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Design and Implementation of Biometrics Personal Security using 3D Face Expression

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Abstract: Face appearance in support of biometric recognition has been conventional with researcher for many years. Face systems have successfully made the changeover from the research laboratory to the commercial zone. Biometric detection should make use of dimensions that are solely subject-intrinsic, avoiding integration of other contaminate inputs and the property of imaging system revolution as much as possible. Many investigate groups are ongoing to focus their hard work on 3D face recognition, which should yield further novel techniques and opportunities for principled assessment in the prospect. The performances of the present face recognition system undergo a great deal from the variation in lighting. To treaty with this problem, this paper presents an illumination normalization move toward by relighting 3D face images to a canonical Illumination based on the singing 3D face images representation. Advantage from the comments that human 3D faces share similar shape, and the albinos of the 3D face surfaces are quasi-constant, we first estimation the low-frequency components of the illumination from the input 3D facial image. In particular, a scheme for the identification of 3D faces with one type of expression and neutral faces was implemented and tested on a database. The 3D face biometric results proved the feasibility of this framework.

Keywords: Biometrics, Expression, Face, Intensity, Recognition and Registration

I. INTRODUCTION

Face recognition has a variety of potential applications in public safety measures, law enforcement and commerce such as mug-shot database matching, identity verification for credit card or driver license, access control, information security, and video surveillance. In addition, there are numerous emerging fields that can advantage from face recognition, such as human-computer interfaces and e-services, including online-shopping and online-banking. Related investigate activities have considerably augmented over the past few years [3].

Two interesting properties of biometric identification are:

1. The person to be identified is required to physically be present at the point of identification.

2. Identification is based on the biometric technique that does not depend on the user to remember a password or to carry a token.

There are two distinct functions for biometric devices:

1. To prove you are who say you are

2. To prove you are not who you say you are not.

The purpose of the first function is to prevent the use of a single identify by multiple people (e.g. a possible attacker or attackers attempting to take over the plane cannot pass themselves off as a registered pilot). In this case it is important that the biometric device be able to differentiate between a live biometric presented to the scanner (i.e. a real finger or a spoofed biometric trying to fool the scanner). The second function is used to prevent the use of multiple identities by a single person. It would have to be ensured that the biometric system either automatically cross checks the enrolled characteristics for duplicates, or otherwise does not allow a person to register their biometric under two different names.

Illumination Cones used distinct images of the same face to estimate its 3D shape and the albino map by using a variation of the photometric stereo, bearing in mind both the attached and cast shadows. After the 3D renovation, the illumination cone of the entity was constructing. The illumination cone-shaped tool algorithm was maintained to achieve the uppermost recognition rate under dissimilar illumination conditions. However, images for each face and the relatively complicated procedure may have prohibited its large application.

The all models have in common is that a compact representation (Few Parameters) describing a wide variety of facial images are desirable. The parameter sets can vary considerably depending on the variability being modeled. The many kinds of variability being modeled/ parameterized include the following.

➢ 3Dimensional motion and pose—the dynamic, 3D position as well as rotation of the head. Tracking involve estimation these parameters for each frame in the 3D face sequence.

➢ Facial action— 3D facial feature movement such as lip and eyebrow motion.

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- Shape and feature design—the shape of the head, face and the facial features (mouth and eyes). This could be estimated or unspecified to be known by the tracker.
- Illumination—the variability in appearance due to unusual lighting conditions.
- Texture and color—the image pattern relating the skin.
- Expression—muscular synthesis of emotions creation the face looks happy or sad [5].

