v_0) = [\tilde{\mathbf{h}}^T_{\Sigma_1}(u_0, v_0),\\
&\tilde{\mathbf{h}}^T_{\Sigma_1}(\mathbf{I}_1(u_0, v_0, R_1)), ..., \tilde{\mathbf{h}}^T_{\Sigma_1}(\mathbf{I}_T(u_0, v_0, R_1)), ...,\\
&\tilde{\mathbf{h}}^T_{\Sigma_Q}(\mathbf{I}_1(u_0, v_0, R_Q)), ..., \tilde{\mathbf{h}}^T_{\Sigma_Q}(\mathbf{I}_T(u_0, v_0, R_Q))]^T
\end{aligned} \tag{1}$$

where $\mathbf{I}_j(u, v, R)$ is the location with distance R from (u, v) in the direction given by j, Q represents the number of circular layers and $\tilde{\mathbf{h}}_{\Sigma}(u, v)$ is the unit norm of vector containing Σ-convolved orientation maps in different directions. DAISY descriptors are suitable for dense computation and offers precise localization and rotational robustness [29], therefore provides improved performance and better accuracy for classification.

For every component of the image, dense DAISY descriptors are computed with parameters radius of descriptor set as 15, number of rings as 3, number of histograms per ring as 8 and number of histogram bins as 8 resulting in a 200 dimension DAISY descriptor. The sampled descriptors are then fitted to a Gaussian Mixture Model (GMM) with 256 parameters. The Fisher vectors are then encoded as derivatives of log-likelihood of the model based on the parameters. The GMM is trained for each component of the image separately so as to encode the color information.

3.3. Color Weber-SIFT Fisher Vector (CWS-FV)

We introduce a new Weber-SIFT Fisher vector (WS-FV) feature that integrates the Weber local descriptor along with

SIFT features so as to encode the color, local as well as relative intensity information and its gradient orientation from an image. The Weber local descriptor (WLD) [2] is based on the Weber's law [7] which states that the ratio of increment threshold to the background intensity is a constant. The descriptor contains two components differential excitation [2] and orientation [2] which are defined as follows.

$$\xi(x_c) = \arctan[\frac{\nu_s^{00}}{\nu_s^{01}}] \; and \; \theta(x_c) = \arctan(\frac{\nu_s^{11}}{\nu_s^{10}}) \qquad (2)$$

where $\xi(x_c)$ is the differential excitation and $\theta(x_c)$ is the orientation of the current pixel x_c, $x_i(i = 0, 1, ...p-1)$ denotes the i-th neighbours of x_c and p is the number of neighbors, ν_s^{00}, ν_s^{01}, ν_s^{10} and ν_s^{11} are the output of filters f_{00}, f_{01}, f_{10} and f_{11} respectively. Since the WLD is based on physiological law, it extracts features from an image by simulating a human sensing his/her surroundings. WLD is robust to noise in the image and also reduces the effects of illumination change [2], therefore acts as a good descriptor for painting images.

To encode the color, relative intensity information and its gradient orientation, Weber local descriptors (WLD) are computed for each component of the image to form the color WLD. We then derive densely sampled SIFT features and the process is repeated separately for the three components of the image resulting in color WLD-SIFT feature. We train a parametric generative model [6, 16], in our case, Gaussian Mixture Model (GMM) by fitting it to the sampled color WLD-SIFT features. The spatial information is also encoded by augmenting the visual features derived by SIFT with their spatial co-ordinates [27]. The Fisher vectors are then extracted by capturing the average first order and second order differences between the computed features and each of the GMM centers.

