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3D Face Reconstruction from 2D Images Using Data Mining Algorithm

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Abstract: Human faces are amazingly comparative in worldwide properties, including size, viewpoint proportion, and area of principle components, however, can differ extensively in subtle elements crosswise over people, gender, race, or because of facial expression. We propose a novel technique for 3D face reconstruction of appearances that adventures the similitude of faces. Our technique uses as info a solitary picture and uses an insignificant 3D reference model of an alternate individual's face. Traditional remaking techniques from single pictures, i.e. shape-from-shading, require learning of the reflectance properties and lighting and also profundity values for limit conditions. Late techniques evade these prerequisites by speaking to information confronts as mixes (of hundreds) of putting away 3D models. We propose instead to use the input image as a guide to "mold" a single reference model to reach a reconstruction of the sought 3D shape.

Keywords: Shape, Photometry, Reference Model, 3d-Reconstruction, Lighting, Single Images, Face, Depth Reconstruction.

I. INTRODUCTION

3D- shape, and reflectance give properties of articles that are invariant to the progressions brought on by the imaging procedure including perspective, enlightenment, and occlusion by other objects. Information of these properties can improve acknowledgment, permit expectation of appearance under novel seeing conditions, and help with an assortment of utilizations counting graphical activity, medicinal applications, and more. In this paper, considering the shading information alongside unpleasant earlier shape learning to 3-dimensional state of a novel face from an input image. In a worldwide sense, diverse countenances are exceptionally comparable [15]. Appearances of changed people have a similar fundamental feature (eyes, nose, and mouth) in generally similar areas. Be that as it may, locally, confront shapes can fluctuate extensively crosswise over people, gender, race, or therefore of facial expression. The worldwide similitude of appearances is abused, for instance, in face acknowledgment techniques, to evaluate the stance of novel faces by adjusting a face picture to a non-exclusive face demonstrate.

We developing a method for shape recovery of a face from a single image that using reference 3D face model of either a different individual or a generic face. Intuitively, our method uses the input image as a guide to"mold" the reference model to reach the desired reconstruction. Here use the shading information to recover the 3D shape of a face while using the reference shape and extract information essential for the recovery process that is unknown a priori, such as lighting and pose.

Following are the key points to working with 3D face reconstruction.

- 3D face reconstruction using 2D images using data mining algorithm.
- Various approaches have been proposed as solutions for this problem but most have their limitations and drawbacks.
- Shape from shading, Shape from silhouettes, Shape from motion and Analysis by synthesis using morphable models are currently regarded as the main methods of attaining the facial information for reconstruction of its 3D counterpart.
- Though this topic has gained a lot of importance and popularity, a fully accurate facial reconstruction mechanism has not yet being identified due to the complexity and ambiguity involved.

II. OBJECTIVES

1. 3D face reconstruction using 2D images.
2. Implementation as solutions Shape from shading, Shape from silhouettes
3. The 3D face reconstruction extended to produce aging software which has the capability to produce younger or the older face of the input image.
4. Analysis by synthesis using morphable models attaining the facial information for reconstruction of its 3D counterpart.

III.RELATED WORK

Among different approaches is considered to achieve a successful 3D face reconstruction from 2D image. In this paper *R. Basri and T. Hassner. [2]* Presents a novel solution to the problem of depth reconstruction from a single image. Single view 3D reconstruction is an ill-posed problem. They address this problem by using an example-based synthesis approach. Given an image of a novel object, they combine the known depths of patches from similar objects to produce a plausible depth estimate. This is achieved by optimizing a global target function representing the likelihood of the candidate depth Author demonstrate how the variability of 3D shapes and their poses can be handled by updating the example database on-the-fly. In addition, he shows how they can employ a method for the novel task of recovering an estimate for the occluded backside of the imaged objects.

