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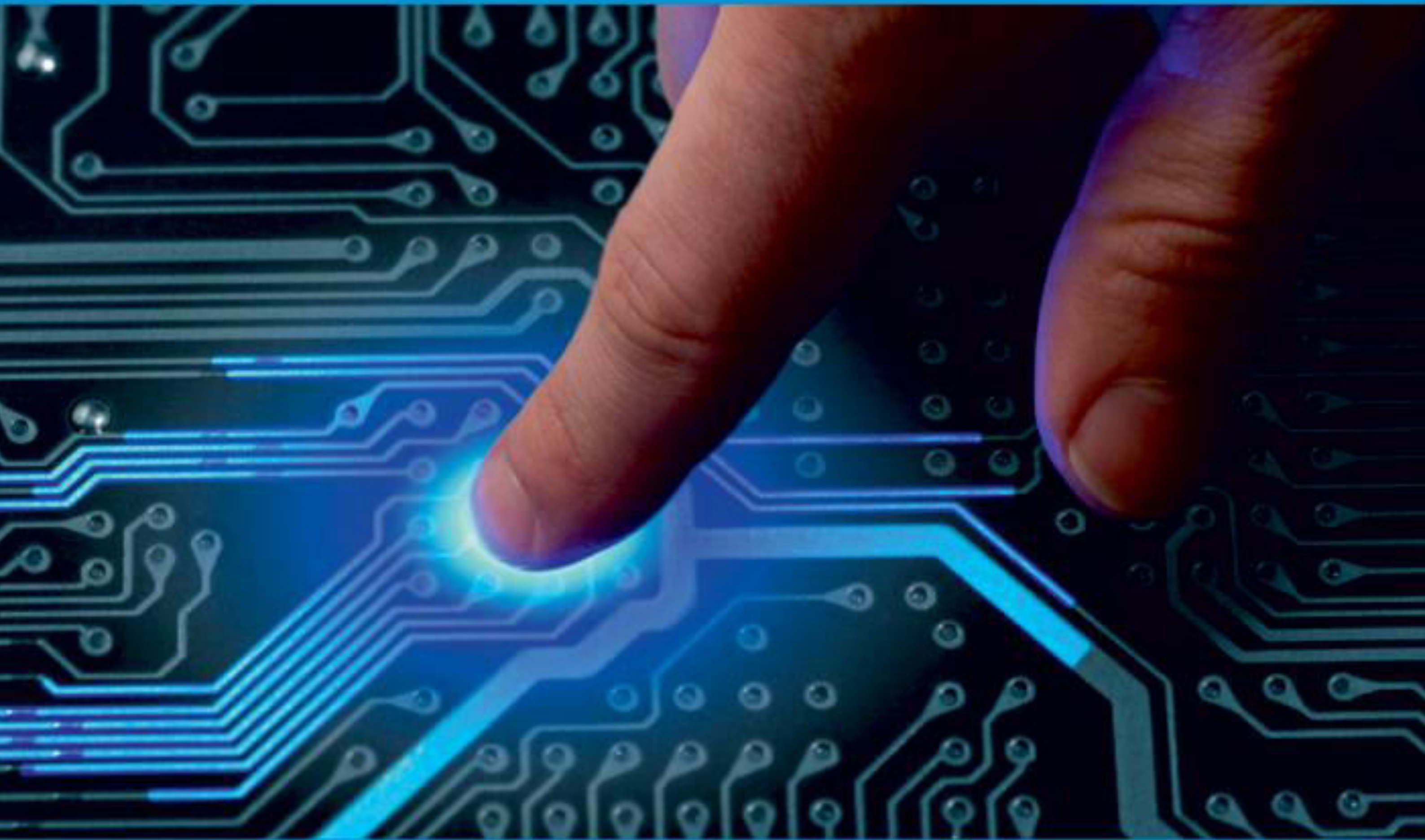

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Video in Pose and Illumination Invariant Face Recognition

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ABSTRACT: The use of video sequence for face recognition has been comparatively less calculated than image-based approaches. In this paper, we present a structure for face recognition from video sequences that is robust to huge changes in facialpose and lighting condition. Our system is based on a newlyobtain theoretical result that can combine the effects of lighting, shape and motion in generating an image using a viewpoint camera. This outcome can be used to approximate the pose and illumination conditions for each frame of the probe sequence. Then, using a 3D face representation, we combine images parallel to the pose and illumination condition estimated in the probe sequences. Similarity amid the synthesized images and the probe video is computed by integrating over the entire progression. The method can grip situations where the pose and lighting conditions in the training and testing data are completely displace.

