

Mining the Royal Portrait Miniature for the Art Historical Context

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Abstract— the eleventh-century royal portrait miniature painting of King Gagik-Abas of Kars, Queen Goranduxt, and Princess Marem is an important image within the realm of Armenian art history. However, conflicting statements about art historical context have been drawn by human visual analysis. In this paper, we investigate a pattern classification algorithm to discover the historic context using the texture information of the art image. Specifically, our goal is using computer-aided techniques to provide the second opinion for the determination of whether the object held by the queen in the image is a silk cloth resembling the veil she wears. Experimental results showed that image data mining techniques is a possible solution to analyze the art image for interesting and useful patterns.

I. INTRODUCTION

WITHIN the realm of Armenian art history, the eleventh-century royal portrait miniature painting of King Gagik-Abas of Kars, Queen Goranduxt, and Princess

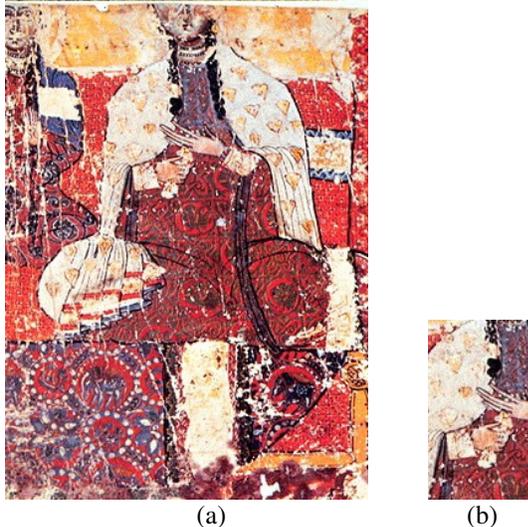


Fig 1. Image examples of the eleventh-century royal portrait miniature painting of King Gagik-Abas of Kars, Queen Goranduxt, and Princess Marem: (a) The image shows the figure “Queen Goranduxt”; (b) A sub image (cropped from (a)) shows the object held by the queen.

Manuscript received October 15, 2007, revision accepted for publication December 15, 2007

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Marem is an important image (Fig 1(a)). It is the only surviving medieval royal portrait painting of the Bagratuni dynastic family, and it provides valuable contextual information regarding the family’s visual representation as nobility in medieval Armenia. This particular family, along with its branches, was under major political and religious pressures and influences of its neighboring hegemonic powers: the Byzantine Empire and the Islamic state of the Sultanate and Muslim emirates, during the early part of the eleventh-century.

There have been several scholarly papers written about the image. While the image is in poor visual condition (as shown in Fig 1(a)) and not readily accessible to the public, there have been several studies that have identified, by human visual analysis, the texture component of image, including the costumes and interior setting. There was one object in the painting about which conflicting information had been stated in scholarly journals. While some scholars remark that the object held by the queen, which is shown in Fig 1(b), is a silk cloth resembling the veil she wears, others have been either silent about it or have provided another interpretation. Confirming the object to be cloth greatly advances other contextual theories about the painting in general and the history of the family.

Recent years have seen many applications of image analysis techniques for art image. For example, in order to show that some painters as early as 1420 used concave mirrors (and, later, converging lenses) to project real inverted images onto their supports which they then traced and painted over, D G. Stork [1] perform analyses of the reflections and shadows to infer the source(s) of illumination. Compelling evidence was obtained to support the conclusion that this source is the candle flame depicted within the painting and held by Christ. In [2], S Lyu et al. introduced an image processing technique for high-resolution digital scans of the original works to authenticate works of art, specifically paintings and drawings. In [3], the authors presented a computer-aided image analysis technique using multi-scale, multi-orientation decomposition analysis (e.g., wavelets) of high resolution digitized versions of drawings and paintings for authentication.

