Paint Loss Detection in Old Paintings by Sparse Representation Classification

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***Abstract*—In this paper, we explore the potential of sparse representation classification (SRC) in digital painting analysis, with the aim to aid the conservation/restoration treatment of old masterpieces. The focus is on detecting paint losses using multimodal acquisitions (such as optical images taken at different time instances before and during the conservation treatment, infrared images and digital radiography images). While SRC has been applied before in different scenarios, the present application requires some specific adaptations due to the nature and the size of the data, as well as the uncertainty to the labelled samples. Our initial results are very promising, compared to some more traditional or commonly used classification approaches, such as linear regression classification and support vector machines.**

I. Introduction

Digital analysis of artworks, including digital painting analysis, is a rapidly growing field, attracting an increasing interest in the signal processing community [1]. Image processing techniques have already demonstrated potential in tasks such as characterization of painting style and forgery detection [2], [3], crack detection [4] and virtual inpainting [5], [6].

In this paper, we address the problem of detecting automatically paint losses revealed during the painting conservation treatments. Loss of paint in one or more layers can arise due to abrasion and mechanical fracture. In old oil paintings, paint losses were often overpainted during various restoration campaigns. Modern conservation treatments typically require not only removal of old varnish, but also removal of old retouches and overpaint, which may reveal paint losses underneath. Detection of such paint loss areas is of great importance to painting conservators for estimating the extent of the damaged area, which needs to be maintained for documenting purposes, but also as a crucial step for virtual inpainting to provide simulations for the actual restoration. Typically, digitized scans of masterpieces are taken in different modalities, including optical imaging, infrared reflectography and radiography. Painting conservators and restorers consult these various modalities to locate more reliably various areas of interest, such as overpaint and retouching, as well as paint losses. A well designed digital signal processing method for this purpose should also be able to combine efficiently this multi-modal informaton. We do not know of any reported signal/image processing techniques that address this specific problem. Currently, painting conservators typically use some semi-automatic tools in commercial programs, which includes a lot of manual work and hence enables annotating paint losses only in relatively small areas.

Fig. 1. A detail of *Prophet Zachariah* in three modalities (left to right): infra red and macro photograph before cleaning, and the macro photograph after the cleaning. Image copyright: Ghent, Kathedrale Kerkfabriek, Luksaweb.

Technically, paint loss detection can be treated as a binary classification problem on a pixel level, assigning paint losses to a class of interest and all the rest to another class. Dictionary-based methods [7]–[14] have shown a great improvement over many popular classifiers (such as support vector machine (SVM) [15] and linear regression (LR) [16]) in many applications (*e.g.*, face recognition and iris recognition). Among the dictionary based methods, Sparse Representation Classification (SRC) [7] is attracting a lot of attention recently. While this method has been proved effective in various computer vision and remote sensing tasks, it has never been applied before to the type of problems that we are dealing with in this paper.

Before evaluating the potential of the SRC framework for paint loss detection, we need to address some specific problems: definition of the right features, dealing with extremely high spatial resolution, corrupted data samples and uncertainty to the labelled data. As a case study, we use the multimodal acquisitions of the *Ghent Altarpiece*, painted by brothers Van Eyck in the 15th century. Fig. 1 illustrates the employed imaging modalities on a piece of the panel *Prophet Zachariah*. The painting before the current conservation treatment (including the first two images from Fig. 1) can be viewed in high resolution at the website of the project *Closer to Van Eyck: Rediscovering the Ghent Altarpiece* (http://closertovaneyck.kikirpa.be/).

Fig. 2. Left to right: original image and paint loss detection results, marked in red, using linear regression classification on the visible modality alone, SVM on all the three modalities, and SRC on the same three modalities illustrated in Fig. 1.