A. Motivation

Verification of identity based on biometric information is essential for many security applications, since the conventional authentication approaches, e.g. user/password mechanisms, have proved unreliable and inconvenient. Examples include access control to physical facilities, security systems or information databases. Suspect tracking, surveillance and intrusion detection are also potential applications [6]. In addition to the wide range of commercial and law enforcement applications mentioned above, there are many emerging fields that can benefit from face verification technology, such as the new generation of intelligent human-computer interfaces and e-services, including teleshopping and banking. There exist many optional biometric cues for identity verification, such as the iris, fingerprint, voice, handprint, signature, and retina. The human face plays an irreplaceable role in biometrics technology due to some of its unique characteristics. First, most cameras are non-invasive; therefore face verification systems are one of the most publicly acceptable verification technologies in use. Another advantage is that face recognition systems can work mostly without the cooperation of the user concerned, which is therefore very convenient for the general users. Furthermore, they can even work in the situation where the subject concerned is not aware of the procedure.

II. MAJOR CHALLENGES

Robust face recognition is still a challenging problem, even many techniques have been proposed, and some significant progress has been made. Up to now, at least two major challenges need to be emphasized [1] that is, **Illumination Variation Problem** and **Pose Variation Problem**. Either one of the problems can cause serious performance degradation in most of the existing systems. An even more difficult situation would be from the combined problem of pose and illumination variations. Unfortunately, this often happens when face images are acquired in an uncontrolled practical environment such as in the case of surveillance [7].

In addition, occlusion and make-up are other sources of appearance variation. Glasses, especially black-frame glasses or sunglasses, will greatly change the appearance of a face image, not to say the modern make-up techniques such as pasting black beards or other accessories. Since quite little work has been done in this area, this section will mainly concentrate on the solutions to these problems.

A. Illumination Problem

Solutions to illumination problem include invariant features-based methods, parameterized illumination manifold, photometric alignment, linear illumination subspace, quotient images and illumination cones etc.

Invariant Features-Based Methods: Some image representations are considered to be illumination invariant to some extent. These include edge maps, derivatives of the grey level, images filtered with 2D Gabor-like functions, and a representation that combines a log function of the intensity with these representations [4]. But none of these representations is sufficient to overcome the image variations.

Illumination and Pose Manifolds: Murase and Nayar [1] proposed a continuous and compact representation of object appearance, the ***parametric eigenspace***, which is parameterized by the variables, namely, object pose and illumination. In this method, an image set of the object is first obtained by varying pose and illumination in small increments. The image set is then normalized in brightness and scaled to achieve invariance to sensor magnification and illumination intensity. The eigenspace for the image set is constructed and all object images (learning samples) are projected onto this space to obtain a set of points. These points lie on a ***manifold*** that is parameterized by pose and illumination and can be constructed from the discrete points using spine interpolation [2].

Recognition, pose and illumination direction estimation can then be achieved as follows: given an image consisting of an interested object, the segmented object region is normalized in scale and brightness such that it has the same size and brightness range as the images used in the learning stage. This normalized image is projected onto the eigen space. The closest manifold reveals the identity of the object, and exact position of the closest point on the manifold determines pose and illumination direction.

3D Linear Illumination Subspaces: This method, as a variant of photometric alignment methods, also exploits the observation that, for a Lambertian surface without self-shadowing, the images of a particular face lie in a 3-D linear subspace [1]. For classification, this observation suggests a simple classification algorithm to recognize Lambertian surfaces invariant to different lighting conditions. For each face, use three or more images taken under different lighting directions to construct a 3-D basis for the linear subspace. To perform recognition, we can simply compute the distances between the new image and each linear subspace and choose the face corresponding to the shortest distance. This recognition scheme is called Linear Subspace method.

If there were no noise or self-shadowing, Linear Subspace algorithm would achieve error-free classification under any lighting conditions, provided that the surfaces obey the Lambertian reflectance model. Nevertheless, there are several compelling reasons to look elsewhere. First, due to self-shadowing, secularities and facial expressions, some regions of the face may have variability that does not satisfy the linear subspace model. Second, to recognize a

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test image, we must measure the distance in the linear subspace for each person's data. While this is an improvement over a correlation scheme that needs a large number of images for each class, it is still computationally expensive. Finally, from the storage point of view, the linear subspace algorithm must keep three images in memory for every person, which is space intensive.