Hinted by the increasing popularity of computer-aided image analysis techniques in the study of art, we investigate pattern classification methods to analysis the royal portrait miniature for the art historical context. Our goal is to determine whether the object held by the queen (as shown in Fig 1.(b)) is a silk cloth resembling the veil she wears. We use texture features as our feature sets and employ both

Principal Component Analysis (PCA) [4] and Linear Discriminant Analysis (LDA) [5] for feature classification. Our preliminary results have shown that image analysis and computer vision techniques are promising methods for the study of art historical context.

The rest of the paper is organized as follows. We briefly introduce the source of the art image in Section II. Then we present our proposed approach in Section III. We show the detailed experimental results in Section IV and draw a conclusion in Section V.

II. SOURCE OF THE ART IMAGE

The miniature painting shown in Fig 1(a) and Fig 1(b) are from the early eleventh-century, suspected to have been commissioned sometime between 1045 and 1055. It was not until 1911 that the image resurfaced in an old book binding shop in Jerusalem. The miniature was cut from its original codex. It has endured much wear and mutilation from its original cut. It is presently preserved within the Gospels of King Gagik-Abas of Kars. A high resolution image is available on the California State University at Fresno, Armenian Studies Program’s Arts of Armenia website [6].

III. PROPOSED APPROACH

The overview of our method is shown in Fig 2. Given an art image, we first perform preprocessing operation. The preprocessing step includes selecting the appropriate image fragmentations and generating the sub images for training and testing. Texture feature extraction step extracts the texture features from each training and testing sub images. Features are sent to train and testing the two classifiers: PCA based classifier and LDA classifier. We present each step as below.

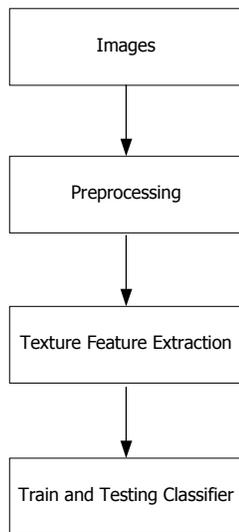


Fig 2 Overview of the proposed approach

The primary basis for our method comes from the methods used in [7]. Firstly, we take the image and convert it to

greyscale, and use the numerical intensity values of each pixel in our calculations. Images are pre-selected to have been $(2^n \text{ by } 2^n)$ pixels. We then create a pyramid from the image which contains 3 levels, the first level is $(2^n \text{ by } 2^n)$, the second level is $[2^{n-1} \text{ by } 2^{n-1}]$, and the third level is $[2^{n-2} \text{ by } 2^{n-2}]$. For each level, a one dimensional filter is applied in the horizontal direction, and then vertical direction. The filter is either a high pass filter, or a low pass filter, with the combinations of filters giving us a horizontal wavelet decomposition (high low), a vertical wavelet decomposition (low high), and a diagonal wavelet decomposition (high high). One of the benefits of wavelet decomposition is that it is a multi-scale multi-orientation approach to image analysis, which we believe will prove useful in our pattern recognition application. With this pyramid we then compute the mean, variance, skewness, and kurtosis of each decomposition at each resolution level to create our feature vector. This gives us a total of $(3 \text{ resolutions}) * (3 \text{ decompositions}) * (4 \text{ computed values}) = 36$ elements of our feature vectors.