II. Paint loss detection with SRC

Suppose there are C classes to be classified and $\mathbf{D}_i \in \mathbb{R}^{m \times n_i}(i = 1, 2, ..., C)$, are the sub-dictionaries of a shared dictionary $\mathbf{D} = [\mathbf{D}_1, \mathbf{D}_2, ..., \mathbf{D}_C] \in \mathbb{R}^{m \times n}(n = \sum_i n_i, m > n)$, where m is the data dimensionality and n_i is the number of training samples from the i-th class. In the SRC algorithm [7], each $\mathbf{D}_i$ is composed of the samples from the i-th class. For a query signal $\mathbf{y} \in \mathbb{R}^m$, its sparse vector $\boldsymbol{\alpha}$ is first obtained

$$\hat{\boldsymbol{\alpha}} = \arg\min_{\boldsymbol{\alpha}} \|\mathbf{y} - \mathbf{D}\boldsymbol{\alpha}\|_2^2 + \lambda\|\boldsymbol{\alpha}\|_1 \quad (1)$$

where $\lambda > 0$ is a parameter that controls the trade-off between reconstruction error and sparsity, and each column of $\mathbf{D}$ is normalized in ℓ_2 norm. The class is then identified as [7]:

$$identity(\mathbf{y}) = \arg\min_i \|\mathbf{y} - \mathbf{D}_i\hat{\boldsymbol{\alpha}}_i\|_2 \quad (2)$$

where $\hat{\boldsymbol{\alpha}}_i$ is the coefficient vector associated with class i.

We use the three modalities illustrated in Fig. 1 and the algorithm of [17] for registering them. Since our data are of extremely high spatial resolution, and may also be affected by scanning artefacts and noise, it would be unreliable to work with pixel-wise features alone. Therefore we make use of the local spatial information. In particular, we define our feature set as follows. Let the three registered imaging modalities make up a data cube, and refer to each of its layers as one component. Assuming raster scanning, let (j, k) denote the jth pixel in the kth component, and denote by $\mathbf{A}_{j,k} \in \mathbb{R}^{3\times3}$ a matrix of pixel intensities from a 3×3 window centred at j in the kth component. We compute a feature vector $\mathbf{y}_{j,k} = \{y_{1,j,k}, ..., y_{N,j,k}\}$ from N features extracted from $\mathbf{A}_{j,k}$. In addition to mean, variance and range, we also utilize the correlation of neighbourhood, $\mathbf{A}'\mathbf{A}$ and $\mathbf{A}\mathbf{A}'$ (the correlation between each column and each row of $\mathbf{A}$). Only six entries are picked up in the upper triangular of $\mathbf{A}'\mathbf{A}$ and $\mathbf{A}\mathbf{A}'$ to avoid repeated elements. Finally, $\mathbf{y}_{j,k}$ are stacked to produce the feature vector $\mathbf{y}_j$ for the jth spatial position.

In our problem, labelling of the training samples is extremely difficult and time consuming, and also highly prone to errors. Therefore, we run the SRC K times, each time using a different portion of the labelled data set for dictionary construction and for testing. This yields K classification results for each pixel. Let N_j^c denote the number of times that pixel j was assigned to class $c \in \{PaintLoss, Other\}$. The fraction $p_j^c = N_j^c/K$ is an empirical probability for the pixel j belonging to the class c. Hence, we finally select the identity (class) of each pixel as:

$$identity(\mathbf{y}_j) = \arg\max_c p_j^c \quad (3)$$

In practice, we obtain satisfactory results with $K = 5$.

III. Results and Discussion

Fig. 2 illustrates the results on a part of the tested panel *Prophet Zachariah*. The size of the test image is 1945×1248 pixels and all training samples (7531 pixels in paint loss areas and 31296 pixels in other areas) were sampled manually. A randomly selected half of the labelled samples are used to construct the dictionary in each run. The second left image in Fig. 2 shows the result of linear regression classification, on a single modality only (visible after cleaning) to illustrate the difficulty of the problem. Notice that some obvious paint losses were not detected, while many false detections were already made (in the lower right part of the image). The SVM classifier (Gaussian kernel) was run using the optimization toolbox in MATLAB 2015b and parameter optimization by fivefold cross-validation. A visual assessment indicates slightly better performance of SRC compared to SVM: both methods locate similarly the paint loss areas, but SVM has more false detections (see the lower and right image parts). Although very encouraging, these initial results should still be taken with a reserve. Quantitative evaluation will be subject to future work, after obtaining reliable 'ground truth' labelling.

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