In this paper *N. Birkbeck, D. Cobzas, M. Jagersand, A. Rachmielowski, and K. Yerex. [3]* Present a system designed for capturing 3D shape and appearance of objects of different sizes from 2D images. The capture system requires only a consumer camera, a rotating table, and a calibration pattern. The whole modeling process takes about 5-10 minutes. To create a 3D model, first, a coarse geometry of the object is generated using a shape from silhouettes. To compensate for the inaccuracies of the coarse geometric model, a novel view-dependent texture, called dynamic texture [1], is calculated from the same input images. The dynamic texture is represented as a collection of basic textures that, at the time of rendering, are modulated together to give the correct object appearance from a certain viewpoint. The resulting model can be imported into conventional modelers and rendered with the dynamic texture using a plug-in we made for Maya and script for Blender.

In this paper *V. Blanz, B. Hwang, S. Lee, and T. Vetter. [4]* Present a reconstruction approach based on a small set of feature points, a reference face, and a database. The locations of the feature points are set in the reference face so that it can be used to automatically extract feature points from the input image. Additional feature points are used for texture reconstruction. The reconstruction is carried out by merging the stored shapes and textures in the database to correspond to the positions and gray values of the actual feature points. In experiments 22 shape reconstruction feature points, 3 texture reconstruction feature points and a '3 by 3' mask have being used. The limitation that face should not have glasses, earrings or beard is a setback in this approach. The resolution of the images is limited to 256 x 256 pixels and colored images are converted to 8-bit gray level images.

In this paper *T. Darrell, L. Morency, and A. Rahimi.[5]* present a method based on cubical ray projection. This algorithm uses a novel data structure named 'linked voxel space'. A voxel space is used to maintain an intermediate representation of the final 3D model. Since connectivity of the meshes cannot be represented and converting a volumetric model to a mesh is difficult, a linked voxel space is used instead of a voxel space. First, the 3D views obtained from stereo cameras are registered based on a gradient-based registration algorithm. The result of this registration is a 3D mesh where each vertex corresponds to a valid image pixel. The location of each vertex in the mesh is calculated and mapped into a voxel. This reduction is done by merging the voxels which fall on the same projection ray.

In this paper *M. Fanany, I. Kumazawa, and M. Ohno. [7]* Presents a neural-network learning scheme for 3D face reconstruction. This system can process the polygon's vertices parameter of the initial 3D shape based on depth maps of several images taken from multiple views. These depth maps are obtained by Tsai-Shah shape from- shading (SFS) algorithm. An appropriate initial 3D shape should be selected in order to improve model resolution and learning stability. The texturing is performed by mapping the texture of face images onto the initial 3Dshape. The NN (Neural Network) scheme can store vertices of a 3D polygonal object shape.

In this paper, *Feng Han and Song-Chun Zhu [10]* discuss common experience for human vision to perceive full 3D shape and scene from a single 2D image with the occluded parts "filled-in" by prior visual knowledge. In this paper author represents prior knowledge of 3D shapes and scenes by probabilistic models at two levels – both are defined on graphs. The first level model is built on a graph representation of single objects, and it is a mixture model for both man-made block objects and natural objects such as trees and grasses. It assumes surface and boundary smoothness, 3D angle symmetry etc. The second level model is built on the relation graph of all objects in a scene.

In this paper *Y. Hu, D. Jiang, S. Yan, H. Zhang, and L. Zhang.[11]* presents An analysis-by-synthesis framework for face recognition with the variant pose, illumination, and expression (PIE) is proposed in this paper. First, an efficient 2D-to-3D integrated face reconstruction approach is introduced to reconstruct a personalized 3D face model from a single frontal face image with neutral expression and normal illumination; Then, realistic virtual faces with different PIE are synthesized based on the personalized 3D face to characterize the face subspace; Finally, face recognition is conducted based on these representative virtual faces. Compared with other related works, this framework has the following advantages: 1) only one single frontal face is required for face recognition, which avoids the burdensome enrollment work; 2) the synthesized face samples provide the capability to conduct recognition under difficult conditions like complex PIE; and 3) the proposed 2D-to-3D integrated face reconstruction approach is fully automatic and more efficient. The extensive experimental results show that the synthesized virtual faces significantly improve the accuracy of face recognition with variant PIE.