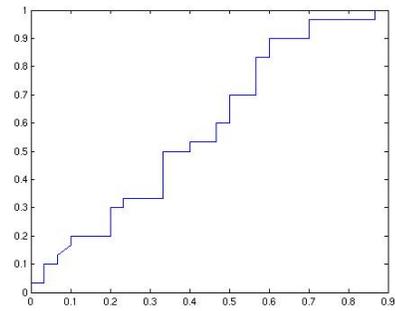
We then try to improve upon the methods used in [7], which used a distance preserving projection, by using more sophisticated and application specific techniques for dimensionality reduction. Firstly, we used Principal Component Analysis (PCA), as our method of dimensionality reduction. PCA is method of dimensionality reduction which tries to preserve the strongest correlation between high dimensional data points. The first step of principal component analysis is to normalize each the of the feature vectors so that the mean of each one is zero. Then we compute the covariance between each of the vectors being considered. In this case the vectors we used were the 36-dimensional feature vectors of each of the training images. After the covariance matrix is computed, then it is diagonalized to find the eigenvalues. We then reduce the dimensionality by considering only the features with the largest corresponding eigenvalues in our covariance matrix. For example, we reduced our vectors to having only five dimensions. So we took the eigenvectors corresponding to the five largest eigenvalues, and projected each of the training vectors into a new reduced dimensionality space. Then, we projected each of our testing vectors, the feature vectors we obtain from our testing images, into this new reduced dimensionality space, and then found the minimum and maximum distances between our test vector, and the training vectors. We also applied PCA with no dimensionality reduction, that is, we projected each of the training vectors into a 36-dimensional space using the covariance matrix, and repeated the procedure for the testing vectors. PCA is very good at taking a large set of training images from a positive class, for example, a large set of face images, and then determining whether or not any new images are in that class, if they are images of a face. In our case, the main difference between our method and existing implementation of PCA was that instead of just taking the image itself to be the high dimensional vector, we used the

feature vector from [2], and then used PCA on the feature vectors.

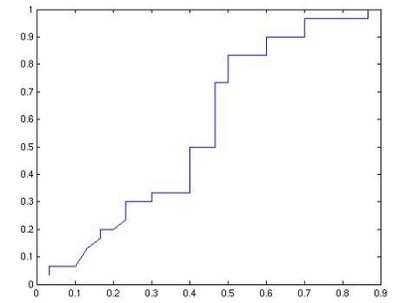
Since the positive class we consider is only a small part of the overall image, PCA was not as successful as we would have liked. Thus, we also used a second method for dimensionality reduction, Linear Discriminant Analysis (LDA), which takes multiple classes of training images and can then determine whether any new images are in one of the classes. The first step in LDA is for each of the classes, we compute the mean for each class, and the total mean of all of the training images. The classes we used for our analysis were two, the class of images belonging to the cloth pattern we were trying to identify, and those which did not belong to the cloth pattern. From this class information, we then compute the within class scatter matrix, by taking the sum over each of the j classes, of the probability for class j multiplied by the covariance matrix of class j . The covariance matrix is computed using vectors normalized with the within class mean. We then compute the between class scatter matrix, which is the sum of a new covariance matrix for each of the j classes, finding the variance between each of the mean vectors for the classes, normalized against the total mean of all the training vectors. Then, we compute the generalized eigenvectors for the between class, and within class scatter matrices. The number of eigenvectors can be at most the number of classes minus one, and since we only had two classes, there was only one generalized eigenvector found. We then projected all of our training vectors into a new reduced dimensionality space, and much like with PCA, any testing vectors are projected into the same space, and their maximum and minimum distances from the training set are computed. For the purpose of our project, we were most concerned with determining whether the object held in the queen's hand was of the same class as the cloth of her robe. The difficulty we found using LDA, is that with only two classes and thirty six features, the matrix from which we compute the eigenvectors is singular.

IV. RESULTS

For the PCA algorithm we used two sizes of training image sets, the first set of thirty six images was used so that we had a square matrix for our covariance calculations. The second set was just an extension of our original set to forty nine training images. For each of these sets, we computed the projected feature vectors, then calculated the smallest and greatest distances from any new image's projected feature vector to the training set. This was done for thirty images within the class, and thirty images outside the class, and from this information an ROC curve was computed. An ROC curve is a graph of the sensitivity versus 1 minus the specificity. The sensitivity and specificity are varied under the condition of a specified parameter. For a good method, we would like the sensitivity and specificity to be as close to one as possible. Given that our parameter varies to identify more images positively, thus increasing our sensitivity from