I. INTRODUCTION

It is believed by many that video-based face recognition systems hold promise in certain applications where motion can be used as a cue for face segmentation and tracking, and the presence of more spatio-temporally coherent data can increase recognition performance [25]. However, these systems have their own challenges such as tracking the face over time, 3D modeling, changes of pose and lighting over the sequence duration, and developing efficient measures for integrating information over the entire sequence. In this paper, we present a novel framework for video-based face recognition that is based on learning joint illumination andmotion models from video, synthesizing novel views based on the learned parameters, and using a metric that can com-pare two time sequences while being robust to outliers. We show experimentally that our method achieves high identi-fication rates under extreme changes of pose and illumina-tion.

1.1 Existing Work:

We focus on reviewing the relevant work in pose and illumination invariant face recognition, and refer the reader to [25] for a broader survey. In [9], the authors propose to arrange physical lighting so that the acquired images of each object can be directly used as the basis vectors of the low-dimensional linear space. The authors in [6, 7] proposed to use Eigen Light-Fields and Fisher Light-Fields to do pose invariant face recognition. They used generic training data and gallery images to es-timate the Eigen/Fisher Light-Field of the subject's head, and then compare the probe image and gallery light-fields to match the face. In [26], the authors used photometric stereo methods for face recognition under varying illumi-nation and pose. Their method requires iteration over all the poses in order to find the best match. A novel method for multilinear independent component analysis was pro-posed in [20] for pose and illumination invariant face recog-nition. The advantage of using 3D models in face recogni-tion has been highlighted in [11, 5], but their focus is on 3D models obtained directly from the sensors and not esti-mated from video. In [24, 23], the authors proposed a 3D Spherical Harmonic Basis Morphable Model (SHBMM) to implement a face recognition system given one single im-age under arbitrary unknown lighting. Morphable model based face recognition algorithm using a single image was proposed in [3], but they use the Phong illumination model, estimation of whose parameters can be more difficult than the spherical harmonics model in the presence of multiple and extended light sources. All of these methods deal with recognition in a single image or across discrete poses and do not consider continuous video sequences. The authors in [10] deal with the issue of video-based face recognition, but concentrate mostly on pose variations. A method for video-based face verification using correlation filters was proposed in [21]. This paper provides a method for estimat-ing the pose and illumination conditions for each frame of a video sequence, and using that information for recognition by integrating over the entire video.

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1.2 Proposed Approach: Recently, in [1] and [15], the authors independently derived a low order (9D) spherical harmonics based linear representation to accurately approxi-mate the reflectance images produced by a Lambertian ob-ject with attached shadows. This was an approximation of the infinite-dimensional convex cone representation deriv ed in [2]. In [22], the authors extended the work and showed that the appearance of a moving object under arbitrary light-ing could be represented as bilinear combination of 3D mo-tion and the spherical harmonics coefficients for illumina-tion. This bilinear model of illumination and motion pa-rameters allows us to develop an algorithm for tracking a moving object with arbitrary illumination variations. This is achieved by alternately projecting onto the appropriate motion and illumination bases of the bilinear space. The method proposed in this paper relies upon image differencesand does not require computation of correspondences be-tween images. In the recognition algorithm, we assume thata 3D model of each face in the gallery is available. This can be estimated from images using standard methods for 3D face modeling [3] or obtained directly from the sensors [5]. Given a probe sequence, we track the face automati-cally in the video sequence under arbitrary pose and illu-mination conditions. 3D modeling is not required for the probes. The estimated parameters are used to synthesize video sequences for each gallery under the motion and illu-mination conditions in the probe. The distance between the probe and synthesized sequences is then computed for each frame. The synthesized sequence that is at a minimum dis-tance from the probe sequence is computed and is declared to be the identity of the person. Experimental evaluation is carried out on a database of 59 people that we collected for this purpose.

1.3 Evaluation: One of the challenges in video-based facerecognition is the lack of a good dataset, unlike in image-based approaches [25]. The dataset in [10] is small and con-sists mostly of pose variations. The dataset described in [12] has large pose variations under constant illumination, and illumination changes in (mostly) fixed frontal/profile pose s (these are essentially for gait analysis). An ideal dataset for us would be similar to the CMU PIE dataset [18], but with video sequences instead of discrete poses. This is the reason why we collected our own data, which has large, simultane-ous pose, illumination and expression variations. It is sim-ilar to the PIE dataset, although in video using pre-existing natural indoor and outdoor lighting that changes randomly.

