Analysis of Cypriot Icon Faces using ICA-Enhanced Active Shape Model Representation*

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ABSTRACT

Religious iconography is an integral component of the cultural heritage of Cyprus, which was once a part of the great Byzantine empire. On one hand, icons exhibit strict adherence to conventional symbols, poses and apparel. On the other hand, there is a great variety in the style of depiction that can be attributed to different schools and periods. This paper proposes an active shape model (ASM) based technique for icon face representation that can be used for style comparison and attribution. For centuries-old icons suffering from loss of paint, cracks and added noise from digitization artifacts, we apply an independent component analysis (ICA) technique to enhance the paintings' original work. The experimental results show that our method can effectively characterize Cypriot icons.

Categories and Subject Descriptors

I.4 [**Image Processing and Computer Vision**]: Enhancement, Feature Measurement (Feature Representation)

General Terms

Algorithms, Theory, Experimentation

Keywords

Cyprus, Byzantine, Iconography, Active shape model, Independent component analysis

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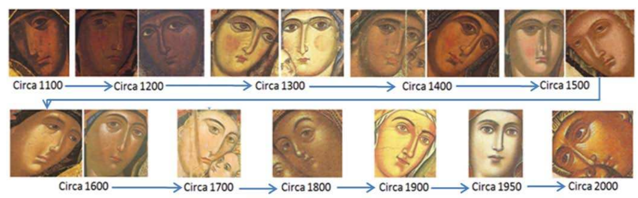

Figure 1: Style variations in the depiction of Mary

1. INTRODUCTION

Iconography is one of the most defining characteristics of the Byzantine empire seated at Constantinople from 330 AD to 1453 AD. Icons are religious artworks that depict important characters and events in the orthodox Christian belief, offering a spiritual comfort through familiarity and at the same time confirming the unchanging truths of Christianity. The constancy is a direct result of a church canon that dictated repetition and copying of subject matter, facial features and poses [3]. For example, Mary, Jesus, saints and angels are depicted with halos. Angels and some saints such as John the Baptist, are conferred wings to emphasize their role as messengers. Even specific colors are used to distinguish the different themes in icons. White color, symbolizing the unrealized essence of God, is used only to depict the resurrection and transfiguration of Jesus. Gold represents heaven while red and blue colors are used to represent divine and human life respectively. These features are ubiquitous in the surviving icons found in many European and Mediterranean countries that were once a part of the Byzantine empire.

Icons from Cyprus present one of the more challenging case-studies in Byzantine iconography. While the content of icons strictly adheres to the church canon, there are distinctive stylistic trends that can be traced to socio-political changes in the last millennium. Fig. 1 shows the faces of sixteen icons of Mary selected from different periods in Cypriot iconography. The strict Byzantine style circa 1100 is identified by ascetic or non-humanized faces. Icons are depicted in complete spiritualization emphasizing smooth lines and flat

