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Contrasting various Skull Identification Schemes: A Review

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Abstract— One of the most noticeable disciplines in forensic medicine is human identification. When this task is done by reviewing the skeleton remains, we refer to the area of Forensic Anthropology. Over the past few decades, anthropologists have pays their attention on improving those techniques that allow a more precise identification. Hence, Forensic Identification has become a very active research area & Skull identification has been emerging as an vital field in this discipline. The existing methodologies rely essentially on the accurate abstraction and depiction of the intrinsic relationship between the skull and face in terms of the morphology, which still remain unresolved. They have high ambiguity and a low identification capability. Thus we are establishing this technique with the help of CCA (Canonical Correlation Analysis) & ICAAM (Inverse Compositional Active Appearance Model) which in which model parameters are institute to maximize the "match" among the input image and the model instance. Then the model parameters are used in any application. For example, the parameters might get delivered to a classifier to yield a face recognition algorithm. Moreover we are focusing on 3D face models reconstructed from 2D face photos, by this way non-intrusive 3D face data capture will become readily available and cost proficient; the construction of huge 3D face databases will be feasible in the field of communal security. The suggested technique will surely come into an extensive application.

Keywords— Canonical Correlation Analysis (CCA), Inverse Compositional Active Appearance Model (ICAAM), Forensic Anthropology, Morphology, Skull Identification, Forensic facial reconstruction.

INTRODUCTION

Forensic facial reconstruction is the art of regenerating the face of an unknown individual from their skeletal remains through the combination of artistry, forensic science, anthropology, osteology, and anatomy. It is one of the most subjective as well as most controversial technique in the field of Forensic Anthropology. Skull Identification has drawn wide attention and been applied in huge number of forensic cases, ranging from the identification of victims of the Indian Ocean tsunami [1], Uttarakhand disaster to the identification of terrorists. Skull identification technique is far different than the various techniques which are based on biological features like DNA Fingerprinting.

However, due to the computational complexity, expensive equipment and fussy pretreatment, 3D technology is yet not used widely in practical applications. Generally, 3D face recognition systems require that probe and gallery set are both 3D face 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 ID card or the snapshot captured by video surveillance camera. The conventional 3D face recognition system cannot work under these circumstances. The second disadvantage of the 3D face recognition system lies in its 3D data acquisi-tion equipment. To procure the accurate 3D face data, some very pricy equipment must be used, like 3D laser scan or stereo camera system. These techniques are not as even and proficient as 2D cameras, and for some cases such as the stereo camera system, standardization is needed before use. Moreover, both of them will take a longer time to obtain (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 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.

This paper is organized as follows: Various Schemes and Literature survey are discussed in section I, proposed scheme is discussed in section II, comparative analysis of different schemes is conducted in section III and section IV gives the conclusion.

I. REVIEW OF LITERATURE

This section describes the various existing schemes which are compared in this paper [10][15-18].

Anthropometric Information.

It is an approach that modifies the existing multiresolution scheme to locate the face in an image. After the face is located successfully, the 2-D position of feature points can be obtained and then the 3-D facial model can be estimated. Since only front-view facial image is required for model synthesis, we do not need two cameras simultaneously and the "pre-processing stage." All it need is for the subject to sit right in front of the camera for front-view facial image capturing that is available in many applications, such as news broadcasting or video conferencing. Firstly it randomly select ten front-view facial images from the database to construct facial templates. These images are face-only and each is appropriately resized and aligned to encompass facial regions ranging from upper eyebrow to lower lips & then average these ten facial images to obtain a level-0 facial template (size 256*256).

Kernel Canonical Correlation Analysis (KCCA).

