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A Hybrid Model for Photographic Supra-Projection

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Abstract— Photographic supra-projection (CS) comes under forensic process in which video shots or photographs of a missing person are compared against the skull that is found. By projecting both photographs on top of each other (or, even better, matching a scanned 3-D skull model against the face photo/video shot), the forensic anthropologist can try to ascertain whether it is the same person. The overall process is affected by inherent uncertainty, mostly because two objects of different nature (a face and a skull) are involved. In this paper, we extended existing evolutionary-algorithm-based techniques to automatically superimpose the 3-D skull model and the 2-D face photo with the aim to overcome the limitations that are associated with the different sources of uncertainty, which are present in the problem. Three different approaches to handle the imprecision will be proposed: Viola- Jones Face Detection Framework, Canonical Correlation Analysis and Inverse Compositional Active Appearance Model.

Keywords—*Photographic Supra-projection, Canonical Correlation Analysis(CCA), Skull Identification, Viola-JonesFace Detection Framework, ICAAM.*

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I. INTRODUCTION

In recent years, Forensic anthropology is best conceptualized more broadly as a part of forensic assessment of human skeletonized remains and their environments. This assessment includes both the identification of the victims physical characteristics and cause and manner of death from the skeleton. This way, the most important application of forensic anthropology is the identification of human beings from their skeletal remains[3]. The 2D-3D face matching method decreased the computation complexity drastically compared to the conventional 3D-3D face matching while keeping relative high recognition rate. Furthermore, to simplify the mapping between 2D face image and 3D face data, a patch based strategy is proposed to boost the accuracy of matching [4]. The experiment results show that CCA based method has good performance and patch based method has significant improvement compared to the holistic method.

In the last decades, numerous skull identification techniques have been stated, Most of them are based on the 2D appearance and thus susceptible to the varying illumination and pose. Because the geometry of faces is independent of the illumination and pose, 3D face recognition has the prospective to improve performance under the unmanaged conditions. Some 3D skull recognition algorithms have been proposed and very high recognition rates are reported [6]. However, due to the computational complexity, expensive equipment and fussy pretreatment, 3D technology is still not used widely in practical applications. Generally 3D face recognition systems require that probe and gallery set are both 3D data. However, in some application, there are only 2D images available for recognition (assuming the enrollment is done), such as the low resolution mugshot on I-card or the snapshot taken by video surveillance camera The conventional 3D skull recognition system cannot work under these situation[4]. The second disadvantage of the 3D skull recognition system lies in its 3D data acquisition equipment. To acquire the accurate 3D face and skull data, some very costly equipment must be used, such as 3D laser scan or stereo camera system. They are not as stable and efficient as 2D cameras, and for some cases like the stereo camera system, calibration is needed before use. Moreover, both of them will take a longer time to acquire (or reconstruct) the 3D face data compared with the 2D camera only taking the 2D images. Besides, in some applications there is not so much time to capture user’s 3D face or skull data on-site, such as airport access control or E-passport. Respecting these facts, 3D face recognition is still not as applicable as 2D face recognition [4].

In order to overcome the restricts of 3D face detection system while reserve its advantages, we can use 2D face image as probe and 3D face data as gallery. In this paper, we introduce a learning based method to match 2D probe against 3D gallery. From an intuitive viewpoint, we could find a very exciting relationship between 2D face image and 3D face data [4]. Different 2D face images from one person (i.e. the faces under different illuminations) will always correspond to the same 3D face shape. However, different face shapes could never match with the same face image, which indicates the mapping between the 2D face image and 3D face shape is actually a many-to-one problem. Based on this mapping, Lei et al propose to recovery the 3D face shape from one single 2D face image. Therefore, once we find the mapping between 2D face images and 3D face shapes, matching between 2D probe and 3D gallery will be achieved.

The rest of the paper is organized as follows: In Section II, The hybrid framework for face and skull matching is presented. In Section III, the required experimental setup is stated. Section IV describes the experimental results whereas section V explains the comparative result analysis and lastly section VI summarize this paper .

