Facial Biometric Templates and Aging: Problems and Challenges for Artificial Intelligence

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Abstract. The performance of face recognition and/or authentication systems is greatly affected by within-person variations encountered in human faces. Within person facial variations distort the appearance of faces leading to inconsistencies between facial features stored in templates and features derived from a face, of the corresponding subject, captured at a different instance. For this reason a considerable amount of effort has been devoted to the development of methods for eliminating within person-variations during face recognition/authentication. Among all types of within-person variations encountered, aging-related variations display unique characteristics that make the process of dealing with this type of variation a challenging task. In this paper we describe experiments that enable the quantification of the effects of aging on the performance of face recognition systems. We also review typical approaches that aim to eliminate the effects of aging in face recognition and outline future research directions for this area.

1 Introduction

Researchers working in this field of face-based authentication aim to define biometric templates containing discriminatory features that are least affected by within-person types of variations in order to enable accurate identity verification [20]. Examples of within-person facial variations include variations due to different image acquisition conditions, different expressions, face orientation, occluding structures and aging. Researchers who compared the impact of within-person variations in different biometric templates [5, 9] conclude that facial templates display reduced permanence when compared to other widely used biometric modalities (i.e iris and fingerprints) hence it is highly important to develop methods for eliminating within-person variations in face recognition/authentication algorithms. Among all types of appearance variations, aging related facial variation displays unique characteristics that require customized attempts for dealing with the problem. One solution to the problem of aging is the frequent update of facial templates through a data acquisition process [19]. However, template updates can be performed only if all subjects whose faces are stored in a database are regularly available and willing to provide up to date face images.

During the recent years an increased research activity in the area of facial aging simulation is recorded [4, 6, 7, 8, 10, 12, 14, 15, 16, 17]. This interest is attributed to the potential of using age modeling techniques for a number of different applications that includes the prediction of the current appearance of missing persons [6], age estimation [4, 7], age-specific human computer interaction and the development of age invariant face authentication systems [10]. Research in facial aging is backed up by the existence of two publicly available face datasets [8, 15] dedicated for use in conjunction with studies related to face aging.

This paper aims to formulate the challenges involved in developing age-invariant face templates. Along these lines we briefly describe the physiological mechanisms that cause age-related variations on human faces and discuss the difficulties involved in dealing with aging variation. We also present results of an experimental evaluation that aims to quantify the effect of aging on face recognition. Challenges associated with the problem of aging are presented and possible ways for dealing with this problem are suggested. The discussion of this issue takes the form of a short review of the topic where different approaches to the problem and possible directions for future research activities are outlined.

2 Face Aging Process

The appearance of a human face is affected considerably by the aging process. Examples of aging effects on faces are shown in figure 1. Facial aging is mainly attributed to bone movement and growth, and skin related deformations. Aging related appearance variation due to bone growth usually takes place during childhood and puberty whereas skin related effects mainly appear in older subjects. Skin related effects are associated with the introduction of wrinkles caused by reduced skin elasticity and reduction of muscle strength [3, 12].

Figure 1: Face images displaying aging variation. Each row shows images of the same individual (Images from the FG-NET Aging Database [8]).

Dealing with aging variation is a challenging task because the aging process has the following unique characteristics:

Control: Unlike other types of variation (i.e face orientation) the effects of aging cannot be controlled and/or reversed. This characteristic of aging variation implies that (1) it is not possible to rely on the cooperation of a subject for eliminating aging variation during face image capture and (2) the process of collecting training data suitable for studying the effects of aging requires long time intervals.

Diversity of Aging Variation: Both the rate of aging and the type of age-related effects differ for different individuals. Typically diverse aging effects are encountered in subjects of different ethnic origins and different genders. External factors may also lead to diversities in the aging pattern adopted by different individuals. Such factors include health conditions, lifestyle, psychological conditions, climatic related factors and deliberate attempts to intervene with the aging process through the use of anti-aging products [3] or cosmetic surgeries. As a result common aging patterns cannot be applied successfully to all subjects.