3.4. Color Multi-Fusion Fisher Vector (CMFFV)

In this section, we present an innovative color multi-fusion Fisher vector feature (CMFFV) that fuses the most expressive features of the CD-FV, CWS-FV and color SIFT-FV. In the color SIFT-FV feature, Fisher vectors are computed on densely sampled SIFT features using a parametric estimation model [16, 25] for every component of the image. The color cue provides powerful discriminating information in pattern recognition in general [26, 10], therefore we also incorporate color information to our proposed feature. The most expressive features are extracted by means of Principal Component Analysis (PCA) [4]. Particularly, let $\mathbf{X} \in \mathbb{R}^N$ be a feature vector with covariance matrix $\mathbf{\Sigma}$ given as follows:$\mathbf{\Sigma} = \mathbb{E}[(\mathbf{X} - \mathbb{E}(\mathbf{X}))][(\mathbf{X} - \mathbb{E}(\mathbf{X}))]^T$ where T represents transpose operation and $\mathbb{E}(.)$ represents expectation. The covariance matrix can be factorized as follows [4]:$\mathbf{\Sigma} = \boldsymbol{\phi}\mathbf{\Lambda}\boldsymbol{\phi}^T$ where $\mathbf{\Lambda} = diag[\lambda_1, \lambda_2, \lambda_3, ..., \lambda_N]$ is the diagonal eigenvalue matrix and $\boldsymbol{\phi} = [\boldsymbol{\phi_1}\boldsymbol{\phi_2}\boldsymbol{\phi_3}....\boldsymbol{\phi_N}]$ is the orthogonal eigenvector matrix. The most expressive features of $\mathbf{X}$ is given by a new vector $\mathbf{Z} \in \mathbb{R}^K : \mathbf{Z} = \mathbf{P}^T\mathbf{X}$ where $\mathbf{P} = [\boldsymbol{\phi_1}\boldsymbol{\phi_2}\boldsymbol{\phi_3}....\boldsymbol{\phi_K}]$ and $K < N$.

To derive the proposed CMFFV feature, we first compute the CD-FV, CWS-FV and the color SIFT-FV for all the components of the image separately. The CD-FV features of the R, G and B components of the image are concatenated and normalized to zero mean and unit standard deviation. The dimensionality of the CD-FV feature is then reduced by using PCA, which derives the most expressive features with respect to the minimum square error. The above process is then repeated for the CWS-FV and color SIFT-FV features. Finally, the computed CD-FV, CWS-FV and the color SIFT FV features are further concatenated and normalized to create the novel CMFFV feature. Figure 1 shows the component image, the process of computation of CD-FV, CWS-FV and the color SIFT-FV features, the PCA process and the CMFFV feature derived from the concatenation and subsequent normalization of the computed features.

4. Experiments

This section assesses the effectiveness of our proposed features on the challenging Painting-91 dataset [9]. The dataset contains 4266 fine art painting images by 91 artists. The images are collected from the Internet and covers artists from different eras. There are variable number of images per artist ranging from 31 (Frida Kahlo) to 56 (Sandro Boticelli). The dataset classifies 50 painters to 13 style labels namely: abstract expressionism, baroque, constructivism, cubbism, impressionism, neoclassical, popart, post-impressionism, realism, renaissance, romanticism, surrealism and symbolism.

4.1. Artist Classification

This section demonstrates the performance of our proposed features with other popular image descriptors on the task of artist classification which involves classifying a painting to its respective artist. The dataset contains 91 artists with 2275 training and 1991 test images. D-FV stands for DAISY Fisher vector and CD-FV stands for color DAISY Fisher vector. Similar notation is used for the other features. The color variants of D-FV, WS-FV, S-FV and MFFV provide much improved performance. The best single feature is CS-FV which gives a classification performance of 55.69%. Experimental results on table 1 show that our proposed CMFFV feature achieves the state-of-the-art classification performance of 59.04% for artist classification and outperforms other popular image descriptors and deep learning methods.

Figure 2 shows some artist categories with the best and lowest classification performance on the Painting-91 dataset. The best performance is achieved on paintings by artists Claude Lorrain, Frida Kahlo, Mark Rothko, etc. The

No.	Feature	Artist CLs	Style CLs
1	LBP [12, 9]	28.50	42.20
2	Color-LBP [9]	35.00	47.00
3	PHOG [1, 9]	18.60	29.50
4	Color-PHOG [9]	22.80	33.20
5	GIST [13, 9]	23.90	31.30
6	Color-GIST [9]	27.80	36.50
7	SIFT [11, 9]	42.60	53.20
8	CLBP [5, 9]	34.70	46.40
9	CN [31, 9]	18.10	33.30
10	SSIM [22, 9]	23.70	37.50
11	OPPSIFT [30, 9]	39.50	52.20
12	RGBSIFT [30, 9]	40.30	47.40
13	CSIFT [30, 9]	36.40	48.60
14	CN-SIFT [9]	44.10	56.70
15	Combine(1 - 14) [9]	53.10	62.20
16	MSCNN-1 [15]	58.11	69.67
17	MSCNN-2 [15]	57.91	70.96
18	CNN F_3 [14]	56.40	68.57
19	CNN F_4 [14]	56.35	69.21
20	D-FV	46.93	56.46
21	WS-FV	41.87	54.28
22	S-FV	49.02	58.95
23	MFFV	57.51	65.54
24	CD-FV	50.18	58.54
25	CWS-FV	51.85	61.99
26	CS-FV	55.69	66.15
27	**CMFFV**	**59.04**	67.43