1.4 Organization of the paper: The rest of the paper isorganized as follows. Section 2 presents a brief overview of the bilinear model of joint motion and illumination vari-ables and the algorithm for learning the parameters of the bilinear model. Section 3 describes our recognition algo-rithm. In Section 4 experimental results are presented. Sec-tion 5 concludes the paper and highlights future work.

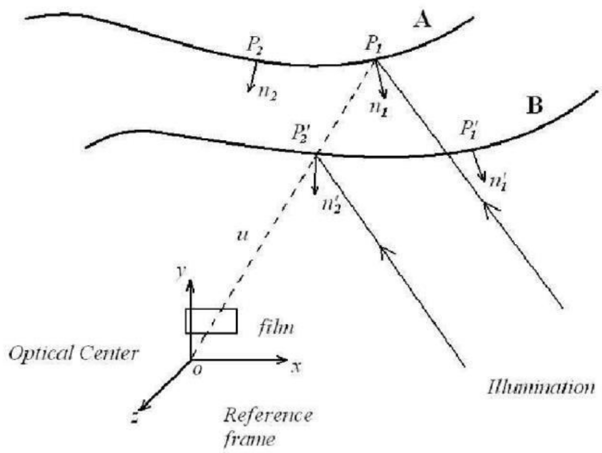

Figure 1. Pictorial representation of the imaging framework for a moving object incorporating illumination variations.

II. LEARNING JOINT ILLUMINATION AND MOTION

Models from Video

2.1. Bilinear Model of Illumination and Motion

In this section, we present the fundamental result on es-timating the illumination and 3D motion parameters. Re-cent

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studies has shown that, for a fixed Lambertian object, the set of reflectance images under distant lighting with-out cast shadows can be approximated by a linear combina-tion of nine basis images, defined using spherical harmon-ics [1, 15]. Several papers have shown the suitability of this model for faces [1, 14].

In [22], the motion was taken into the consideration and it was shown that for moving objects it is possible to ap-proximate the sequence of images by a bilinear subspace. It was proved that if the motion of the object from time $\mathbf{t_1}$ to new time instance $\mathbf{t_2}$ is small, then upto a first order approx-imation, the reflectance image $\mathbf{I}$ **(x, y)** at $\mathbf{t_2}$can be expressed as [22]:

$$I(x,y,t_2) = \sum_{i=0}^{2} \sum_{j=-i}^{i} l_{ij}^{t_2} b_{ij}(n_{P_2'}), \qquad (1)$$

where

$$b_{ij}(n_{P_2'}) = b_{ij}(n_{P_1}) + AT + B\Omega. \qquad (2)$$

In the above equations, $\mathbf{b_{ij}}$ are the basis images, and $\mathbf{n}$ is the unit norm vector at the reflection points $\mathbf{P_1}$ and $\mathbf{P_2'}$ that project to the same pixel index **(x, y)** before and af-ter motion. The basis images are represented in terms of the spherical harmonics. $\mathbf{l_{ij}}$ are the illumination coefficients de-termined by the illumination condition at time instances $\mathbf{t_1}$ and $\mathbf{t_2}$. $\mathbf{b_{ij}(n_{P'_2})}$ and $\mathbf{l_{ij}^{t_2}}$ are the basis images and illumina-tion coefficients after motion, while $\mathbf{b_{ij}(n_{P_1})}$ are the orig-inal basis images before motion. $\mathbf{T} = [T_x\ T_y\ T_z]^T$ and $\Omega = [\omega_x\ \omega_y\ \omega_z]^T$ are the translation and rotation about the centroid of the object. A and B con-tain the structure and camera intrinsic parameters, and are functions of pixel index **(x, y)**. Thus (1,2) relate the im-age appearance with the geometric and photometric effects. Please refer to [22] for the derivation of (1,2) and explicit expression for **A** and **B**.