In this paper, *J. Lee, R. Machiraju, B. Moghaddam, and H. Pfister 2003 [12]* presents the creation of realistic 3D face models is still a fundamental problem in computer graphics. In this paper, we present a novel method to obtain the 3D shape of an arbitrary human face using a sequence of silhouette images as input. Our face model is a linear combination of Eigen heads, which are obtained by a Principal Component Analysis (PCA) of laser-scanned 3D human faces. The coefficients of this linear decomposition are used as our model parameters. We introduce a near-automatic method for reconstructing a 3D face model whose silhouette images match closest to the set of input silhouettes.

In this paper *N. Rasiwasia. [13]* Present a simple and easily understood approach based on two orthogonal pictures - frontal view and profile view. The input images can be obtained by a stereo camera or a hand held the camera but with the constraint of being in normal white light with a background which is free from any skin-colored objects. 35 feature points and a generic model are used in this reconstruction process. The complete system is implemented using MATLAB. The user is asked to indicate four specific points in each image - Eye, Nose, Mouth and Ear. The transformations for aligning the two images are calculated based on those points. When aligning, the images are scaled, rotated and translated till the frontal and profile images are in a horizontal line.

IV. METHODOLOGIES

The employed algorithm cascades both types of reconstruction-based and learning-based algorithms. The size of the smallest face that our face detector can detect is 24 × 24.Since the subjects are moving in the video sequence; we have faces of different sizes in the obtained face log. However, in order to be able to apply the RBSR to the images in the refined face-log, we resize all of them to 46×56 pixels after face quality assessment. The RBSR produces an HR image of size 92×112 from the LR images of the refined face-log. Then, the proposed system feeds this image (of size 92×112) to the learning-based part to improve its quality even more.

A. Face Image Registration:

This approach takes into account horizontal shift a, vertical shift b and rotation angle θ between the LR images in the refined face-log. Suppose Y is the reference image in the refined face-log and Xi is the i^{th} face image in the log and it is going to be registered with Y.

$$X_i(K.l) = Y(K\cos(\emptyset) - l\sin(\emptyset) + a, l\cos(\emptyset) + k\sin(\emptyset) + b) \quad (1)$$

B. Reconstruction-Based Super-Resolution:

In order to reconstruct the HR image from the LR images of the refined face-log, we assume that these images have been produced from the HR image by following an imaging model. Based on the imaging model each LR image has been created by warping, blurring and down-sampling the HR image. It means that each Xi, i = {1, 2 . . . m3} LR images in the refined face-log have been obtained by

$$Xi = DBiWiH + ni \quad (2)$$

Where D, Bi, and Wi are the down-sampling, blurring, and warping matrix, respectively, H is the HR image and n_i is the introduced noise to the imaging process for producing the i^{th} LR image from the HR image H.

Obtaining the HR image H from is an inverse problem that is extremely ill-posed and ill-conditioned. Following [11], a MAP method has been employed to obtain the HR response image and a Markov regularization term to convert the problem to a well-posed one.

V. PROPOSED SYSTEM

Repairing the damaged areas

The input image’s condition might not always be satisfactory; they may be damaged or corrupted. Noise pixels of the image, if exist, might lead to inaccurate reconstructions. Shadows, poor lighting conditions, and occlusions prevent accurate feature extraction of the face. Due to these reasons, these damaged areas need to be eliminated prior to reconstruction.