Table 1. Comparison of Classification Performance(%) of the proposed features for Artist and Style Classification

method provides inferior performance on artist categories Gustave Courbet, Diego Velazquez, Max Ernst, Titian etc. As mentioned previously, one of the issues for artist classification are the large variations in appearance, topics and styles within the same paintings.

The artist with the worst performance in Figure 2 have very high variations in their paintings. For instance, the paintings of artist Gustave Courbet range from unidealized peasants and workers, landscapes, seascapes, hunting scenes and still lifes. The paintings also incorporate characteristics of multiple styles such as realism, impressionism and cubbism therfore resulting in few discriminating features for classification. Figure 3 shows the different themes of paintings by artist Gustave Courbet. Due to the large variations in the theme and styles of paintings, the number of misclassification for these artisits are higher.

4.2. Style Classification

This section evaluates the performance of our proposed features on the task of style classification. Style Classification deals with the problem of categorizing a painting to the 13 style classes defined in the dataset. The third column in table 1 shows the results obtained using different features for style classification. The D-FV, WS-FV and S-FV features provide classification performance of 56.46%, 54.28% and 58.95% respectively. The color variants of these features significantly improve the performance re-emphasizing

Figure 2. Classification performance of artist categories of the Painting-91 dataset. (a) shows some artist categories with best performance (b) shows some artist categories with worst performance

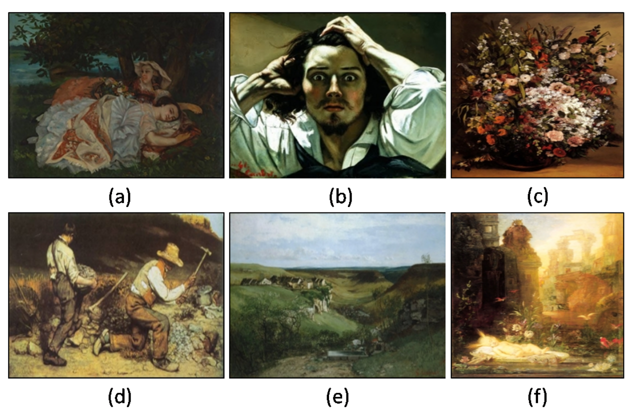

Figure 3. Different paintings by artist Gustave Courbet

Style	CD-FV	CWS-FV	CS-FV	CMFFV
(1)Abstract expressionism	81.36	83.05	89.83	91.53
(2)Baroque	72.32	73.21	76.79	77.68
(3)Constructivism	61.33	64	73.33	68
(4)Cubbism	62.5	73.86	73.86	79.55
(5)Impressionism	52.44	50	53.66	59.76
(6)Neoclassical	40	40	46	42
(7)Popart	57.89	57.89	64.91	59.65
(8)Post Impressionism	66.04	67.92	69.81	75.47
(9)Realism	44.44	42.22	47.78	50
(10)Renaissance	40.85	49.30	46.48	47.89
(11)Romanticism	63.12	67.38	71.63	70.92
(12)Surrealism	60.33	61.98	65.29	73.55
(13)Symbolism	58.33	75	80.56	80.56

Table 2. Comparative mean average classification performance of proposed features on the 13 style categories

Art Movement	Art Style
Renaissance	renaissance
Post Renaissance	baroque, neoclassical, romanticism, realism
Modern Art	popart, impressionism, post impressionism, surrealism, cubbism, symbolism, constructivism, abstract expressionism

Table 3. Art movement associated with different art styles

the fact that adding color information is particularly suitable for classifying painting images. Table 2 shows the mean average classification performance of the CD-FV, CWS-FV, CS-FV and CMFFV features on the 13 style categories. The results demonstrate that the CMFFV feature achieves comparable result to the state-of-the-art deep learning methods for style classification.