3 Effects of Aging on Face Recognition

In this section we discuss the results of an experimental evaluation that aims to quantify the effects of aging on face recognition. As part of the experiment we use images from the FG-NET Aging Database [8] for training and testing face recognition systems in cases that we deal with significant aging variation. For the needs of our experiments we have used images from the FG-NET Aging database that contains 1002 images from 82 subjects. The database was divided in the following groups:

Group A and Group B: Each group contains half of the images of each of the 82 subjects. The separation of images was done in such way so that both groups contain similar distribution of ages for each subject. On average for each subject the age difference between samples in Groups A and B is 1.6 years, the minimum difference is 0 years and the maximum difference is 5 years.

Group C and Group D: Each group contains half of the images of each of the 82 subjects. However in this case Groups C and D contain the samples of each subject corresponding to younger and older ages respectively. The separation between younger and older faces of each subject is done based on the mean age among all samples belonging to the subject in question. On average for each subject the age difference between samples in Groups C and D is 15 years, the minimum difference is 6 years and the maximum difference is 34 years.

Figure 2 shows typical samples belonging to groups A,B,C and C for a one subject from the dataset.

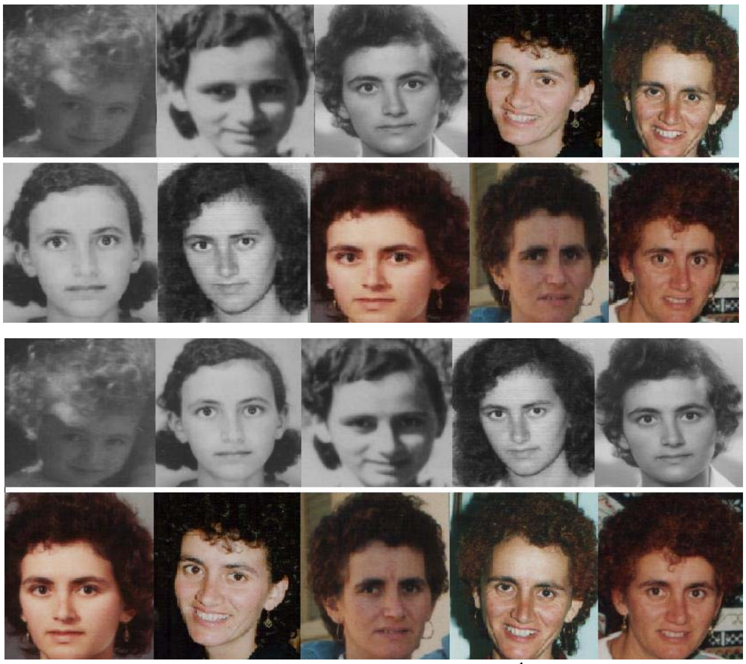

Figure 2: Samples from Groups A and B (1st and 2nd row) and Groups C and D (3rd and 4th row). Age distributions of samples in groups A and B are similar whereas age distributions of samples in groups C and D are distinctively different.

Face templates used in the experiments correspond to different facial parts so that it is feasible to compare the effects of aging for different parts. In particular templates derived from the overall internal facial region, upper face and lower face are used in our experiments (see figure 3). For the needs of the experiments facial templates are constructed based on a low dimensional Active Appearance Model-based representation [2] of the faces in the training and test sets. As part of the experiments two classification methods are used – the first method is based on a shortest Mahalanobis distance classifier and second is based on a Support Vector Machine Classifier. In both cases classifiers are trained using images from the train sets (sets A and C) and tested using sets B and D respectively. In our results (see table 1) we quote the reduction of the correct recognition rate when dealing with extreme aging variation (test set D) when compared to the case that we deal with reduced aging variation (test set B).