They manually situate 34 points as landmark from each facial image and then transfer these geometric points into a label edge graph (LG) vector with the help of Gabor wavelet transformation to represent the facial features. While for training every facial image, the semantic ratings explaining the basic expressions are grouped into a six-dimensional semantic expression vector. KCCA is a nonlinear extension of CCA via the "kernel trick" to overcome the singularity problem of the Gram matrix by simply adding a regularization to the Gram matrix such that the Gram matrix becomes invertible. Theoretical optimality of canonical vectors can only be guaranteed via complete bases. Computationally this leads to the problem of estimating the dimensions of the effective feature spaces by looking at the eigenspectra of the kernel Gramians during the computation of KCCA.

Face Matching using Volumetric Data.

The customary manual method for regenerating a face is to reconstruct the head using a cast of the identified skull as a basis. It requires an skillful knowledge of anatomy as well as artistic cleverness. This method recognizes skull which is to be scanned by a CT scanner to gather volumetric data. A reference head is chosen that has the equal sex, racial and age characteristics as the recognized skull & a correspondence is created between the two heads, and through this the soft tissue from the reference head is profiled onto the discovered skull giving a candidate face for the unknown person. the most significant being the fact in this method is that the reconstruction is based upon one view in the direction of the viewing angle, which causes some tissue such as the ears not be be reconstructed, removing this restriction has implications for several stages of the pipeline [18].

Weighted and Fuzzy-Set-theory-based landmarks.

It is a method based on an evolutionary algorithm which superimposes automatically the 2-D face photo and the 3-D skull model with the aim to conquer the drawback that are related to the various sources of uncertainty, which are currently in the problem. Completely two different approaches to solve the imprecision are proposed, which are fuzzy-set-theory-based and weighted landmarks [9].

Craniofacial Superimposition & Craniofacial Reconstruction.

Craniofacial superimposition is a practice that leads to recognize a person by overlaying a photograph and a copy of the skull. This technique is geneally carried out physically by forensic anthropologists; thus being very lengthy, time consuming and showing several difficulties in finding a proper fit among the 3D model of skull and the 2D face photo.Hence Craniofacial Reconstruction becomes quite tedious when performed through superimposition. It mainly uses Principle component analysis (PCA) is a powerful tool for building statistical shape models. PCA finds the major and minor modes of the shape variation across the training dataset and represents a mean normalized shape as a combination of variation modes & lastly To boost the matching accuracy, this method has divided the skull and face skin into five physiological feature regions, establish five correlation analysis models, and make a decision by model fusion.

II. PROPOSED SCHEME

Various Skull Identification schemes are discussed in the above section this section focuses on the enhanced scheme which overcomes all the drawback of previous schemes. Therefore the mentioned research work is being implemented through CCA. CCA is a powerful multivariate analysis method [3]. It has various applications in pose estimation [8] and face matching [15]. For two sets of variables, CCA is to construct the CCA subspace to mutually maximize the corre-lation between these two sets variables. This method consists of two steps. In learning step, 2D-3D face data pairs are given as a subjects for training, & similar steps like PCA is firstly employed on 2D face image and 3D face data to avoid the curse of di-mensionality and minimize noise & then CCA regression is performed in between features of 2D-3D in the preceding subspaces. In the recognition step, 2D face image is given as a probe, the correlation between probe and gallery is evaluated as corresponding score by using the learnt re-gression [2] or face recognition task, different parts of face do not have the same contribution to the final recognition results.

The correlation obtained through CCA will be transferred to ICAAM(Inverse Compositional Active Appearance Model) [17] where, 3D figure of the object and the geometry of the camera are involveded as part of the minimizing parameters of the AAM algorithm in order to decide the full 6 degree-of-freedom (DOF) view of the object. This work is a bifold, major advancement of this method is, first by employing the inverse compositional algorithm to the image alignment phase and second, by integrating the image gradient information into the same image alignment formulation. Both phases make the method not only more time efficient, but they also increase the tracking accuracy, especially when the object is not rich in texture. Moreover, since this method is appearance-based, it does not require any customized feature extractions, which also translates into a more flexible alternative to situations with cluttered background, complex and irregular features.