II. PROPOSED METHODOLOGY

The automatic recognition of an unknown skull against a gallery of facial images of missing persons is a difficult task. There is uncertainty associated with the soft-tissue of the deceased and information regarding the imaging conditions of the gallery will be imperfect [9]. To our knowledge this type of automatic recognition has never been accomplished. In this paper we seek evidence that the task of automatic recognition is achievable. Our approach starts by taking advantage of the fact that each reconstruction is structurally identical. Landmark positions in the images can then be associated with specific points on the reconstructions. Such image landmarks are found using Active Appearance Models (AAM). The task at hand is to determine whether or not a given set of reconstruction and image landmarks constitutes a match [11]. Two approaches are considered. In the first method, constrained optimization based on the landmark positions with the least amount of soft-tissue variance is used to determine a projective transformation between the 3D reconstruction and the 2D image. Projection residuals are then calculated providing a ranking of the missing person image [3]. In the second approach, boosting is used to construct a strong match/no-match classier [13]. In this way we learn which landmarks are both reliable and discriminating.

The training phase will be carried out through Viola-Jones Face detection Framework and the Identification phase will be performed through Canonical Correlation Analysis to identify an unknown skull for the shape parameter features of the training skulls and face skins, obtaining the two basis vectors, w_x and w_y.

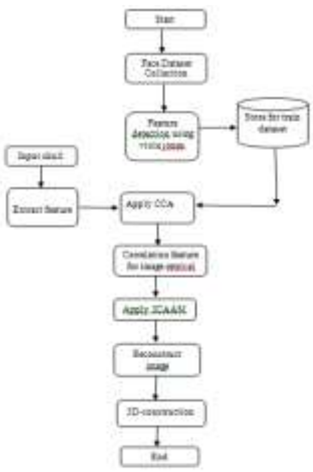

Figure 1: System Architecture.

A. *Extracting parameters from Face and Skull Images through Viola-Jones.*

The Viola–Jones object detection framework is the first object detection framework to provide competitive object detection rates in real-time proposed in 2001 by Paul Viola and Michael Jones[20]. This algorithm should be capable of functioning in an unconstrained environment meaning that it should detect all visible faces in any conceivable image. In order to ease the task Viola-Jones limit themselves to full view frontal upright faces. That is, in order to be detected the entire face must point towards the camera and it should not be tilted to any side. The algorithm has mainly 4 stages:

1. Haar Features Selection given as-

   $h_t(x) = h(x, f_t, p_t, \theta_t)$ where f_t, p_t, θ_t are the minimizers

2. Creating Integral Image-

   Sum of grey rectangle = D – (B + C) + A

3. Adaboost Training algorithm-

   For selecting weak classifier by calculating weighted error as

$$h(x, f, p, \theta) = \begin{cases} 1 & if \quad pf(x) > p\theta \\ 0 & otherwise \end{cases}$$

   and converting it into strong classifier

$$C(x) = \begin{cases} 1 \; if \; \sum_{t=1}^{T} \alpha_t h_t(x) \geq \frac{1}{2} \sum_{t=1}^{T} \alpha_t \\ 0 \quad Otherwise \end{cases}$$

4. Cascaded Classifiers-

   To discard the non-face and retain the face only

B. *Correlating Extracted Features through CCA.*

In statistics, canonical-correlation analysis (CCA) is a way of making sense of cross-covariance matrices. If we have two vectors X = (X1, …, Xn) and Y = (Y1, …, Ym) of random variables, and there are correlations among the variables, then canonical-correlation analysis will find linear combinations of the Xi and Yj which have maximum correlation with each other. Here we are taking two sets as one for face representation and other for skull, as we minimizes the distance between X1 and Y1 mutually the angle between X and Y get minimizes but inversely the correlation between them get maximizes. Following fig. will describe it more clearly:

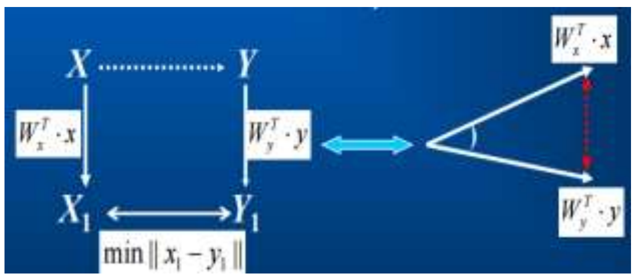

Figure 2: Maximizing Correlation between X & Y via CCA.