Substituting (2) into (1), we see that the new image spans a bilinear space of six motion and approximately nine il-lumination variables.We can express the result in (1) succinctly using tensor notation as

$$I = \left(B + C \times_2 \begin{bmatrix} T \\ \Omega \end{bmatrix}\right) \times_1 l, \qquad (3)$$

where $\times_n$ is the mode-n product [8][1], and $\mathbf{l} \in \mathbf{R}^{N_l}$ is the vector of $\mathbf{l_{ij}}$ components. $\mathbf{N_l}$ is the dimension of the illu-mination basis, and $\mathbf{N_l \approx 9}$ for Lambertian objects with cast shadow. For each pixel **(p, q)** in the image, $\mathbf{C_{klpq}}$=[**A B**] of size$\mathbf{N_l \times 6}$. Thus for an image of size$\mathbf{M \times N}$, **C** is$\mathbf{N_l \times 6 \times M \times N}$. **B** is a sub-tensor of dimension$\mathbf{N_l \times 1 \times M \times N}$, comprising the basis images $\mathbf{b_{ij}(n_{P_1})}$,and **I** is a sub-tensor of dimension $\mathbf{1 \times 1 \times M \times N}$, represent-ing the image. **l** is still the $\mathbf{N_l \times 1}$ vector of the illumination coefficients.

Implications of the Result: From (3), we see that the im-age spans a bilinear space of six motion variables and nine illumination variables. The result assumes that the motion between two consecutive frames is small enough to be ap-proximated by a first order Taylor approximation (which is true for most video sequences) and the object is Lamber-tian so that a ninth order spherical harmonics expansion is enough to represent the energy in the image. The shape of the object is encoded in the **A** and **B** matrices and in $\mathbf{b_{ij}(n_{P_1})}$. The camera intrinsic parameters are implicitlypresent in **A** and **B** through **u**. Therefore, equation (1) in-tegrates the relative motion between the object and camera, Lambertian component of illumination, 3D shape, albedo and camera parameters into one single framework. When the object does not move, the second and third motion terms of the basis image $\mathbf{b_{ij}(n_{P'_2})}$ are zero, and the result is the same as the one in [1, 15]. When the illumination changes gradually, it can be shown that the bilinear space becomes a combination of two linear subspaces, defined by the motion and illumination variables. This result is valid for both slow

[1] The mode-n product of a tensor $A \in R^{I_1 \times I_2 \times \ldots \times I_n \times \ldots \times I_N}$ by a vector $\mathbf{V} \in \mathbf{R}^{1 \times I_n}$, denoted by $\mathbf{A \times_n V}$, is the $I_1 \times I_2 \times \ldots \times 1 \times \ldots \times I_N$ tensor

$$(A \times_n V)_{i_1 \ldots i_{n-1} 1 i_{n+1} \ldots i_N} = \sum_{i_n} a_{i_1 \ldots i_{n-1} i_n i_{n+1} \ldots i_N} v_{i_n}.$$

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and sudden changes in illumination and also accounts for attached shadows. It can handle large changes of scale ofthe object. Another nice feature of our formulation is that it depends upon the image intensities, not the image gradi-ents; this will make the algorithms proposed for the inverseproblems described later less sensitive to image noise. The theory is applicable to color images by treating each color channel separately.

2.2. Estimation of Illumination and Motion Model

The joint illumination and motion space provides us with a novel method for 3D motion estimation under varying il-lumination. This is based on inverting the generative model for motion and illumination modeling. It can not only track the 3D motion under varying illumination, but also can es-timate the illumination parameters. The estimates are ob-tained as:

i

(ˆl,Tˆ,Ωˆ) = arg min$_{l,T,\Omega}$ kIt2− X$_{i=0}$ X$_{,1,2j=-i}$ lij bij (nP2 ')k2

+α||m||^2

= arg $_l$min$_{T,\Omega}$ kIt2 − (Bt1 + Ct1 ×2 $_\Omega^{T_3}$)×1lk2

+α||m||^2,(4)

where **x**ˆ denotes an estimate of **x**. Motion and illumination estimates are obtained for each frame. Since the motion between consecutive frames is small, but illumination can change suddenly, we add a regularization term to the above cost function. It is of the form **α||m||**^{2} .

Since the image $\mathbf{I}_{t2}$ lies approximately in a bilinear space of illumination and motion variables (ignoring the regular-ization term for now), such a minimization problem can be achieved by alternately estimating the motion and illumina-tion parameters by projecting the video sequence onto the appropriate basis functions derived from the bilinear space. Assuming that we have tracked the sequence upto some frame for which we can estimate the motion (hence, pose) and illumination, we calculate the basis images, $\mathbf{b}_{ij}$, at the current pose, and write it in tensor form **B**. Unfolding[2] **B** and the image **I** along the first dimension [8], which is the illumination dimension, the image can be represented as:

$$\mathbf{I}_{(1)}^T = \mathbf{B}_{(1)}^T \mathbf{l}. \quad (5)$$

This is a least square problem, and the illumination **l** can be estimated as:

$$\hat{\mathbf{l}} = (\mathbf{B}_{(1)}\mathbf{B}_{(1)}^T)^{-1}\mathbf{B}_{(1)}\mathbf{I}_{(1)}^T. \quad (6)$$

