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LEVERAGING COMPUTERIZED FACE RECOGNITION FOR IDENTIFYING RENAISSANCE PORTRAIT ARTS

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Abstract: In this work, we explore the feasibility of face recognition technologies for analyzing works of portraiture, and in the process provide a quantitative source of evidence to art historians in answering many of their ambiguities concerning identity of the subject in some portraits and in understanding artists' styles. Works of portrait art bear the mark of visual interpretation of the artist. Moreover, the number of samples available to model these effects is often limited. Based on an understanding of artistic conventions, we show how to learn and validate features that are robust in distinguishing subjects in portraits (sitters) and that are also capable of characterizing an individual artist's style. This can be used to learn a feature space called Portrait Feature Space (PFS) that is representative of quantitative measures of similarities between portrait pairs known to represent same/different sitters. Through statistical hypothesis tests we analyze uncertain portraits against known identities and explain the significance of the results from an art historian's perspective. Results are shown on our data consisting of over 270 portraits belonging largely to the Renaissance era

1. INTRODUCTION

Face recognition is one of the major issues in biometric technology. It identifies and/or verifies a person by using 2D/3D physical characteristics of the face images. The baseline method of face recognition system is the eigenface by which the goal of the eigenface method is to project linearly the image space onto the feature space which has less dimensionality. One can reconstruct a face image by using only a few eigenvectors which correspond to the largest eigenvalues, known as eigenpicture, eigenface, Karhunen- Loeve transform and principal component analysis ,Several techniques have been proposed for solving a major problem in face recognition such as fisher face , elastic bunch graph matching and support vector machine. However, there are still many challenge problems in face recognition system such as facial expressions, pose variations, occlusion and illumination change. Those variations dramatically degrade the performance of face recognition system. It is evident that illumination variation is the most impact of the changes in appearance of the face images because of its fluctuation by increasing or decreasing the intensities of face images due to shadow cast given by different light source direction. Therefore the one of key success is to increase the robustness of face representation against these variations.

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In order to reduce the illumination variation, many literatures have been proposed. Belhumeur et. al.suggested that discarding the three most significant principal components can reduce the illumination variation in the face images. Nevertheless, the three most significant principal components not only contain illumination variations but also some useful information, therefore, the system was also degraded as well. Wang et. al. proposed a Self Quotient Image (SQI) by using only single image. The SQI was obtained by using the weighted Gaussian function as a smoothing kernel function. The Total Variation Quotient Image (TVQI) and Logarithmic Quotient Image (LTV) have been proposed by which the face image was decomposed into a small scale (texture) and large scale (cartoon) images. The normalized image was obtained by dividing the original image with the large scale one. The TVQI and LTV has a very high computational complexity due to the second order cone programming as their kernel function.

2. LITURE SURVEY

We present a system for recognizing human faces from single images out of a large database with one image per person. The task is difficult because of image variation in terms of position, size, expression, and pose. The system collapses most of this variance by extracting concise face descriptions in the form of image graphs. In these,ducial points on the face (eyes, mouth etc.) are described by sets of wavelet components (jets). Image graph extraction is based on a novel approach, the bunch graph, which is constructed from a small set of sample image graphs. Recognition is based on a straight-forward comparison of image graphs. We report recognition experiments on the FERET database and the Bochum database, including recognition across pose

The human face conveys to other human beings, and potentially to computer systems, information such as identity, intentions, emotional and health states, attractiveness, age, gender and ethnicity. In most cases analyzing this information involves the computer science as well as the human and medical sciences. The most studied multidisciplinary problems are analyzing emotions, estimating age and modeling aging effects. An emerging area is the analysis of human attractiveness. The purpose of this paper is to survey recent research on the computer analysis of human beauty. First we present results in human sciences and medicine pointing to a largely shared and data-driven perception of attractiveness, which is a rationale of computer beauty analysis. After discussing practical application areas, we survey current studies on the automatic analysis of facial attractiveness aimed at: (i) relating attractiveness to particular facial features; (ii) assessing attractiveness automatically; (iii) improving the attractiveness of 2D or 3D face images. Finally we discuss open problems and possible lines of research.

