AGE INVARIANT FACE RECOGNITION

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ABSTRACT

The challenges are face recognition across ages and how age gaps affect face recognition. Human identification, human faces convey a significant amount of information on one’s age, gender, ethnicity etc. In addition, facial expressions and facial gestures often reveal the emotional state of an individual. The goal is to come up with a representation and matching scheme that is robust to changes due to facial aging. Facial aging is a complex process that affects both the 3D shape of the face and its texture. In automatic face recognition shapes and textures degrade the performance. We proposed 3D aging modeling technique and show how it can be used to compensate for the age variations to improve the face recognition performance. The aging modeling technique adapts view-invariant 3D face models to the given 2D face aging database.

**Keywords:** Biometrics, Face recognition, facial aging, aging simulation

INTRODUCTION

It’s a combination of two Greek words: *Bios* means Life and *Metrics* means To Measure. Biometrics refers to the method of automatically identifying or verifying identity based upon behavioural or physical traits. It is the science and technology of measuring and statistically analyzing biological data, data that is represented in humans by patterns unique to every individual.

The security field uses three different types of authentication:

- Something you know—a password, PIN, or piece of information
- Something you have—a card key, smart card, or token
- Something you are—a biometric.

Of these, a biometric is the most secure and convenient authentication tool. It can't be borrowed, stolen, or forgotten, and forging one is practically impossible. The characteristics could be physiological or behavioural characteristics, which can be measured on a part of the body at some point in time (passive), are physiological biometrics. On the other hand, characteristics, which are learned or acquired over time (active), are called behavioural. These last characteristics are produced by an individual with a special effort, and are hence dependent to some degree on his state of mind. For example, fingerprint, hand geometry and face are physiological biometrics, while dynamic signature, gait, keystroke dynamics and lip motion are behavioural once.

Ideally the biometric characteristics used should satisfy the following properties Universality, Uniqueness, Permanence, Necessity, Acquisition, Conservation, Precision, Robustness, Accessibility
BIOMETRICS MODES

Identification is one to many comparisons of the captured biometric against a biometric database in attempt to identify an unknown individual. Verification is one to one comparison of a captured biometric with a stored template to verify that the individual is who he claims to be.

Figure 1: Identification

Figure 2: Verification

CHALLENGES IN FACE RECOGNITION

Face recognition is challenging task because human faces can vary a lot over time including many factors such as facial texture, shape, facial, presence of glasses. In addition, the image acquisition conditions and environment often undergo number of changes. We need to overcome the problem of face recognition across ages and how age gaps affect face recognition tasks. Passport verification is important in the process of passport renewal and related face authentication applications. For example when person submits new photo for renewal, the ideal system can automatically tell whether he is an imposter by comparing the new photo to previous photos that were usually taken years before. Appearance variation due to aging displays some unique characteristics so main problems encountered are [4]

Diversity in aging variation: Although all people age they do so in different ways.

- Dependence on external factors: Aging variation can be affected by external factors such as health, standard of living, and exposure to extreme weather conditions
- Collecting training data: Because the process of aging is slow, the collection of suitable data for training a machine to learn about this type of variations is difficult.

Facial aging is a complex process that affects both the shape and texture (e.g., skin tone or wrinkles) of a face. This aging process also appears in different manifestations in different age groups. While facial aging is mostly represented by the facial growth in younger age groups (i.e., <18 years old), it is also represented by relatively large texture changes and minor shape changes (e.g., due to the change of weight or stiffness of skin) in older age groups (i.e., >18). Therefore, an age correction scheme needs to be able to compensate for both types of aging processes.

FACE RECOGNITION IN 2D
2D face recognition is susceptible to a variety of factors encountered in practice, such as pose and lighting variations, expression variations, age variations, and facial occlusions. Local feature based recognition has been proposed to overcome the global variations from pose and lighting changes. The use of multiple frames with temporal coherence in a video and 3D face models have also been proposed to improve the recognition rate.

Figure 3: Images showing Occlusions

(a) glasses  (b) sunglasses  (c) hat  (d) scarf

Figure 4: Images showing pose, lighting, and expression variation

(a) frontal  (b) non-frontal  (c) lighting  (d) expression

FACE RECOGNITION IN 3D

3D Representation of face is less susceptible to isometric deformations (expression changes) 3D approach overcomes problem of large facial orientation changes. The true craniofacial aging model can be appropriately formulated only in 3D. The 3D face models from a number of subjects at different ages are then used for building the aging model through both shape and texture [1]. A combination of the shape and texture gives the aging simulation capability, which will be used to compensate for age variations, thereby improving the face recognition performance.