Quotient Images Based Method: More recently, Shashua et al. [8] propose a Quotient images based method to address the problem of "classbased" image-based recognition and rendering with varying illumination. Their key result is based on the definition of an illumination invariant signature image, which enables an analytic generation of the image space with varying illuminations.

They show that the set of all images, generated by varying lighting conditions on a collection of Lambertian objects that have the same shape but different surface albedoes, can be characterized analytically using images of a prototype object and an illumination invariant "signature" image per object of the class. The Cartesian product between the signature image of an object y and the linear subspace determined by the images of the prototype object generates the image space of y. They also show how to obtain the signature image from a database of example images of several objects, and prove that the signature image obtained is invariant to illumination conditions. The method works remarkably well on real face images using a very small set of example objects, as few as two example objects. In many cases, the rerendering results are indistinguishable from the "real" objects, and the recognition results outperform conventional methods by far.

Illumination Cones: In the last few years, Belhumeur and Kriegman et al. have proposed a generative appearance-based method, named illumination cones, for recognizing human faces under variations of lighting and viewpoint. Their work is well summarized in [2]. Belhumeur et al. first prove that the set of images of an object in a fixed pose, seen under all possible illumination conditions, is a convex cone in the space of images. Particularly, the illumination cone of a convex object with Lambertian reflectance can be completely determined by several properly chosen images.

Although faces are neither Lambertian surfaces nor convex, experimental results show that the illumination cone of a face can be also established from a few images acquired under different lighting conditions. To construct the illumination cone of a face, its shape and albedo should be recovered first. Georghiades et al. use seven images of a face in a fixed pose, but under different and unknown lighting conditions, to reconstruct its surface geometry and albedo map. In turn, this reconstruction serves as a generative model to render or synthesize images of the face under new given poses and illumination conditions. The pose space is then sampled and, for each pose, the corresponding illumination cone is approximated by a low-dimensional linear subspace whose basis vectors are estimated using the generative model.

Once the illumination cone of a specific face is constructed, recognition can be achieved by assigning to a test image the identity of the closest approximated illumination cone, based on Euclidean distance within the image space. Because illumination cones represent the whole image set of an object under all possible configurations of point light sources at infinity, nearly perfect recognition rates can be still achieved even under extreme illumination conditions.

III. THREE-DIMENSIONAL REPRESENTATION

Each individual face can generate a variety of images. This huge diversity of face images makes their analysis difficult. In addition to the general differences between individual faces, the appearance variations in images of a single faces can be separated into the following four sources. • Pose changes can result in dramatic changes in images. Due to occlusions different parts of the object become visible or invisible. Additionally, the parts seen in two views change their spatial configuration relative to each other.

➢ Illumination changes influence the appearance of a face even if the pose of the face is fixed. Positions and distribution of light sources around a face have the effect of changing the brightness distribution in the images, the locations of attached shadows, and specula reflections. Additionally, cast shadows can generate prominent contours in facial images.

➢ Facial expressions, an important tool in human communication, are another source of variations in images. Only a few facial landmarks that are directly coupled with the bony structure of the skull, such as the intraocular distance or the general position of the ears, are constant in a face. Most other features can change their spatial configuration or position via articulation of the jaw or muscle action e.g. a moving eyebrows, lips or cheeks.

➢ In the long term, a face changes because of aging, changing a hairstyle, or use of makeup or accessories.

The isolation and explicit description of all these sources of variations must be the ultimate goal of a face analysis system. For example, it is desirable that the parameters that code the identity of a person are not perturbed by a modification of pose. In an analysis by synthesis framework this implies that a face model must account for each of these variations independently by explicit parameters.

The main challenge for the design of such systems is to find or choose a description of these parameters that allows the appropriate modeling of images on the one hand and gives a precise description of an image on the other. Some of the sources of variations, such as illumination and pose, obey the physical laws of nature. These laws reflect constraints derived from the three-dimensional geometry of faces and the interaction of their surfaces with light. They are optimally imposed by a 3D representation, which was therefore chosen for the morph able model. On the other hand, there are additional regularities between faces that are not formulated as physical laws but can be obtained by exploiting the

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general statistics of faces. These methods are also denoted as learning from examples. It is expected that learning schemes that conform or incorporate the physical constraints are more successful in tasks such as generalizing from a single image of a face to novel views or to different illumination conditions [9].

