Sparse Representation Based Complete Kernel Marginal Fisher Analysis Framework for Computational Art Painting Categorization

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INTRODUCTION

- This paper presents a sparse representation based complete kernel marginal Fisher analysis (SCMFA) framework for categorizing fine art images.
- First, we introduce several Fisher vector based features for feature extraction so as to extract and encode important discriminatory information of the painting image.
- Second, we propose a complete marginal Fisher analysis method so as to extract two kinds of discriminant information, regular and irregular.
- In particular, the regular discriminant features are extracted from the range space of the intraclass compactness using the marginal Fisher discriminant criterion whereas the irregular discriminant features are extracted from the null space of the intraclass compactness using the marginal interclass separability criterion.
- Experimental results on the challenging Painting-91 dataset show that our framework achieves the state-of-the-art performance for fine art painting categorization and outperforms other popular image descriptors and deep learning methods

FEATURE EXTRACTION USING FUSED FISHER VECTOR FEATURES

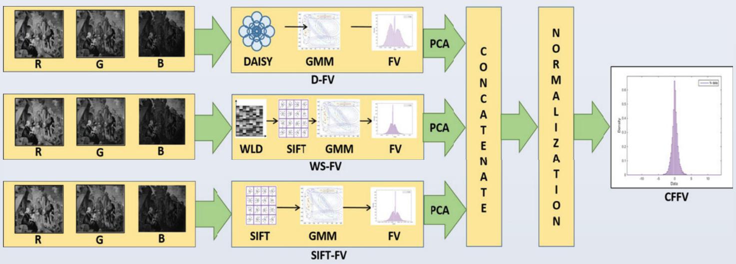

Figure 1. Framework of the feature extraction process.

SPARSE REPRESENTATION BASED COMPLETE KERNEL MARGINAL FISHER ANALYSIS FRAMEWORK

Complete Marginal Fisher Analysis (CMFA) Method:

The motivation for CMFA method is that the traditional MFA method uses a PCA projection in the initial step that may discard the null space of the intraclass compactness which may contain useful discriminatory information.

In the complete kernel marginal Fisher analysis method, the strategy is to split the intraclass compactness into two subspaces namely the range space and null space so as to extract two kinds of discriminant features: regular and irregular discriminant features.

$$\mathbf{T}^r = \arg\max \frac{\mathbf{tr}(\mathbf{C}_r^T \mathbf{S}_p^k \mathbf{C}_r)}{\mathbf{tr}(\mathbf{C}_r^T \mathbf{S}_c^k \mathbf{C}_r)}$$

$$\mathbf{S}_p^k \mathbf{C}_r = \lambda \mathbf{S}_c^k \mathbf{C}_r$$

$$\mathbf{U}^r = \boldsymbol{\xi}^T \mathbf{C}_r^T \mathbf{K}$$

$$\hat{\mathbf{S}_p^k} = \mathbf{C}_n^T \mathbf{S}_p^k \mathbf{C}_n$$

$$\mathbf{T}^{ir} = \arg\max \mathbf{tr}(\mathbf{C}_n^T \mathbf{S}_p^k \mathbf{C}_n) = \arg\max \mathbf{tr}(\hat{\mathbf{S}_p^k})$$

$$\mathbf{U}^{ir} = \boldsymbol{\zeta}_{ir}^t \mathbf{C}_n^t \mathbf{K}$$

$$\mathbf{U} = \begin{bmatrix} \mathbf{U}^r \\ \mathbf{U}^{ir} \end{bmatrix}$$

Discriminative Sparse Representation Model:

The objective of the discriminative sparse representation model is to integrate the representation criterion with the discriminant criterion in order to enhance the discriminative ability of the proposed method.

$$\min_{\mathbf{D},\mathbf{S}} \sum_{i=1}^{m} \{||\mathbf{u}_i - \mathbf{D}\mathbf{s}_i||^2 + \lambda ||\mathbf{s}_i||_1\} + \alpha \mathbf{tr}(\beta \hat{\mathbf{H}}_w - (1-\beta)\hat{\mathbf{H}}_b)$$
$$s.t. ||\mathbf{d}_j|| \leq 1, (j = 1, 2, ..., r)$$

EXPERIMENTS

Method	Artist Classification	Style Classification
SIFT	42.60	53.20
LBP	28.50	42.20
Color-LBP	35.00	47.00
Color-PHOG	22.80	33.20
CN-SIFT	44.10	56.70
RGBSIFT	40.30	47.40
CLBP	34.70	46.40
CN	18.10	33.30
Combined Descriptors	53.10	62.20
CNN F_3	56.40	68.57
CNN F_4	56.35	69.21
MSCNN-1	58.11	69.67
MSCNN-2	57.91	70.96
SCMFA (Proposed)	**65.78**	**73.16**

Table 1. Comparison of methods on the Painting-91 dataset.

Method	Artist Classification	Style Classification
MFA	59.57	66.79
SCMFA (Proposed)	**65.78**	**73.16**

Table 2. Comparison with marginal Fisher analysis method.

INFLUENCE CLUSTER GRAPHS

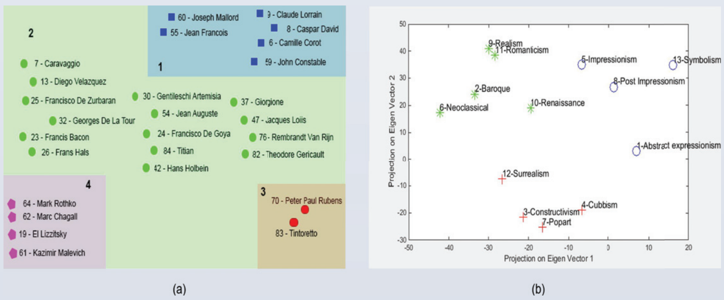

Figure 2. (a) shows the artist influence graph and (b) shows the style influence graph.

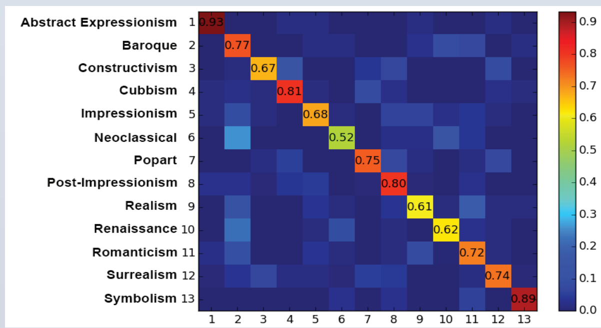

Figure 3. The confusion matrix for 13 style categories of the Painting-91 dataset.

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