Figure 4 shows the confusion matrix for the 13 style categories of the Painting-91 dataset using the CMFFV feature. In the confusion matrix, the rows show the actual classes while the columns show the assigned classes. It can be seen from Fig. 4 that the best classified categories are 1 (abstract expressionism), 4(cubbism) and 13(symbolism) with classification rates of 91%, 80% and 81% respectively. Category 6 (neoclassical) is the most difficult category to classify as there are large confusions between the style categories baroque and neoclassical. The other categories that create confusion are styles neoclassical and renaissance.

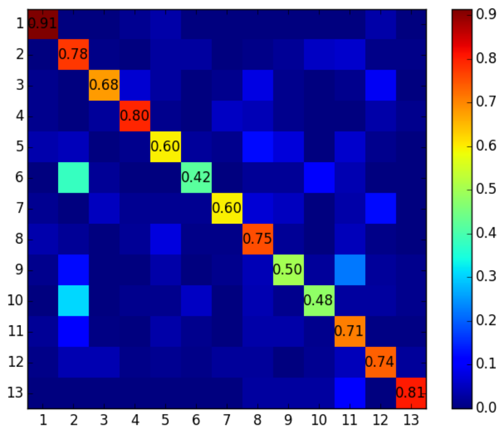

Figure 4. The confusion matrix for 13 style categories using the CMFFV feature with categories listed as in table 2.

4.3. Comprehensive Analysis of Results

Table 3 shows the art movements associated with different art styles. Interesting patterns can be observed from the confusion diagram in figure 4. The art styles within an art movement show higher confusions compared to the art styles between the art movement periods. An art movement is a specific period of time wherein an artist or group of artists follow a specific common philosophy or goal. It can be seen that there are large confusions for the styles baroque and neoclassical. Similarly, the style categories romanticism and realism have confusions with style baroque. The style categories baroque, neoclassical, romanticism and realism belong to the same art movement period - post renaissance. Similarly, popart paintings have confusions with style category surrealism within the same art movement but none of the popart paintings are misclassified as baroque or neoclassical. The only exception to the above observation is the style categories renaissance and baroque as even though they belong to different art movement period, there are large confusions between them. The renaissance and baroque art paintings have high similarity as the baroque style evolved from the renaissance style resulting in few discriminating aspects between them [18].

4.4. Artist Influence

In this section, we analyze the influence an artist can have over other artists. We find the influence among artists by looking at similar characteristics between the artist paintings. Artist influence may help us to find new connections among artists during different art movement period and also understand the influence among different art movement periods. In order to calculate the artist influence, we calculate the correlation score between the paintings of different artists. Let $\mathbf{a}_{ik}$ denote the feature vector representing the painting by artist k where $i = 1, .., n_k$ and let n_k be the to-

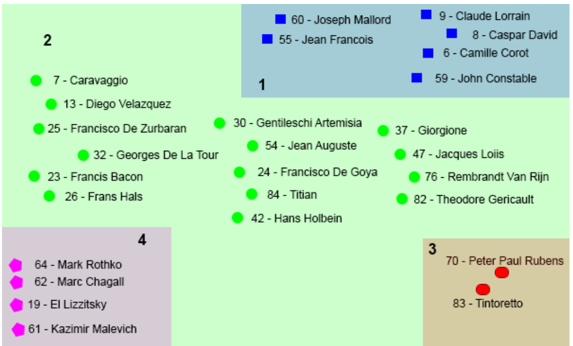

Figure 5. Artist influence cluster graph

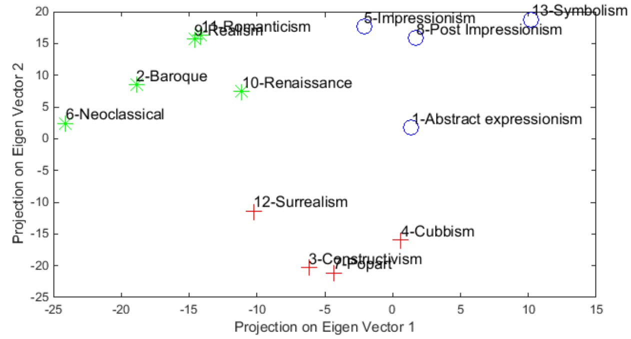

Figure 6. Style influence cluster graph with k set as 3

tal number of paintings by artist k. We calculate $\mathbf{A}_k$ which is the average of the feature vector of all paintings by artist k. We then compute a correlation matrix by comparing the average feature vector of each artist with all other artists. Finally, clusters are defined for artists with high correlation score. Figure 5 show the artist influence cluster graph with correlation threshold of 0.70.