As a result, the 3D morph able model uses physical laws to model pose and illumination as well as statistical methods to model identity and expression. As we see in the next two sections, these statistical methods require the faces to be put into *correspondence.*

A. Image Analysis with 3D Morph Able Model

In the analysis by synthesis framework, an algorithm seeks the parameters of the model that render a face as close to the input image as possible. These parameters explain the image and can be used for high-level tasks such as identification. This algorithm is called a *fitting algorithm*. It is characterized by the following four features.

- **Efficient**: The computational load allowed for the fitting algorithm is clearly dependent on the applications. Security applications, for instance, require fast algorithms (i.e., near real time).
- **Robust** (against non-Gaussian noise): The assumption of normality of the difference between the image synthesized by the model and the input image is generally violated owing to the presence of accessories or artifacts (glasses, hair, specular highlight).
- **Accurate**: As we have already pointed out, accuracy is crucial for the application that is to use the fitting results (and generally the level of accuracy required depends thereon).
- **Automatic**: The fitting should require as little human intervention as possible, optimally with no initialization.

An algorithm capable of any of the four aforementioned features is difficult to set up. An algorithm capable of *all* four features is the holy grail of model-based computer vision. In this chapter we present two fitting algorithms. The first one, called *Stochastic Newton Optimization* (SNO) is accurate but computationally expensive: a fitting takes 4.5 minutes on a 2 GHz Pentium IV. SNO is detailed elsewhere [7]. The second fitting algorithm is a 3D extension of the *Inverse Compositional Image Alignment* (ICIA) algorithm introduced by Baker and Matthews [1]. It is more efficient than SNO, and a fitting requires 30 seconds on the same machine. Our ICIA algorithm was introduced by Romdhani and Vetter [6]. As initialization, the algorithms require the correspondences between some of the model vertices (typically eight) and the input image. These correspondences are set manually. They are required to obtain a good initial condition for the iterative algorithm.

IV. System Methodology

Regardless of the move in the direction of to face matching global, local feature extraction, or ‘hybrid’, numerous of the 3D face imaging detection scheme employed in the prose make use of some *ad hoc* post-acquisition image to decrease noise, remove holes, and get better the quality of the 3D face imaging data shaped by the range 3D face imaging sensor. While the 3D face imaging techniques vary generally from system to system, it is widespread to see some of the following general processing operations:

Smoothing – The smoothing process is intended to suppress random noise occur from the 3D face sensor. Different 3D face sensors can exhibit dissimilar types of noise. It is usually an oversimplification to assume that the noise contagion is zero-mean, usually distributed, and affecting the z coordinates (the gaze direction) exclusively. Hence, smoothers such as mean filters designed to counterpart that sort of noise may not achieve the desired 3D face results. For example, range 3D face scanners that employ lasers can generate 3D face data contaminated by laser speckle. 3D face imaging of concavities can produce significant range excursions due to complex light reflections within those concavities. This frequently happens at the eyes in 3D face imaging with laser scanners, as the incident lighting is reflected into the eyeball through the lens, emerges again, and is 3D face detected. Stereo 3D face scanners and those projected-light 3D face sensors that employ patterns, wherein two scene points in a stereo pair are mistakenly corresponded, or the coordinates of a position on the projected pattern are poorly estimated. Such correspondence errors also yield gross errors in position estimates.

Local Feature Extraction – Local shape descriptors can be practical in the recognition of 3D face features that can be used consequently in matching or registration. 3D face sensors present a color image along with the 3D face shape data if they employ color cameras in the depth extraction process. This has led to a number of techniques for 3D face recognition of faces using 2D (color) and 3D face information gathered from the camera. We note that intensity 3D face detection techniques may also require preprocessing of the input color 3D face image using method such as normalization, smoothing, and re-sampling.