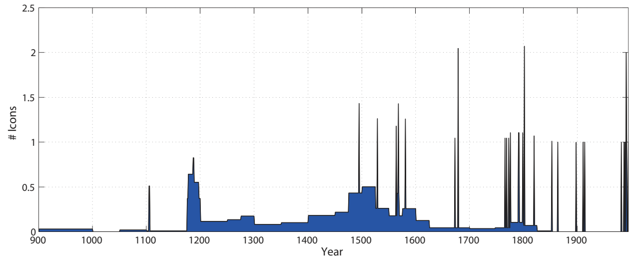

Figure 2: Temporal distribution of icon dataset

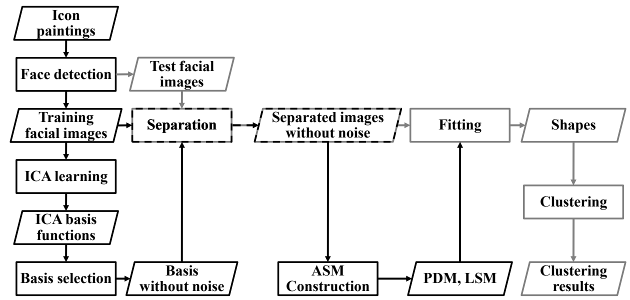

Figure 3: System flowchart

contours with careful shunning of naturalistic effects. Facial contours are accented with red, brown and black lines. The next two icons in the Comnenian style are characterized by strong accent on contours, flat clear colors and semitic features in faces. The third group of icons circa 1300 coincides with the reign of the Frankish kings. The attempt to render intense red cheeks is a noticeable characteristic from the late Comnenian period. For the next two centuries, the Venetian rulers brought a simultaneity of Latin and Christian Orthodox culture under which icon art flourished and two main factions came into existence: Italo-Byzantine (renaissance influence) and Palaeologan (conservative Byzantine). The icons circa 1400 and 1500 indicate western borrowings in the slight humanization of faces in the Italo-Byzantine style. Some 16th century icons depict seriousness in expression, large features and intense tonal gradations. After Cyprus fell to Ottoman Turks in 1571, many artists abandoned the country. A few artists developed individual styles that deviated from established schools and strict Byzantine form. The example icon circa 1800 is attributed to the school of Ioannis Kornaros, specifically to Hiermonk Charalambos. This style is characterized by round fat faces with narrow foreheads and arched eyebrows. By late 19th and early 20th century, western style of icon painting such as the Russian icon art became a major influence on Cypriot art. Icons from this period are known for their strong naturalism. Finally icons in post-independence Cyprus show a return to the strict Byzantine style similar to circa 1100.

Our collection encompasses 400 icon faces. The exact year of production is known for recent icons. Remaining icons have been analyzed by art historians and assigned to specific centuries. The plot of temporal density distribution in Fig. 2 shows the diversity of icon images. The area bounded between two years on the temporal axis (X-axis) indicates the average number of icon faces available in that time period. The spikes in the distribution (magnitude 1) correspond to paintings associated with specific production years. On the other hand, if a painting is associated with a century (such as the 12th), its density is distributed uniformly across the entire century (from 1101 to 1200). The location and style metadata is available for most icons.

1.1 Problem Definition

The problem of icon style identification and attribution is of great interest to art historians. The knowledge required to solve such inference problems is not coded in any church canon but is scholastically acquired by studying icons in detail. In this paper we propose a technique to represent and compare icons based on an automated characterization of facial features. Such tool may aid analysis of painting styles and provide an independent judgment to supplement expert opinions. The timely nature of this study may germinate many directions to preserve Cypriot cultural heritage and demonstrate the use of technology for societal good.

1.2 Related Work

The most relevant work in the analysis of Byzantine art involved automatic icon classification into categories such as Jesus, Mary, different angels and saints using explicit encoding of icon depiction rules obtained from a 16th century manual by Monk Dyonsios [8]. The rules cater to the proportions and general appearance of postures, hair and beard styles, apparel and symbols for different icons. The authors encoded these rules using Fuzzy logic, detected face components such as eyes, nose, beard, moustache and computed between-component distances and proportions. One similarity between their approach and the proposed work is the focus on facial features of icons. However, our focus is on using unsupervised techniques to identify stylistic trends not explained by color codes and written rules.

In other notable work, the research on cultural heritage spans globally. Pham conducted a style classification on Vietnamese folk paintings using color and deformable shape descriptors [7]. Classification of traditional Chinese paintings has been addressed in [6] using Brush-stroke analysis and in [5] using color, shape and texture analysis.

2. SYSTEM OVERVIEW

Centuries-old icons suffer from loss of paint and cracks. If images are obtained by scanning icon plates, artifacts such as punch holes are introduced. To handle this issue, we propose an image enhancement strategy using independent component analysis (ICA) [4]. We then apply Active Shape Model (ASM) [2] to extract facial features from ICA-enhanced icon images. As our goal is style comparison, we use a clustering approach whereby icons of different deities are grouped together if drawn in similar styles.

Fig. 3 presents the flowchart of the proposed scheme for icon face representation. The first step after acquisition of icon images is to detect faces and divide the data into train and test partitions. The training faces are processed using ICA to identify basis with maximum signal noise separation. Faces enhanced using the learned basis are input to the ASM-based feature extraction module. For the present work, we only focus on the shape information and accordingly convert color images to gray-scale. Finally, images are clustered using the extracted shape features. We now discuss the four main aspects of the system: face detection,

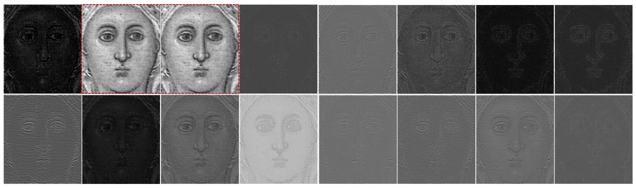

Figure 4: The separated images by 16 basis functions of ICA (contrast enhanced for illustration)

ICA decomposition and noise separation, ASM fitting, and facial feature extraction.