Interesting observations can be deduced from figure 5. Every cluster can be associated with a particular style and time period. Cluster 1 shows artists with major contributions to the styles realism and romanticism and they belong to the post renaissance art movement period. Cluster 2 has the largest number of artists associated with the styles renaissance and baroque. Cluster 3 represents artists for the style Italian renaissance that took place in the 16^{th} century. And cluster 4 shows artists associated with style abstract expressionism in the modern art movement period (late 18^{th} - 19^{th} century).

We further show the k-means clustering graph with cosine distance to form clusters of similar artists. Figure 7 shows the artist influence graph clusters for paintings of all artists with k set as 8. First the average of the feature vector of all paintings of an artist is calculated as described above. We then apply k-means clustering algorithm with k set as 8. The artist influence graph is plotted using the first two principal components of the average feature vector. The results of figure 7 have high correlation with the results of the artist influence cluster graph in figure 5.

4.5. Style Influence

In this section, we study the style influence so as to find similarities between different art styles and understand the evolution of art styles in different art movement periods. The style influence is calculated in a similar manner as the artist influence. First, we calculate the average of the feature vector of all paintings for a style. We then apply k-means clustering method with cosine distance to form clusters of similar styles. We set the number of clusters as 3 based on the different art movement periods. The style influence graph is plotted using the first two principal components of the average feature vector.

Figure 6 shows the style influence graph clusters with k set as 3. Cluster 1 contains the styles of the post renaissance art movement period with the only exception of style renaissance. The reason for this may be due the high similarity between styles baroque and renaissance as the style baroque evolved from the style renaissance [18]. The styles impressionism, post impressionism and symbolism in cluster 2 show that there are high similarities between these styles in the modern art movement period as the three styles have a common french and belgian origin. Similarly, styles constructivism and popart in cluster 3 show high similarity in the style influence cluster graph.

We further show the results based on the correlation matrix computed by comparing the average feature vector of all paintings of each style with all other styles. We set the correlation threshold as 0.7.

$$
\begin{aligned}
&Renaissance => Baroque, Neoclassical\\
&Romanticism => Realism\\
&Impressionism => Post\ impressionism\\
&Constructivism => Popart
\end{aligned}
$$

The results are in good agreement with the style influence cluster graph and support the observation that the art styles within an art movement show higher similarity compared to the art styles between the art movement periods. The styles baroque and neoclassical belong to the same art movement period and the style baroque has evolved from the style renaissance. Similarly, other styles belong to the modern art movement period. It can be observed from the style influence cluster graph that the style pairs romanticism:realism, impressionism:post impressionism and constructivism:popart are plotted close to each other in the graph indicating high similarity between these styles.