Interconnect Repair – Any structured-light range face scanner that produce a raster structured output will produce 3D face images with “missing” pixels from time to time. These invalid pixels should be ignored and treated as holes if the data is construe as a polygonal mesh interpolating the valid range data. Small holes in the interconnect are relatively easy to fill; local averaging can produce x, y, z estimates at the gone astray location. Larger holes can be filled by ‘nibbling’ away the unacceptable pixels one at a time by averaging, or through fitting a surface to the whole area using available 3D image data as constraints, followed by re-sampling within the hole.

V. Implementation of 3D Face Recognition

The acquisition of 3D face data illustration of faces using such data, and method for face detection based on these representations. The prose demonstrates that the stage of interest in 3D face detection is far above the ground among biometric system. 3D face recognition has possible to be a strong biometric. However, the use of 3D data for face gratitude is not without challenges and drawbacks, and some of these have contributed to the relatively small position of 3D face recognizers. One key drawback is the difficulty of the sensor. Although a variety of method exists for acquisition of 3D face data, as a rule they are more luxurious and slower to produce output 3D data than commodity 2D sensors. These 3D face sensors can also be delicate and can also necessitate recalibration periodically. In order for 3D face detection scheme to assume a greater role in employment, improved and less expensive 3D face sensors will need to emerge. Looking forward, a few themes in research and development for this technology area are apparent and are worth mentioning.

Sensing: 3D face sensors for face detection tend to be expensive and (depending on the technology) can be slow to produce 3D face data, produce 3D face data with artifacts and other noise contaminants, or produce low resolution 3D face data. New technologies and improvements in processing speed may make video-rate range 3D face imaging a reality if appropriate research effort is devoted to the task.

Scaling: Increasing attention is being paid to the problems of large subject databases for face recognition. Although the sizes of 3D face databases are increasing rapidly, all such databases are too small to do more than scratch the surface of the scaling problem. Synthesis of artificial imagery may offer benefits, but there is no substitute for a large database of real imagery from a good 3D face sensor. The systems issues surrounding large scale 3D face matching *i.e.*, keeping response time reasonable when the number of 3D face matches performed increases by an order of magnitude also need attention.

Variability: Toughness of 3D face matchers to facial expression variation has been a popular investigate topic recently. It is heartening to see so many dissimilar types of move toward to this problem, including both isolated local features (data driven) and global deformation models (anatomically driven). The relative scarcity of data that captures expression variation is a factor here.

Time Dimension: We see an opportunity for 3D face 'range video' processing for 3D face detection in the near future, as 3D face sensors improve. This issue has received relatively little attention to date. Active investigate groups looking at color video in face detection may yield valuable lessons that can engender a critical examination of range 3D face video analysis.

A. Global and Local Point Set Representation

The Iterative Closest Point (ICP) algorithm methods for 3D face data set registration that can be applied to any 3D face data dimensionality. It processes two 3D face data sets: the *3D face data shape* to which a transform is applied, and the *model shape* to which the transformed 3D face data shape is progressively aligned. A key assumption of ICP is that the 3D face data shape is a "3D face subset" of the model shape, in that it will, if successfully transformed, be aligned with a portion of the 3D face model shape. The ICP concept is easily applied to 3D face detection using 3D data; systems that employ this method are noted below. All such 3D face systems employ a sampling of 3D points from the input range 3D face data and a sampling from each model face as the basis for matching. Some new work has employed multiple local point set models as the basis for 3D face matching. Robustness to 3D face expression variation motivates this idea. If a region of the 3D face is both distinctive in shape and invariant to 3D face expression change, it can be used in 3D face matching.

B. Deformation Representation

A deformation-modeling method that is used in conjunction with ICP algorithm alignment to match 3D faces in the presence of 3D faces expression variation. This method expresses a 3D faces design (possibly including 3D faces expression-based deformation) using a subject-specific 3D face mesh captured with a neutral expression plus the locations of control points whose positions are sensitive to face expression. Control points are matched between different 3D face images and used to deform the neutral mesh to 3D faces match. In addition, control point locations are used to estimate a rigid head pose transform.