2.1 Face Detection

Designing icon-specific face detectors similar to Viola-Jones human face detection [9] is difficult as training requires thousands of positive samples. We have only a limited collection of faces from Cyprus, many of which are severely deteriorated. The existing detectors trained on human faces were able to detect icon faces with 65.4% precision and 29.8%. recall. Therefore, we employed manual supervision to precisely extract faces from all icon images.

2.2 ICA Decomposition and Noise Separation

The presence of noise influences local structure around facial landmarks, leading to a failure in precise feature extraction. Such noise cannot be mitigated using a conventional low-pass filter. In stead we propose an ICA-based method to get a better result. ICA is a statistical technique for decomposing a complex dataset into independent components by a linear transform. It is widely used for blind signal separation [1]. Since the basic rules of icon depiction are the same, we assume they are drawn from a blind signal source. The deterioration is treated as a noise, which we need to separate using ICA. The goal is to identify noise-free basis functions and construct ASM over enhancement of images separated by these basis functions.

To train ICA, we sampled 10,000 patches from random positions in icon face images as the training set. Each patch sample is 4×4 pixels in size, thus, we obtained 16 basis functions. An image can be decomposed into 16 components by projecting on to the subspace formed by the basis. Suppose a Cypriot icon face image is mixed by several unknown signals, it can be separated into 16 independent images as shown in Fig. 4. Using the separated images, we empirically identified projections with and without noise. For ASM construction, we choose images corresponding to the second and the third basis (the second and the third figure in the top row of Fig. 4).

2.3 ASM Construction

Originally introduced by Cootes et al.[2], ASM has been successfully applied for automatic shape extraction of deformable objects such as face, hand, and vertebra. Compared to the active contour models or snakes, ASM adds considerable variability to structure representation.

For point distribution models of ASM (PDM), we manually selected 44 landmark points (as shown in Fig. 5) to represent the shape of each Cypriot icon face. To reduce the influence of noise, each image of the training set is projected onto the 2^{nd} and the 3^{rd} basis of the ICA basis functions. The projected images are combined into a single image by overlapping and intensity normalization. Further, the combination is smoothed using a low pass filter. Resulting relatively noise-free images are used to train local structure models (LSM). One limitation of our approach is that the shape model does not handle large pose variations (tilted faces of some icons). We propose to remedy this issue by training additional shape models for different poses.

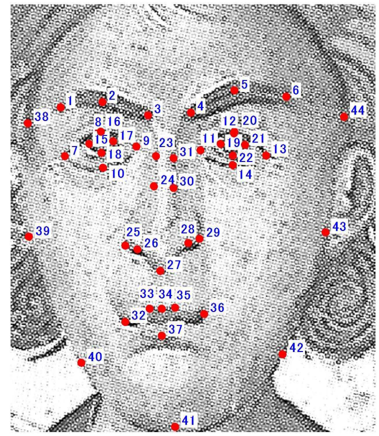

Figure 5: The 44 facial landmarks

2.4 Facial Feature Representation

Two types of representations can be extracted from active shape models. The x, y locations of landmarks are concatenated into a Type-1 representation. Since each face is represented by 44 landmarks, the dimension of a shape vector is 88. In order to reduce the influence of pose variations, shape features are normalized by Generalized Procrustes Analysis (GPA) [2]. This approach helps align shapes by minimizing the sum of distances of each of the N shapes from the mean.

An alternate Type-2 feature representation can be computed by modeling the inner distances of all landmarks from a fixed landmark. As shown in Fig. 5, the point of the nose needle (the point of No. 27) is selected as a reference point and its distance from each of the remaining 43 points is concatenated into a feature vector. These distances represent local shape composition. The local shape feature of the i^{th} face can be denoted as a 43 dimensional vector: $\mathbf{d}_i = \left[d_1^i, d_2^i, \cdots, d_{43}^i\right]$, and normalized to account for size variations as: $\hat{\mathbf{d}}_i = \mathbf{d}_i / \sqrt{\mathbf{d}_i{}^T \mathbf{d}_i}$.