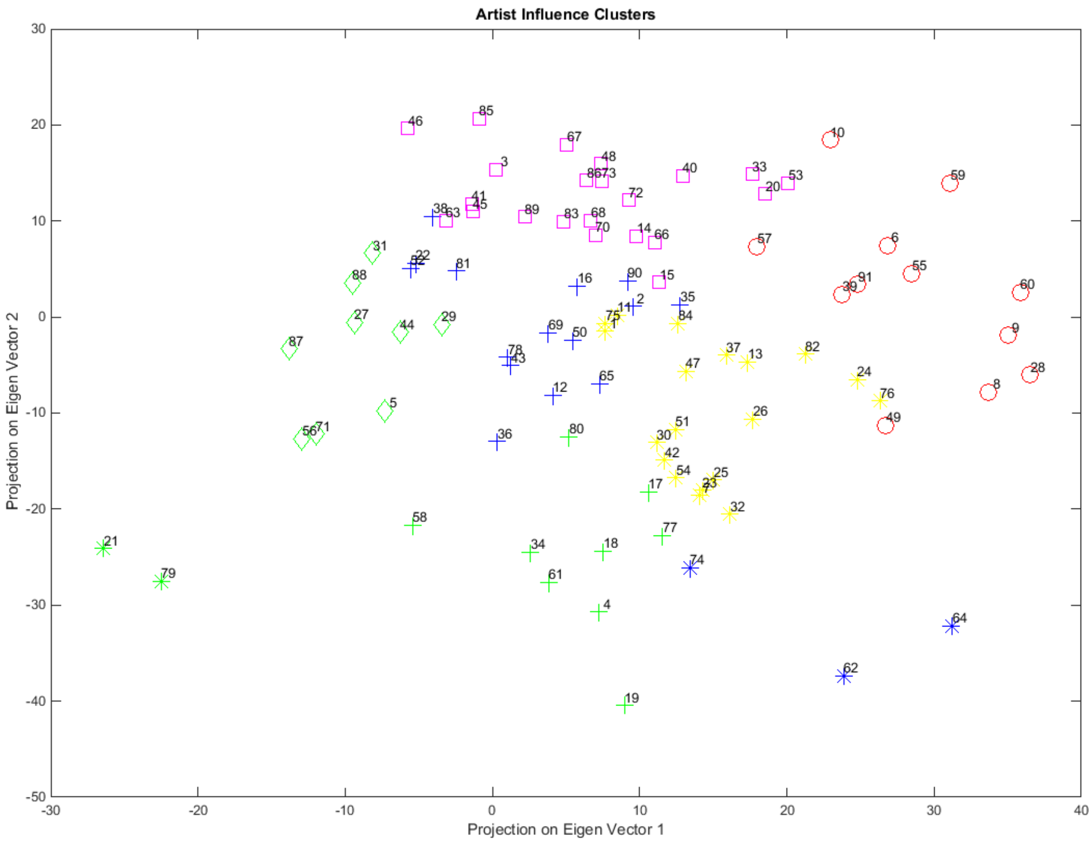

Figure 7. Artist influence cluster graph with k set as 8

1:ALBRECHT DURER (43)	24:FRANCISCO DE GOYA (49)	47:JACQUES LOUIS DAVID (50)	70:PETER PAUL RUBENS (50)
2:AMEDEO MODIGLIANI (50)	25:FRANCISCO DE ZURBARAN (50)	48JAMES ENSOR (50)	71:PICASSO (50)
3:ANDREA MANTEGNA (47)	26:FRANS HALS (50)	49:JAMES MCNEILL WHISTLER (50)	72:PIERRE AUGUSTE RENOIR (50)
4:ANDY WARHOL (32)	27:FRANZ MARC (50)	50:JAN VAN EYCK (40)	73:PIETER BRUEGEL THE ELDER (45)
5:ARSHILLE GORKY (33)	28:FREDERIC EDWIN CHURCH (50)	51:JAN VERMEER (35)	74:PIET MONDRIAN (38)
6:CAMILLE COROT (50)	29:FRIDA KAHLO (31)	52:JASPER JOHNS (50)	75:RAPHAEL (39)
7:CARAVAGGIO (41)	30:GENTILESCHI ARTEMISIA (50)	53:JEAN ANTOINE WATTEAU (50)	76:REMBRANDT VAN RIJN (47)
8:CASPAR DAVID FRIEDRICH (49)	31:GEORGES BRAQUE (50)	54:JEAN AUGUSTE DOMINIQUE INGRES (50)	77:RENE MAGRITTE (50)
9:CLAUDE LORRAIN (50)	32:GEORGES DE LA TOUR (50)	55:JEAN FRANCOIS MILLET (50)	78:ROGER VAN DER WEYDEN (39)
10:CLAUDE MONET (36)	33:GEORGES SEURAT (38)	56:JEAN MICHEL BASQUIAT (43)	79:ROY LICHTENSTEIN (50)
11:DANTE GABRIEL ROSSETTI (50)	34:GEORGIA O'KEEFE (50)	57:JOACHIM PATINIR (40)	80:SALVADOR DALI (46)
12:DAVID HOCKNEY (50)	35:GERHARD RICHTER (50)	58:JOAN MIRO (50)	81:SANDRO BOTTICELLI (56)
13:DIEGO VELAZQUEZ (39)	36:GIORGIO DE CHIRICO (50)	59:JOHN CONSTABLE (50)	82:THEODORE GERICAULT (50)
14:EDGAR DEGAS (51)	37:GIORGIONE (47)	60:JOSEPH MALLORD WILLIAM TURNER (50)	83:TINTORETTO (50)
15:EDOUARD MANET (45)	38:GIOTTO DI BONDONE (48)	61:KAZIMIR MALEVICH (50)	84:TITIAN (51)
16:EDVARD MUNCH (49)	39:GUSTAVE COURBET (40)	62:LUCIO FONTANA (50)	85:UMBERTO BOCCIONI (50)
17:EDWARD HOPPER (50)	40:GUSTAVE MOREAU (50)	63:MARC CHAGALL (44)	86:VINCENT VAN GOGH (42)
18:EGON SCHIELE (50)	41:GUSTAV KLIMT (36)	64:MARK ROTHKO (50)	87:WASSILY KANDINSKY (50)
19:EL LISSITZKY (50)	42:HANS HOLBEIN THE YOUNGER (43)	65:MAX ERNST (50)	88:WILLEM DE KOONING (43)
20:EUGENE DELACROIX (48)	43:HANS MEMLING (50)	66:NICOLAS POUSSIN (50)	89:WILLIAM BLAKE (45)
21:FERNAND LEGER (50)	44:HENRI MATISSE (50)	67:PAUL CEZANNE (50)	90:WILLIAM HOGARTH (39)
22:FRA ANGELICO (47)	45:HIERONYMUS BOSCH (50)	68:PAUL GAUGUIN (51)	91:WINSLOW HOMER (50)
23:FRANCIS BACON (50)	46:JACKSON POLLOCK (41)	69:PAUL KLEE (50)	