3D aging modeling: We use a pose correction stage model the aging pattern more realistically in the 3D domain. Considering that the aging is a process occurring in the 3D domain, 3D modeling is better suited to capture the aging patterns. We have shown how to build a 3D aging model given a 2D face aging database. The proposed method is the only viable alternative to building a 3D aging model directly, because there is no 3D aging database currently available. Separate modeling of shape and texture changes: The effectiveness of different combinations of shape and texture in an aging model has not yet been systematically studied. We have compared three different modeling methods, namely, shape modeling only, separate shape and
texture modeling, and combined shape and texture modeling (e.g., applying PCA to remove the correlation between shape and texture after concatenating the two types of feature vectors). We have shown that a separate modeling of shape and texture (or shape modeling only) is better than combined shape and texture modeling method, given the FG-NET database as the training data.

All the previous studies on facial aging have used PCA based matchers. We have used a state-of-the-art face matcher, FaceVACS from Cognitec to evaluate our aging model. The proposed method can be useful in practical applications requiring age correction processes. Even though we have evaluated the proposed method on only one particular face matcher, it can be used directly in conjunction with any other face matcher.

Diverse Databases: We have used FG-NET for aging modeling and evaluated the aging model on two different databases, FG-NET (in leave-one-person-out fashion) and MORPH. We have observed substantial performance improvements on the two databases. This demonstrates the effectiveness of the proposed aging modeling method.

3D MODEL FITTING

The 3D model enables us to perform pose correction and to build the 3D aging model. We use a simplified deformable model based on Blanz and Vetter's model. The geometric part of their deformable model is essentially a linear combination (weighted average) of a set of sample 3D face shapes, each with \( \approx 75,000 \) vertices. The vector that describes the 3D face shape is expressed in the Principle Component Analysis (PCA) basis. For efficiency, we drastically reduced the number of vertices in the 3D morph able model to 81 (from \( \approx 75,000 \)); 68 of these points correspond to the features already present in the FG-NET database, while the other 13 delineate the forehead region. Following we performed a PCA on the simplified shape sample set, \( f_{Smmg} \). We obtained the mean shape \( S_{mm} \), the eigen values \( \lambda_l \)'s and eigenvectors \( W_l \)'s of the shape covariance matrix. The top \( L (= 30) \) eigenvectors were used, which accounted for 98% of the total variance, again for efficiency and stability of the subsequent fitting algorithm performed on the possibly noisy data set. A 3D face shape can then be represented using the eigenvectors as:

\[
S_{cx} = S_{mm_{123456}} + \sum_{l=1}^{L} c_{l} W_{l},
\]

Figure 5: 3D Model Fitting Process Using Reduced Morph able Model [1]
3D AGING MODEL

Shape pattern space captures the variations in the internal shape changes and the size of the face. The pose-corrected 3D models obtained from the preprocessing phase are used for constructing the shape pattern space. Under age 19, the key effects of aging are driven by the increase in the cranial size; while, at later ages, the facial growth in height and width is very small. To incorporate the growth pattern of the cranium for ages under 19, we rescale the overall size of 3D shapes according to the average anthropometric head width found in The texture pattern Tji for subject i at age j is obtained by mapping the original face image to frontal projection of the mean shape $S$ followed by column-wise concatenation of the image pixels. After applying PCA on Tji, we calculate the transformation matrix $V_t$ and the projected texture $t_{ji}$. We follow the same filling procedure as in the shape pattern space to construct the complete basis for the texture pattern space using $t_{ji}$. 
Figure 6: 3D Aging Model Construction [1]

AGE SIMULATION

Face image of a subject at a certain age, aging simulation involves the construction of the face image of that subject adjusted to a different age. The purpose of the aging Simulation is to generate synthetically aged ($y > x$) or de-aged ($y < x$) face images to eliminate or reduce the age gap between the probe and gallery face images.
CONCLUSION

The extension of shape modeling from 2D to 3D domain gives additional capability of compensating for pose and, potentially, lighting variations. The use of a 3D model provides more powerful modeling capabilities than the 2D age modeling methods. Evaluated approach was using a state-of-the-art commercial face recognition engine (FaceVACS), and seen improvements in face recognition performance on two different publicly available aging databases.

FUTURE SCOPE

Exploring different (nonlinear) methods for building aging pattern space given noisy 2D or 3D shape and texture data with cross validation of the aging pattern space and aging simulation results in terms of face recognition performance can further improve simulated aging.

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