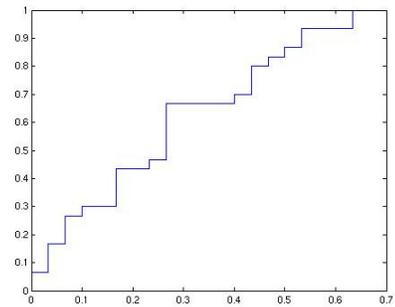


(a)

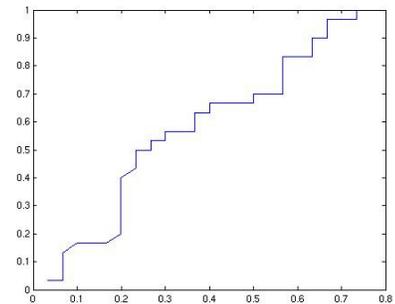


(b)

Fig 3. ROC curve of PCA analysis: (a) The ROC curve of 36 training images; (b) The ROC curve of 49 training images



(a)

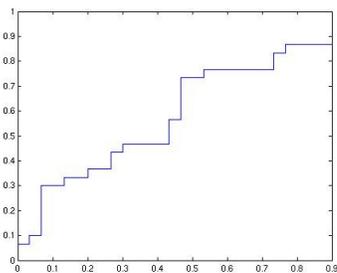


(b)

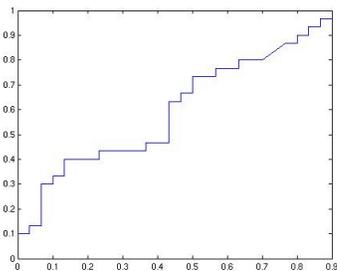
Fig 4. ROC curve of LDA analysis using 2 classes: (a) The ROC curve of 36 training images; (b) The ROC curve of 49 training images

zero to one, we would like to have less truly positive images identified as negative, which would mean having 1 minus

specificity less than the sensitivity. Overall, we can then measure the performance of our method by finding the area under the ROC, and seeing if it is close to one. In our case the parameter used for the ROC curve computation was a threshold on the maximum distance from the projected training data. In addition to using different sizes of training data, we also computed ROC curves for the PCA algorithm with thirty six principal components, and for five principal components. For the LDA algorithm, we used the original forty nine positive training images, and added to those forty nine more negative training images. The same sets of thirty positive and negative test images again had their maximum and minimum distances computed, and the ROC curve was computed using an upper threshold on the maximum distance.



(a)



(b)

Fig 5. ROC curve of LDA analysis using 5 classes: (a) The ROC curve of 36 training images; (b) The ROC curve of 49 training images

As indicated in the ROC curves (Fig 3, Fig 4, and Fig 5), the basic application of PCA or LDA did not fare well with our particular set of data. For a good ROC curve, we would like the area underneath it to be less than one half. In our curves, none of the areas are less than one half. Each method on its own has some drawbacks with the data that we used. For PCA, the fact that we had a small area from which to choose positive class images limited the amount of training data that we could use. For LDA, the small number of classes available to us, coupled with the large number of features, created a very singular matrix for our computations. Thus a natural area to explore further would be the use of a hybrid PCA / LDA algorithm for dimension reduction. Hopefully the hybrid algorithm will be able to overcome the difficulties we encountered with each method alone. Since we were unsatisfied with the identification algorithm for the first problem in the introduction, there was no exploration into the use of our algorithm for the other two problems.

V. CONCLUSION

In this paper, we introduce a vision-based image analysis technique to discover the historic context using the texture information extracted from the royal portrait miniature. Two classifiers are employed: one is based on Principal Component Analysis and the other is based on Linear Discriminant Analysis. Extensive experiments have been performed and showed that the methods we proposed have the potential to be used in mining art context. However, the performance we have achieved is not as good as we expect. In the future, we plan to explore other more sophisticated classification methods, such as Supporting Vector Machine. Using other features (such as shape descriptors) will also be considered as one of the future directions.

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