Figure 8. List of artists and their paintings in the Painting-91 dataset

5. Conclusion

This paper presents a novel set of image features that encode the local, color, spatial as well as relative intensity information and gradient orientation of the image. The proposed color DAISY Fisher vector (CD-FV) feature is created by computing Fisher vectors on densely sampled DAISY features. A color WLD-SIFT Fisher vector (CWS-FV) feature is developed by fusing Weber local descriptors with SIFT descriptors and Fisher vectors are computed on the fused WLD-SIFT features. Finally, an innovative color multi-fusion Fisher vector (CMFFV) feature is developed by integrating the most expressive features of CD-FV, CWS-FV and color SIFT-FV features. Further analysis on artist and style influence show the evolution of art paintings and their connection to different art movement periods. Experimental results show the effectiveness of our proposed method in the artist and style classification task of the challenging Painting-91 dataset.

References

[1] A. Bosch, A. Zisserman, and X. Munoz. Representing shape with a spatial pyramid kernel. In *Proceedings of the 6th ACM International Conference on Image and Video Retrieval*, CIVR '07, pages 401–408, 2007.

[2] J. Chen, S. Shan, C. He, G. Zhao, M. Pietikainen, X. Chen, and W. Gao. Wld: A robust local image descriptor. *Pattern Analysis and Machine Intelligence, IEEE Transactions on*, 32(9):1705–1720, Sept 2010.

[3] M. Culjak, B. Mikus, K. Jez, and S. Hadjic. Classification of art paintings by genre. In *MIPRO, 2011 Proceedings of the 34th International Convention*, pages 1634–1639, May 2011.

[4] K. Fukunaga. *Introduction to Statistical Pattern Recognition*. Academic Press Professional, Inc., San Diego, CA, USA, 1990.

[5] Z. Guo, D. Zhang, and D. Zhang. A completed modeling of local binary pattern operator for texture classification. *Image Processing, IEEE Transactions on*, 19(6):1657–1663, June 2010.

[6] T. S. Jaakkola and D. Haussler. Exploiting generative models in discriminative classifiers. In *Proceedings of the 1998 Conference on Advances in Neural Information Processing Systems II*, pages 487–493, Cambridge, MA, USA, 1999. MIT Press.

[7] A. K. Jain. *Fundamentals of Digital Image Processing*. Prentice-Hall, Inc., Upper Saddle River, NJ, USA, 1989.

[8] H. Jegou, F. Perronnin, M. Douze, J. Sanchez, P. Perez, and C. Schmid. Aggregating local image descriptors into compact codes. *Pattern Analysis and Machine Intelligence, IEEE Transactions on*, 34(9):1704–1716, Sept 2012.

[9] F. Khan, S. Beigpour, J. van de Weijer, and M. Felsberg. Painting-91: a large scale database for computational painting categorization. *Machine Vision and Applications*, 25(6):1385–1397, 2014.

[10] C. Liu. Extracting discriminative color features for face recognition. *Pattern Recognition Letters*, 32(14):1796 – 1804, 2011.