[2] Assume an Nth-order tensor $\mathcal{A} \in C^{I_1 \times I_2 \times \ldots \times I_N}$. The matrix unfolding $A_{(n)} \in C^{I_n \times (I_{n+1} I_{n+2} \cdots I_N I_1 I_2 \cdots I_{n-1})}$ contains the ele-ment $a_{i_1 i_2 \ldots i_N}$ at the position with row number i_n and column num-ber equal to $(i_{n+1}-1)I_{n+2}I_{n+3}\ldots I_N I_1 I_2 \ldots I_{n-1} + (i_{n+2}-1)I_{n+3}I_{n+4}\ldots I_N I_1 I_2 \ldots I_{n-1} + \cdots + (i_N - 1)I_1 I_2 \ldots I_{n-1} + (i_1 - 1)I_2 I_3 \ldots I_{n-1} + \cdots + i_{n-1}$.

Keeping the illumination coefficients fixed, the bilinear space in equations (1) and (2) becomes a linear subspace, i.e.,

$$\mathbf{I} = \mathbf{B} \times_1 \mathbf{l} + (\mathbf{C} \times_1 \mathbf{l}) \times_2 \Omega^{3} \mathbf{T}^{3}. \quad (7)$$

Similarly, unfolding all the tensors along the second dimen-sion, which is the motion dimension, and adding the effect of the regularization term, **T** and **Ω** can be estimated as:

$$\hat{\Omega^3 \mathbf{T}^3} = \left(\mathbf{G}\mathbf{G}^T + \alpha\mathbf{I}\right)^{-1} \mathbf{G}(\mathbf{I} - \mathbf{B} \times_1 \mathbf{l})_{(2)}^T, \quad (8)$$

where $\mathbf{G} = (\mathbf{C} \times_1 \mathbf{l})_{(2)}$ and **I** is an identity matrix of di-mension **6×6**. The above procedure for estimation of the motion should proceed in an iterative manner, since **B** and **C** are functions of the motion parameters. This should con-tinue until the projection error does not decrease further. This process of alternate minimization leads to the local minimum

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of the cost function (which is quadratic in mo-tion and illumination variables) at each time step. This can be repeated for each subsequent frame. We now describe the algorithm formally.

2.3. Motion and Illumination Estimation Algo-rithm:

Consider a sequence of image frames $\mathbf{I}_t$, **t= 0, ..., N−1**. **Initialization:** Take one image of the object from the videosequence, register the 3D model onto this frame and map the texture onto the 3D model. Calculate the tensor of the basis images $\mathbf{B}_0$ at this pose. Use (6) to estimate the illumi-nation coefficients. Now, assume that we know the motion and illumination estimates for frame **t**, i.e., $\mathbf{T}_t,\mathbf{\Omega}_t$ and $\mathbf{l}_t$.

• Step 1. Calculate the tensor form of the bilinear basis im-ages $\mathbf{B}_t$ at the current pose using (2). Use (8) to estimate the new pose from the estimated motion.

• Step 2. Using the last estimate of the illumination, com-pute the motion **m** by minimizing the difference between an input frame and the rendered frame $\mathbf{kI}_{t+1} - (\mathbf{B}_t + \mathbf{C}_t \times_2$

3^3 $^{T}\mathbf{t+1})\times\hat{}^{k}{}_{2}$

$\hat{\Omega}_{t+1}$ $_1$ $\mathbf{l}_{t+1}$, and estimate the new pose.

• Step 3. Using the new pose estimate, re-estimate the illu-mination using (6).

• Step 4. If the difference error between the input frame and the rendered frame is above a certain threshold, perform a local optimization (using any gradient descent method) ini-tializing with the estimates of motion and illumination.

• Step 5. Set t = t + 1. Repeat Steps 1 to 4.

• Step 6. Continue till t = N - 1.

The local optimization in Step 4 is necessary in many cases because the bilinear space theory is an approxima-tion under small motion conditions and does not account fornoise in the image. However, it gives a very good intial es-timate which is required for any local optimization method. In our case, a stochastic optimization method known as Si-multaneous Perturbation Stochastic Approximation (SPSA) was used [19]. This is particularly efficient for optimization of multi-dimensional functions since it requires only one measurement in each iteration step (see Chapter 7 of [19]).