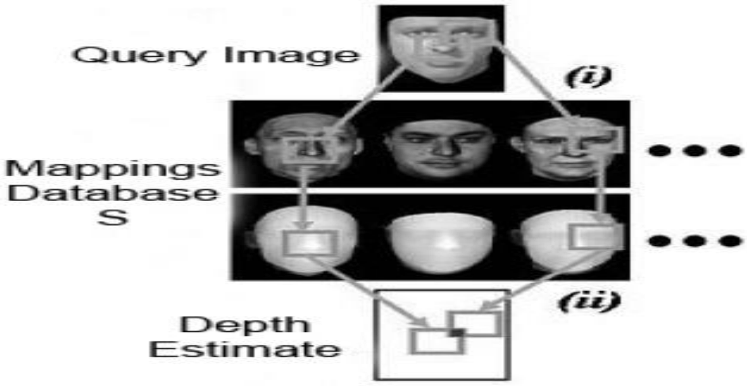


Figure 1: Basic System

Face localization

Few approaches like Rasiwasia’s method [13] involve predefined restrictions in the input images. Although these restrictions introduce inflexibility, they reduce the complexity and preclude other face localization difficulties. Since input images in non-restricted approaches may contain other background elements apart from the human face, the face region should be identified and cropped. The distinctive color of the human skin can be used as a guide in identifying the face region. This process is labeled as face localization. In approaches where multiple images are being taken as input, each input image has to be cut and resized to obtain face regions. In addition, all these obtained image parts should be precisely aligned with each other.

$$\theta = \sin^{-1}\left(A/(B^2 + C^2)\right) - \tan^{-1}(C/B) \quad (3)$$

Theta in (1) is the angle by which the profile image needs to be rotated.

A = desired Y difference calculated from the ear and nose point in frontal image
B = actual X difference between the ear and nose in the profile image
C = actual Y difference between the ear and nose in the profile image

Facial component detection

After the face region is isolated, the components of the face can be easily identified. Image-based techniques, silhouettes, and feature points can be used to detect these facial components. In identifying these facial components, recognizing the two corners of the eyes, the tip of the nose and the center and end points of the mouth would prove enough.

Depth estimation:

For an accurate and realistic reconstruction, both location and depth of the facial features of the reconstructed face should be equivalent to the real face. Constructing the depth map of the input image will assist in depth estimation.

3D face reconstruction

In [16] after face components' locations and depth are identified the 3D face can be reconstructed. A default 3D model can be deformed according to the real features to obtain the final 3D face. The texture should be mapped onto the 3D face. This is an intricate process since the texture information gained from2D space has to be mapped onto a 3D space. Some approaches project the frontal image directly onto the 3D face but if the approach takes multiple input images these images can be warped into the texture space to generate a more realistic effect. The above mentioned Microsoft's approach [11] projects the frontal image directly onto the 3D face while Birkbeck et al. [3] warps the input images to the texture space.

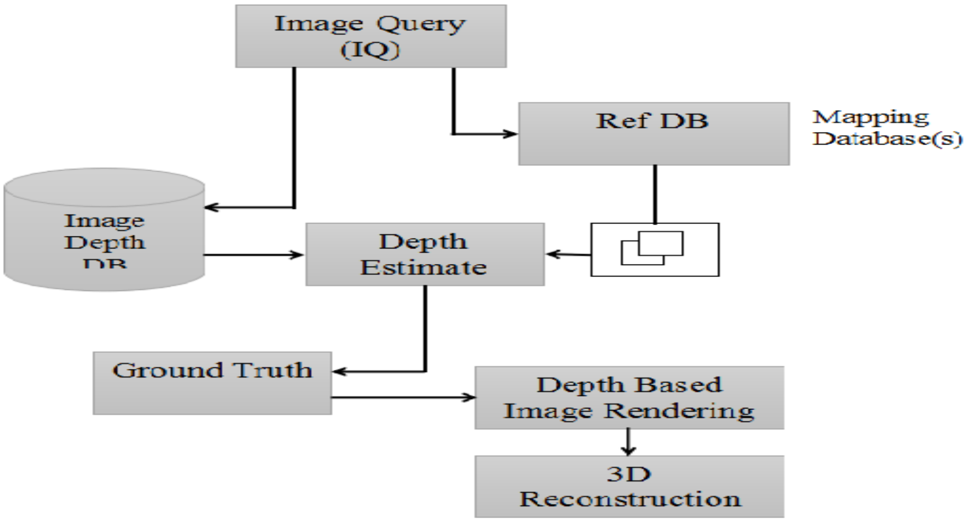


Figure 2: Proposed System Design

Following are the steps to process on 2d input images using data mining algorithm.

Step 1: KNN Search

There are two types of images in a 3D image repository: those which are relevant for determining depth from a 2D query image, and those which are irrelevant.