3. EXISTING SYSTEM

Local Binary Patterns (LBP) is a type of feature used for classification in computer vision. LBP was first described in 1996.[1] It has since been found to be a powerful feature for texture classification; it has further been determined that when LBP is

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combined with the Histogram of oriented gradients (HOG) classifier, it yields the best classifier of humans (i.e. person vs. non-person) among the classifiers usually considered in academic literature

The LBP feature vector, in its simplest form, is created in the following manner:

- Divide the examined window to cells (e.g. 16x16 pixels for each cell).
- For each pixel in a cell, compare the pixel to each of its 8 neighbors (on its left-top, left-middle, left-bottom, right-top, etc.). Follow the pixels along a circle, i.e. clockwise or counter-clockwise.
- Where the center pixel's value is greater than the neighbor, write "1". Otherwise, write "0". This gives an 8-digit binary number (which is usually converted to decimal for convenience).
- Compute the histogram, over the cell, of the frequency of each "number" occurring (i.e., each combination of which pixels are smaller and which are greater than the center).
- Optionally normalize the histogram.
- Concatenate normalized histograms of all cells. This gives the feature vector for the window.

The feature vector now can be processed using the Support vector machine or some other machine-learning algorithm, to produce a classifier.

4. PROPOSED SYSTEM

Renaissance portraits were depictions of some important people of those times. These encompass a wide range of art works such as sculptures, death masks, mosaics, etc. Apart from being used for a variety of dynastic and commemorative purposes, they were used to depict individuals often to convey an aura of power, beauty or other abstract qualities [1]. A large number of these portraits, however, have lost the identities of their subjects through the fortunes of time. Analysis of faces in portraits can offer significant insights into the personality, social standing, etc. Of the subject they represent. However, this is not a simple task since a portrait can be “subject to social and artistic conventions that construct the sitter as a type of their time” [1], thus resulting in large uncertainty regarding the identity of many of these portraits. Traditionally, identification of many of these portraits has been limited to personal opinion, which is often quite variable. The project *FACES* (*F*aces, *A*rt, and *C*omputerized *E*valuation *S*ystems) was conceptualized to evaluate the application of face recognition technology to portrait art and in turn aid art historians by providing a quantitative source of evidence to help answer questions regarding subject identity and artists’ styles. This paper will describe the challenges inherent in face recognition in art images, and summarize the results obtained in this project over the last two years