[11] D. Lowe. Distinctive image features from scale-invariant keypoints. *International Journal of Computer Vision*, 60(2):91–110, 2004.

[12] T. Ojala, M. Pietikainen, and T. Maenpaa. Multiresolution gray-scale and rotation invariant texture classification with local binary patterns. *Pattern Analysis and Machine Intelligence, IEEE Transactions on*, 24(7):971–987, Jul 2002.

[13] A. Oliva and A. Torralba. Modeling the shape of the scene: A holistic representation of the spatial envelope. *International Journal of Computer Vision*, 42(3):145–175, 2001.

[14] K.-C. Peng and T. Chen. Cross-layer features in convolutional neural networks for generic classification tasks. In *Image Processing (ICIP), 2015 IEEE International Conference on*, pages 3057–3061, Sept 2015.

[15] K.-C. Peng and T. Chen. A framework of extracting multi-scale features using multiple convolutional neural networks. In *Multimedia and Expo (ICME), 2015 IEEE International Conference on*, pages 1–6, June 2015.

[16] F. Perronnin and C. Dance. Fisher kernels on visual vocabularies for image categorization. In *CVPR*, June 2007.

[17] F. Perronnin, J. Snchez, and T. Mensink. Improving the fisher kernel for large-scale image classification. In *Computer Vision ECCV 2010*, pages 143–156. 2010.

[18] L. Rathus. *Foundations of art and design*. Wadsworth Cengage Learning, Boston, MA, 2008.

[19] R. Sablatnig, P. Kammerer, and E. Zolda. Hierarchical classification of paintings using face- and brush stroke models. In *ICPR*, 1998.

[20] L. Shamir, T. Macura, N. Orlov, D. M. Eckley, and I. G. Goldberg. Impressionism, expressionism, surrealism: Automated recognition of painters and schools of art. *ACM Trans. Appl. Percept.*, 2010.

[21] L. Shamir and J. A. Tarakhovsky. Computer analysis of art. *J. Comput. Cult. Herit.*, 2012.

[22] E. Shechtman and M. Irani. Matching local self-similarities across images and videos. In *CVPR*, pages 1–8, June 2007.

[23] J. Shen. Stochastic modeling western paintings for effective classification. *Pattern Recognition*, pages 293 – 301, 2009. Learning Semantics from Multimedia Content.

[24] B. Siddiquie, S. Vitaladevuni, and L. Davis. Combining multiple kernels for efficient image classification. In *Applications of Computer Vision (WACV), 2009 Workshop on*, pages 1–8, 2009.

[25] K. Simonyan, O. M. Parkhi, A. Vedaldi, and A. Zisserman. Fisher Vector Faces in the Wild. In *BMVC*, 2013.

[26] A. Sinha, S. Banerji, and C. Liu. New color gphog descriptors for object and scene image classification. *Mach. Vis. Appl.*, 25(2):361–375, 2014.

[27] J. Snchez, F. Perronnin, and T. de Campos. Modeling the spatial layout of images beyond spatial pyramids. *Pattern Recognition Letters*, 33(16):2216 – 2223, 2012.

[28] R. L. Solso. *Cognition and the visual arts*. 1996.

[29] E. Tola, V. Lepetit, and P. Fua. Daisy: An efficient dense descriptor applied to wide-baseline stereo. *Pattern Analysis and Machine Intelligence, IEEE Transactions on*, 32(5):815–830, May 2010.

[30] K. van de Sande, T. Gevers, and C. Snoek. Evaluating color descriptors for object and scene recognition. *Pattern Analysis and Machine Intelligence, IEEE Transactions on*, 32(9):1582–1596, Sept 2010.

[31] J. van de Weijer, C. Schmid, J. Verbeek, and D. Larlus. Learning color names for real-world applications. *Image Processing, IEEE Transactions on*, 18(7):1512–1523, July 2009.

[32] S. Zeki. *Inner Vision: An Exploration of Art and the Brain*. Oxford University Press, 1999.

[33] J. Zujovic, L. Gandy, S. Friedman, B. Pardo, and T. Pappas. Classifying paintings by artistic genre: An analysis of features and classifiers. In *Multimedia Signal Processing, 2009. MMSP '09. IEEE International Workshop on*, pages 1–5, Oct 2009.