3. EXPERIMENTAL RESULTS

To limit the complexity introduced by large pose or viewpoint variation, we performed pilot experiments on frontal icon faces. A number of images suffering from heavy noise, low resolution and missing facial features were not included. Image sizes were normalized to 640×640 pixels.

3.1 Automatic Shape Extraction by ASM

We used a leave-one-out strategy to learn active shape models. In each setting, one image is used to test the model learned over the remaining images. The manually marked landmarks of a test image were not included in training but used as the ground truth for performance assessment. To determine the number of modes in point distribution models, the fraction of total variation is kept at 95%. The aver-

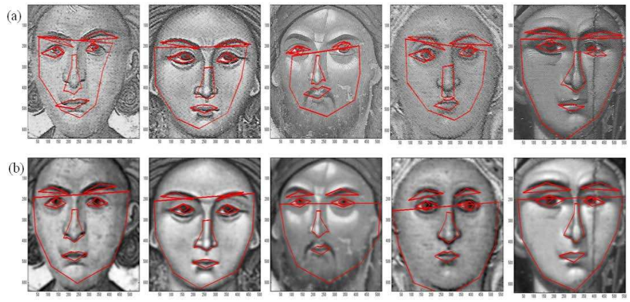

Figure 6: Fitting results by (a) conventional ASM and (b) proposed ASM with ICA

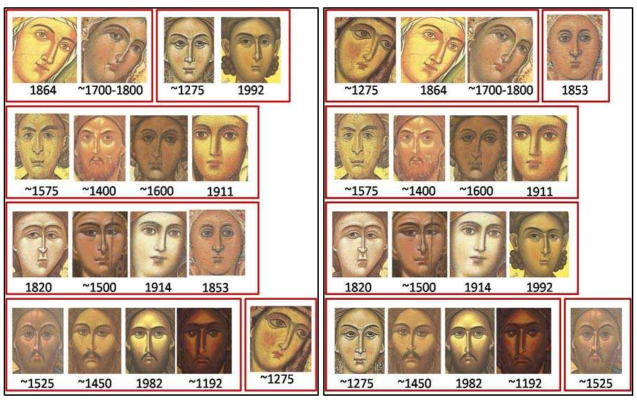

Figure 7: Clustering icons with Type-1 features (left) and with Type-2 features (right)

age mean square error (MSE) from our implementation is only 11.85% of that obtained from the conventional ASM (average MSE 440.84). Fig. 6 compares the sample results of automatic shape extraction obtained using conventional ASM and the proposed approach with ICA. It is seen that our method is significantly more accurate in locating and correctly annotating the required facial landmarks.

3.2 Clustering Icons with Style Similarity

We clustered the facial features of icons using the K-means algorithm. Fig. 7 shows the resultant groupings computed on Type-1 (GPA-normalized location features) and Type-2 features (inner distances from nose point) respectively.

Qualitative observations indicate that the Type-1 features yield more reasonable groupings as compared to the Type-2 features. The groupings also show a promising ability to draw parallels across different periods of the Cypriot art and by extension of the Byzantine art. Consider cluster 5 in both types of clustering results in Fig. 7. The last two icons from circa 1982 and 1192 respectively, are both drawn in the style of strict Byzantine. This is a purely computational support to art historians' belief that post-independence, the icon art in Cyprus returned to the traditional Byzantine art. Also, the first two images in the third clusters show icons of Saint Timon ($\sim$1575) and Jesus Christ ($\sim$1400) drawn in the Palaeologan style. These examples demonstrate how techniques for image analysis can be used to match an unknown icon to other icons with known metadata and automatically infer the attributes of the unknown icon.

4. CONCLUSION

Cypriot icons present an intriguing case study of cultural heritage. We presented a scheme for icon face representation using active shape model. Shape models for frontal poses were learned using icon images enhanced with independent component analysis. The experimental results showed that the adapted ASM method exceeds the conventional ASM approach in representing noisy Cypriot icons. Two types of facial features were constructed and used to group icons of similar styles. Overall, we find that the present research direction holds great promise in analyzing icons. This system can be extended to Byzantine art from other regions. One major task for future work is to systematically evaluate icon groupings with the help of art historians.

5. ACKNOWLEDGMENTS

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