C. Subspace Methods for Matching

The application of ICP algorithm to 3D face image data is simple if one retains the depth (z) component of the 3D face image and treats it as a pseudo intensity value. As with intensity 3D face images, the 3D face image data must be geometrically normalized, often using automatically detected face features such as the nose tip or eye corners. The use of geometric information in PCA offers intriguing possibilities not available to 2D face imagery. Normally, 3D illumination artifacts are not present (although extreme lighting situations can badly corrupt the data). In addition, the depth component likely contains more low-frequency and less high-frequency content than an intensity 3D face image, which would typically mean that fewer principal mechanisms are needed for a representation of fixed fidelity. However, these potential advantages may be offset by traditional criticisms of ICP algorithm, namely its global character and thus its sensitivity to expression variation.

VI. Performance of 3D Face Biometric

In 3D face recognition and biometrics, performance is reported on three standard tasks: verification and open-set and closed-set identification. Each task has its own set of performance measures. All three tasks are closely related, with open-set identification being the general case. A biometric system works by processing biometric samples. Biometric samples are recordings of a feature of a person that allows that person to be recognized. Examples of biometric samples are 3D face images. A biometric sample can consist of multiple recordings: for example, five images of a person acquired at the same time or a facial image.

Computing performance requires three sets of images. The first is a gallery which contains biometric samples of the people known to a system. The other two are probe sets. A probe is a biometric sample that is presented to the system for recognition, where recognition can be verification or identification. The first probe set is PG which contains biometric samples of people in a gallery (these samples are different from those in the gallery). The other probe set is PN, which contains biometric samples of people who are not in a gallery. Closed-set identification is the classic performance measure used in the automatic face recognition community, where it is known as identification. With closed-set identification, the basic question asked is: Whose face is this? This question is a meaningful one for closed-set identification because a biometric sample in a probe is always that of someone in the gallery.

The general case of closed-set identification is open-set identification. With open-set identification, the person in the probe does not have to be somebody in the gallery; and here the basic question asked is: Do we know this face? With open-set identification, a system has to decide if the probe contains an image of a person in the gallery. If a system decides that a person is in a gallery, the system has to report the identity of the person. When a gallery is small, open-set identification can be referred to as a watch list task. The gallery is large, then open-set identification models.

Open-set and closed-set identification are sometimes referred to as 1 to many matching or 1: N matching depending on the context and author, 1 to many matching or 1: N matching can refer to either open-set or closed-set identification. In a verification task, a person presents a biometrics sample to a system and claims an identity. The system then has to decide if the biometric sample belongs to the claimed identity. During verification, the basic question asked is: Is this person who he claims to be? Verification is also called authentication and 1-to-1 matching.

VII. CONCLUSION

The work represents an attempt to recognize and account for the presence of expression on 3D face images, towards their improved identification. It also serves as a model for a realistic biometric application that addresses the major shortcomings of the current technology. It is evident that face expressions can produce significant deformations in the face surface. As such, facial expressions may cause deterioration in the performance of 3D face recognition systems that have been developed to process neutral faces. This was, in fact, the case when a classifier attempted to match smiling probe faces to neutral faces in a gallery. This work presented a framework in which an incoming probe face would first be processed to detect which kind of expression, if any, might be present in it, so that this extra piece of information can be used to employ an adequate specialized face recognition subsystem for its identification. As shown in this work, we have tested the feasibility of the framework proposed by developing a minimal implementation of it, in which the only non-neutral expression considered is for smiling faces. Notwithstanding the simplicity of this implementation, it served the purpose of demonstrating that the rank-one recognition of a mixture of neutral and smiling faces was about 10% higher when the complete structure of the proposed framework was used, i.e., when an expression recognition sub-system sorted the incoming faces and channeled them to matched recognition modules (i.e., one for neutral faces and a different one for smiling faces).

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Biography

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