Where correlation range is decided depending upon the value
of correlation coefficient calculated as-

$$\rho = \frac{E[xy]}{\sqrt{E[x^2]E[y^2]}} = \frac{E[\hat{w}_x^T]xy^T\hat{w}_y]}{\sqrt{E[\hat{w}_x^T XX^T\hat{w}_x]E[W_y^T YY^T\hat{w}_y]}}$$

C. Implementing ICAAM for Multi-Variant Faces.

Active Appearance Models (AAMs) and the closely related concepts of Morphable Models and Active Blobs are generative models of a certain visual phenomenon[18]. Although linear in both shape and appearance, overall, AAMs are nonlinear parametric models in terms of the pixel intensities. The most frequent application of AAMs to date has been face modeling. However, AAMs may be useful for other phenomena too. In a typical application, the first step is to fit the AAM to an input image, i.e. model parameters are found to maximize the “match” between the model instance and the input image. The model parameters are then used in whatever the application is. For example, the parameters could be passed to a classifier to yield a face recognition algorithm. Many different classification tasks are possible. Fitting an AAM to an image is a non-linear optimization problem. The usual approach is to iteratively solve for incremental additive updates to the parameters (the shape and appearance coefficients).

In this module, the 3D shape of the object and the geometry of the camera are added as part of the minimizing parameters of the AAM algorithm in order to determine the full 6 degree-of-freedom (DOF) pose of the object. This work is a twofold, major improvement of our previous work: First by applying the inverse compositional algorithm to the image alignment phase; and second, by incorporating the image gradient information into the same image alignment formulation. Both improvements make the method not only more time efficient, but they also increase the tracking accuracy, especially when the object is not rich in texture.

III. MATERIAL

The faces were taken from the standard database such that it should be also compatible for inverse compositional AAM. Some example of faces and skull are shown in following Figures.

Figure 3: Database of Frontal Faces.

Figure 4: Database of Frontal image of Skull.

Figure 5: Multi-variant Database for ICAAM

IV. EXPERIMENTAL RESULTS

By performing the implementation of the above research work, we have detected the required features i.e. eyes, nose, mouth, profile with the help of Viola-Jones and then extracted by considering the pixel values enclosed inside the highlighted region and are stored into separate databases. In order to maximize the matching accuracy you may work on additional features like forehead, jawbone etc. so that the entire face parameters can independently be correlated [1].

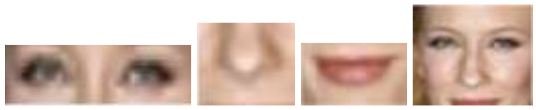

Figure 6: Detecting Face features through Viola-Jones and Extraction.

Similar task will be carried out with the skull images for determining its various physiological features.

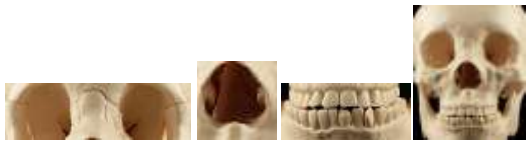

Figure 7: Detecting Skull features through Viola-Jones and Extraction.

Further these features are correlated with each other with the help of Canonical Correlation Analysis [4]. The Canonical Correlation Analysis will evaluate each combination by generating the Correlation Coefficient and the final match will be made after getting the highest possible value thereby decides whether it fall in one of the four categories i.e best, better, good or poor. Based on these results the top five images will be retrieved and only one

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amongst them will be displayed as the best match whoever having the highest correlation. Following is the example:

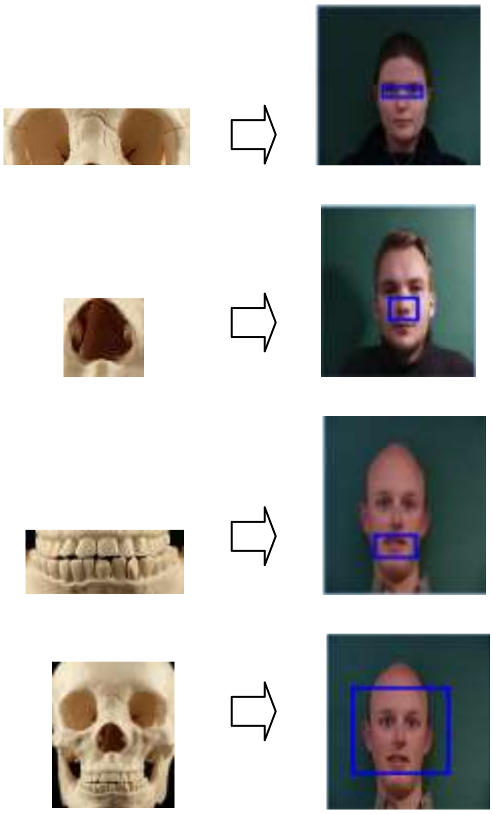


Figure 8: Representing the Face image having highest correlation with extracted eyes of skull.

simultaneously for each result inverse compositional active appearance model employed over it to form a mesh on face for multi-view faces.

Figure 9: ICAAM on resultant Image for Profile after correlation.

Respectively all of the maximum match for various physiological regions will be collected for the described features of skull and lastly we need to merge them all together to form a simple morph.

Figure 10: Mounting of Correlated Feature on resultant Face Profile.

After this the above image is processed with the FaceGen Modeller for Morphing, here we have to locate 11 points on face as shown in fig.

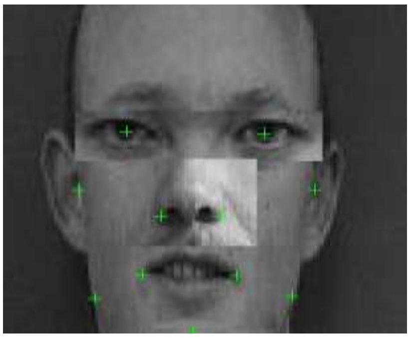


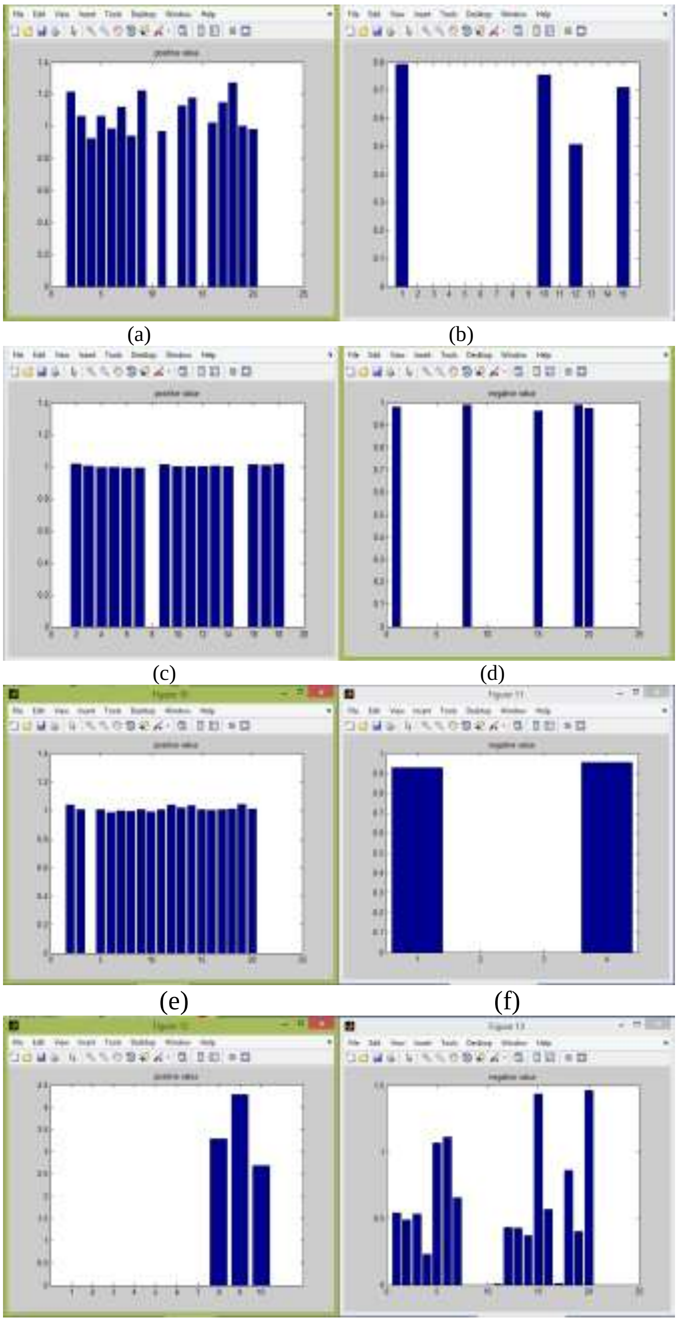
Figure 11: Locating 11 feature points for Morphology via FaceGen Modeller.