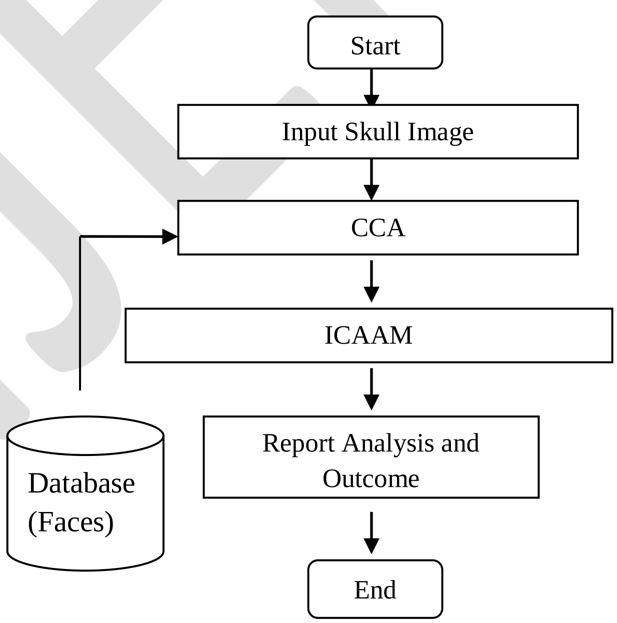

Fig. 1.Content Flow Architecture

Active Appearance Models (AAMs) and the strongly related concepts of Active Blobs and Morphable Models are the generative models of visual phenomenon. Even though linear in both shape and appearance, in terms of pixel intensities AAMs are the nonlinear parametric models. An efficient fitting algorithm for AAMs depend upon the inverse compositional image alignment algorithm to shows that effects of emergence deviation during fitting can be pre-computed and can be extended to incorporate a global shape normalizing warp, typically a 2D similarity makeover. It also analyse that which of its unique aspects improve AAM fitting performance [17].

III. COMPARATIVE ANALYSIS

A multiresolution scheme [7] is proposed for locating the face in an image and on the basis of this 2-D position of feature points 3D facial model is estimated. this scheme requires only front view facial image hence this method does not requires multiple cameras this scheme lacks in extracting the physiological features.

Some schemes such as [6] indicated in figure.2 uses landmark points from each facial image and convert this geometric points into a label graph vector using the gabor wavelet transform method this scheme has less accuracy as compared to the other schemes. A powerful multivariate analysis method [2] for pose estimation and face matching is proposed along with a patch based method to deal with 2D to 3D face matching problem. Principle component analysis (PCA) is a most commonly used algorithm in forensic science because it minimizes the redundancy of data related to image grouping but simultaneously maximizes the computing complexity and it can only process the faces have the same face expression. While CCA comprises of reducing the error among closest model instance and input image, hence solving a non-linear optimization problem.

Fig. 2. Locating 34-Landmark Points on Face[6].

Patch	1	2	3	4	5	6	7	8	9
Weight	0.5	0.7	0.5	0.4	0.6	0.4	0.2	0.3	0.2

Fig. 3. The Weight of each Patch[2].

The supported features and comparison between different schemes is illustrated in the Table-1.

TABLE I
COMPARATIVE ANALYSIS OF SCHEMES.

Schemes / Features	Anthropo-metric info.	KCCA	Volum-etric Data	Weighted & Fuzzy Set Theory	CS & CR	CCA & ICAAM
2D & 3D support	×	×	×	✓	✓	✓
Physiological Features Eradication	×	✓	×	×	✓	✓
Gradient Information	×	×	✓	×	✓	✓
Prophetic Efficiency	✓	×	✓	×	×	✓
Time Draining	×	×	×	×	×	✓

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IV. CONCLUSION

In this paper a comparative analysis of different schemes is given based on their features which briefly describes the various schemes of skull identification. Analysis shows that the proposed scheme overcomes the limitations of other existing schemes also solve the problem of becoming intrusive, costlier and provides better accuracy. An extension to this paper will be published showing the results and evaluation based on parameters mentioned in table-1 of the proposed scheme.

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