Step 2: Depth Fusion

None of the NN image + depth pairs (Ii, di), i ∈ K may match a query Q accurately. If a similar object (e.g., table) appears at a similar location in several kNN images, then such an object can also appear in the query and the depth field being sought should reflect this. This depth field is computed by applying the median operator across the kNN depths at each spatial location x as follows:

d[x] = median{di[x], ∀i ∈ K}.

Step 3: Cross Bilateral Filtering

While the median-based fusion helps make depth more consistent globally, the fused depth is overly smooth and locally inconsistent with the query image due to the following reasons:

1. Misalignment of edges between the fused depth field and query image,
2. Lack of fused depth edges where sharp object boundaries occur,
3. Lack of fused depth smoothness where smooth depth changes are expected.

Step 4: Stereo Rendering

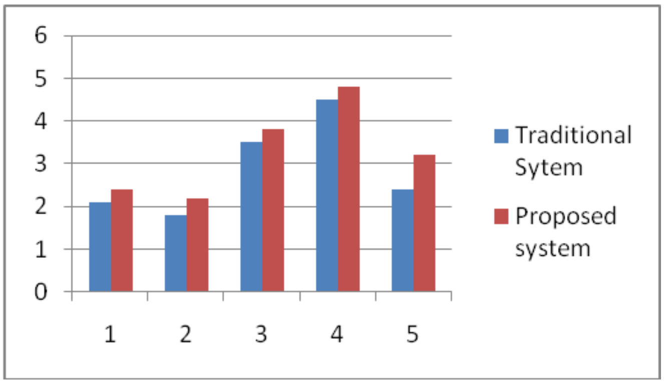
In order to generate an estimate of the right image QR from the 2D query Q, we need to compute the disparity δ from the estimated depth d. Assuming that the fictitious image pair (Q, QR) was captured by parallel cameras with baseline B and focal length f, the disparity is simply δ[x, y] = Bf/_d[x], where x = [x, y]T. We forward-project the 2D query Q to produce the right image:

$$QR[x+\delta][x,y],y] = Q[x,y] \qquad (4)$$

while rounding the location coordinates (x + δ[x, y], y)

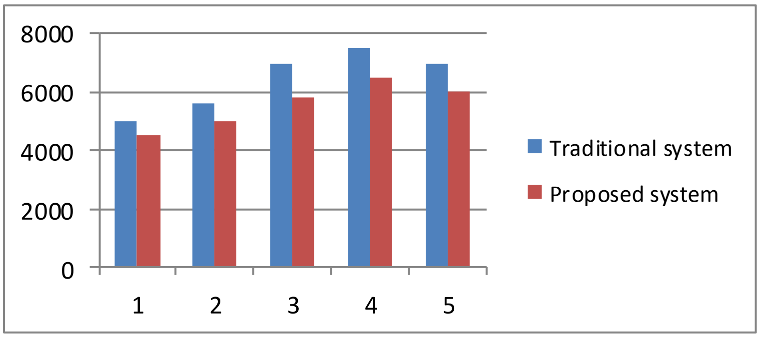
VI. RESULT AND DISCUSSION

I. Graph: 1 Comparison Traditional system and proposed system for 3D face Reconstruction



Dataset	Traditional Sytem	Proposed system
1	2.1	2.4
2	1.8	2.2
3	3.5	3.8
4	4.5	4.8
5	2.4	3.2

Table1: -Comparison Traditional system and Proposed system for Accuracy



Graph2: -Comparison Traditional system and Proposed system for Execution time

Table2: - Comparison Traditional system and Proposed system for Execution time

Dataset	Traditional system	Proposed system
1	5000	4500
2	5600	5000
3	7000	5800
4	7500	6500
5	7000	6000

CONCLUSION

The 2D picture of a face is exceptionally touchy to changes in head pose and expressions so a successful reconstruction approach ought to have the capacity to extricate these face subtle elements in resentment of these progressions. Approaches based on silhouettes and prior knowledge can be advantageous in addressing this problem when reconstructing 3D faces from 2D images the key source of information is the intensity-based features and landmarks of the image. But intensity alone is not enough in the case of low intensity, noise, occlusion, illumination variations and/or shadows being present in the input images.

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