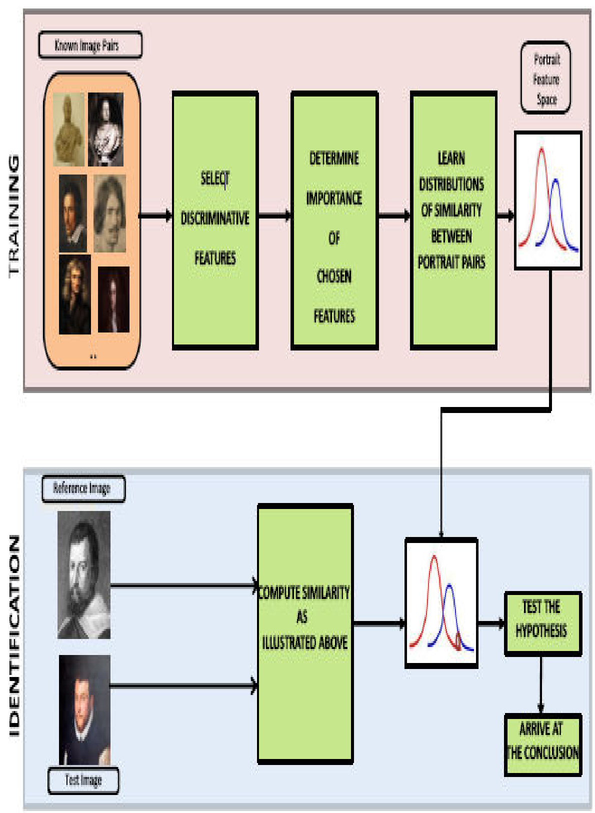


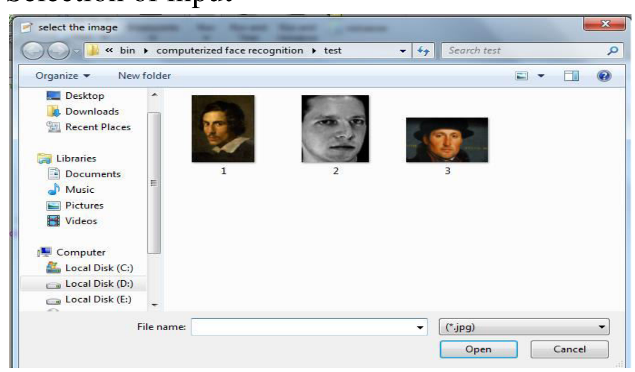
Fig. 1. Illustration of the training (top) and identification framework (bottom)

Some preliminary results have been presented in

we leverage upon a number of portrait pairs that are *known* to represent a certain person as shown in top part of Fig.1. The task then is to train the computer in identifying discriminative features that can not only distinguish one sitter from another, but also learn the importance of the chosen features depending on the amount of emphasis given to that feature by an artist. Using the learned features, quanti- tative measures of similarity between portrait pairs known to represent the same person can be computed to yield what we call "match scores". Analogously, similarity scores between portrait pairs not known to represent the same person yield "non-match scores". The resulting match (blue curve) and non-match scores (red curve) together constitute what we refer to as the Portrait Feature Space (PFS). Subsequently, using hypothesis tests, the similarity score between test and reference image, as shown by the brown ball in bottom part of Fig.1, is analyzed with respect to the learned PFS to arrive at appropriate conclusions of a possible match or non-match. If both match or non-match happen to be likely, then no decision can be made.

5. RESULTS

Selection of input



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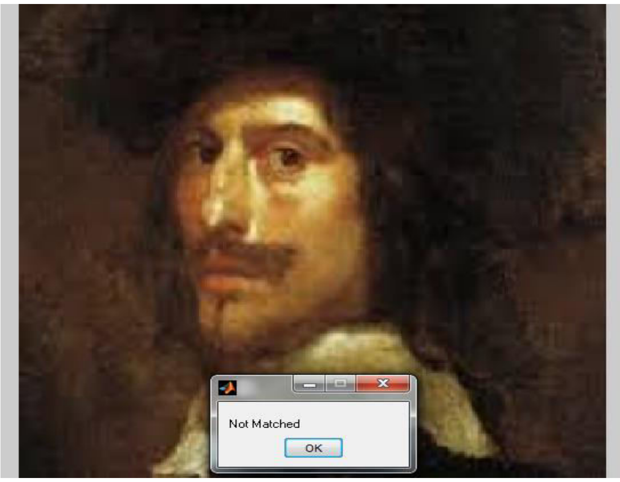
Output



6. CONCLUSION

We presented a work that explores the feasibility of computer based face analysis for portraiture. After a careful understanding of artistic conventions, we arrived at relevant features for analysis. Subsequently, using machine learning tools, we learned a feature space describing the distribution of similarity scores for cases known to match/not match and also validated the same. We proposed a novel method to model artists' styles and to analyze uncertain portrait pairs. We believe that these results can serve as a source of complementary evidence to the art historians in addressing questions such as verifying authenticity, recognition of uncertain subjects, etc. As future work, we would like to explore modeling age variations inportraits and building family trees of artists/sitter

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