At last we can perform smoothing with the help of Detail Texture Modulation and Texture Gamma Correction to form the final face which will be resemble to skull given as an input at the start.

Figure 12: Smoothing the final Reconstructed Face.

V. RESULT ANALYSIS

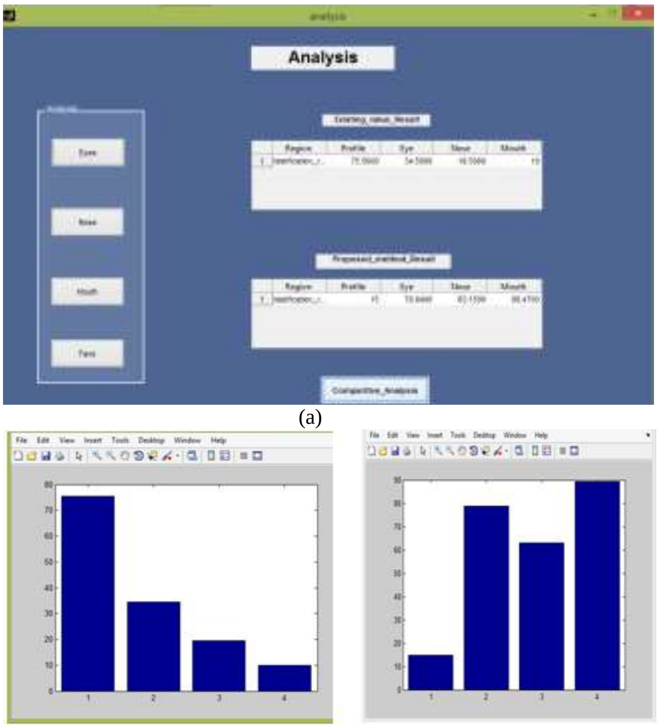
Following results shows the accuracy for each four Feature, depending upon the value of correlation coefficient, whose mean gets calculated and then the probability for each value is decided, further the support is generated and the result which is above the threshold value is sorted as a valid or invalid example i.e. positive or negative.



(a) (b) (c) (d) (e) (f) (g) (h)

Figure 13: (a), (b), (c), (d), (e), (f), (g), (h) represents Positive and Negative responses for Proposed method for Eyes, Nose, Mouth & Profile Respectively.

Following fig. 14. shows the comparative analysis between our proposed methodology and the existing techniques which shows the better responses for eyes, nose and mouth.



(a) (b) (c)

Figure 14: (a) shows outcome values of existing and proposed methods. (b), (c) shows Comparative Analysis of Proposed method with existing methods.

VI. CONCLUSION

A wide variety of researches have been made on Skull Identification. Every work has its own technique, some contribution have limitations also. As in the Classical approach techniques, it becomes challenging when skulls of persons damaged badly to recognize face with better accuracy or it is very time consuming and expensive process when we tried to gather the required data through digitization technologies. Thus after comparatively analyzing all the the schemes we have chosen this hybrid combination of Viola-Jones, CCA and ICAAM for better output and the results obtained confirms that we have achieved far better Identification Ratio for Eyes, Nose and Mouth. In addition to this, we are focusing on 3D geometry of an object achieved by inverse composition of each image so that the proposed method should be applicable for multi-variate faces too and then morphing over it with efficient image processing tool for revealing its identity which will definitely come out as an efficient technique in future.

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