III. FACE RECOGNITION FROM VIDEO

The generative framework for integrating illumination and motion models and the method for learning the model parameters as described in Section 2 set the stage for devel-oping a novel face recognition algorithm that is particularly suited to handling video sequences. The method is able to handle arbitrary pose and illumination variations and can integrate information over an entire video sequence.

In our method, the gallery is represented by a 3D model of the face. The model can be built from a single image [4], a video sequence [17] or obtained directly from 3D sensors [5]. In our experiments, the face model will be estimated from video. Given a probe sequence, we will estimate the motion and illumination conditions using the algorithms de-scribed in Section 2. Note that the tracking does not require a person-specific 3D model - a generic face model is usually sufficient. The 3D model is registered to the first frame of the probe sequence manually by chosing five points on the face. Given the motion and illumination estimates, we will then render images from the 3D models in the gallery. The rendered images can then be compared with the images in the probe sequence. Given the rendered images from the 3D models in the gallery and the probe images, we will use a robust metric for comparing these two sequences. The fea-ture of this metric will be its ability to integrate the identity over all the frames, ignoring some frames that may have the wrong identity. Since 3D shape modeling is done for the gallery sequences only, we avoid the issues of high compu-tational complexity of 3D modeling algorithms in real-time.

One of the challenges faced is to design a suitable met-ric capable of comparing two video sequences. This metric should be general enough to be applicable to most videos and robust to outliers. Let $\mathbf{I}_i$, **i= 1, ..., N** be **N** frames from the probe sequence. Let $\mathbf{SG}_{i,j}$, **i= 1, ..., N** be the frames of the synthesized sequence for galley **j**, where **j = 1, ..., M** and **M** is the total number of individualsin the gallery. Note that the number of frames in the two sequences to be compared will always be the same in our method. By design, each corresponding frame in the two se-quences will be under the same pose and illumination con-ditions, dictated by the accuracy of the estimates of these parameters from the probes and the synthesis algorithm. Let $\mathbf{d}_{ij}$be the distance between the $\mathbf{i}^{th}$frames $\mathbf{I}_i$and $\mathbf{SG}_{i,j}$.

3.1. **Video-based Face Recognition Algorithm**

We now describe formally the video-based face recognition algorithm. Using the above notation, let Ii, i = 1, ..., Nbe

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N frames from the probe sequence. Let G1, ..., GM bethe 3D models for each of M galleries.

• Step 1. Register a 3D generic face model to the first frame of the probe sequence. Estimate the illumination and motion model parameters for each frame of the probe sequence using the method described in Section 2.

• Step 2. Using the estimated illumination and motion parameters, synthesize, for each gallery, a video sequence using the generative model of (2). Denote these as SGi,j, i =1, ..., N and j = 1, ..., M.

• Step 3. Compute dij and obtain the identity using (9).

IV. EXPERIMENTAL RESULTS

1.1 Face Database and Experimental Setup Ourdatabase consists of videos of 57 people. Each person wasasked to move his/her head as they wished and the illumination was changed randomly. The illumination consisted ofceiling lights, lights from the back of the head and sunlightfrom a window on the left side of the face. Random combinations of these were turned on and off and the window wascontrolled using dark blinds. An example of some of theimages in the video database is shown in Figure 2. Some ofthe subjects had expression changes also, e.g., the last rowof the Figure 2. The resolution of the face varied depending on the person and the movement. A statistical analysisshowed that the average size was about 70 x 70, with theminimum size being 50 x 50. Each sequence was dividedinto two parts - gallery and probe. The frames in Figure 2are arranged in the same order as in the original video, withthe first column (where the face is approximately frontal)representing a frame from the gallery, while the remainingcolumns represent samples from the probe.

V. CONCLUSIONS AND FUTURE WORK

In this paper, we have proposed a method for videobased face recognition that relies upon a novel theoreticalframework for integrating illumination and motion models for describing the appearance of a video sequence. Westarted with a brief exposition of this theoretical result, followed by methods for learning the model parameters. Then,we described our recognition algorithm that relies on synthesis of video sequences under the conditions of the probe.Finally, we demonstrated the effectiveness of the method onvideo databases with large and arbitrary variations in poseand illumination. Future work will concentrate on applyingthese methods for tracking people in outdoor environmentsby integrating appearance and identity information in occluded and cluttered environments.

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