Figure 3: Face templates used in our experiments

	Reduction in Recognition Performance (Percentage units)	
	Shorter Distance Classifier	Support Vector Machine
Upper Face	13	14
Lower Face	8	8
Internal Face	15	16

Table 1: Reduction of correct recognition when dealing with extreme aging variation, compared to the case that we deal with reduced aging variation

According to the results the following conclusions can be derived.

- On average the performance of face recognition drops by about 12% when dealing with faces with different age distributions than the ones in the training set. Therefore it is of utmost importance to deal with aging variation.
- The effects of aging have greater impact when using face templates that include the upper face region. When using templates based on the lower part of the face aging effects cause smaller decrease in the recognition performance. However, the regions affected more intensively by aging are at the same time the most discriminatory regions.

The results of this preliminary experiment suggest that researchers, who work in the area of face recognition/verification, should run age invariance tests in order to assess the robustness of their approaches to aging variation. As part of this exercise along with the standard performance evaluation metrics that are usually quoted, the ability of an algorithm to deal with aging variation also needs to be specified. The framework used in the experiment described above could form the basis of developing standardized age-invariance test methodologies.

4 Discussion

We presented an overview where we outlined how aging affects human faces and we presented experimental results that demonstrate that face aging can affect dramatically the performance of face recognition systems. In order to deal with this problem we need to use techniques capable of simulating/eliminating aging effects on biometric facial templates. Aging simulation can be performed based on data driven approaches or methods based on modeling physiological mechanisms that cause the process of aging.

Data Driven Approaches: Data driven approaches rely on the analysis of aging datasets so that aging patterns are defined and used as the basis for simulating aging effects on previously unseen face templates. This method requires suitable datasets that contain face images of the same individual at different ages. Ideally such samples should be normalized so that only aging variation is observed among the samples. Data driven age modeling approaches described in the literature include the use of machine learning algorithms for defining aging patterns [4, 6, 15, 17] which can later be applied to novel faces in an attempt to simulate age effects. A different approach to the problem involves the use of statistical modeling for establishing the distributions of faces belonging to different age groups enabling in that way the application of aging effects by forcing a face to move closer to a target age distribution [8, 16].
From a different perspective data driven approaches can be used for the definition of age invariant facial representations. For example Ling et al [10] suggest that a face representation based on differences in gradient orientation displays increased tolerance to aging variation. These findings were verified in a scenario involving face verification experiments in the cases that the age between faces in a pair differ by up to 10 years.

Modeling Physiological Aging Mechanisms: This approach involves the use of complex mathematical models of physiological mechanisms that can be used for simulating aging effects on human faces and/or face templates. The process of defining such models requires deep understanding of the physical nature of the process of aging so that this process can be artificially reproduced. Thompson [18] was among the first researchers who proposed the use of mathematical models for modeling the growth of biological organisms. Based on this proposition several researchers attempted to derive functions that can be used for simulating the process of aging on 2D or 3D face outlines [11, 13]. Ideally physiological models of aging should take into account different aspects of personal characteristics in order to be able to produce aging simulations customized for different individuals.

As an alternative to the two categories of approaches mentioned above, it is possible to adopt combined data-driven and model-based approaches. In this respect the parameters of physiological models of aging are optimized through a machine-learning process that operates on suitable aging datasets [1, 14].

5 Conclusions

The aging process causes significant alterations on faces affecting in that way the long term performance of face authentication systems. The solution to this problem is to develop smart systems that will be able to modify biometric facial templates in an attempt to simulate aging effects ensuring in that way that face templates are always consistent with the current facial appearance of a subject. This task is extremely difficult because aging in combination with external factors that influence the process of aging, cause compounded effects that are difficult to predict and model. For this reason modeling aging variation requires state of the art Artificial Intelligence techniques that will be able to deal with this highly demanding problem. Issues that need to be addressed in order to address the problem include the establishment of accurate person specific aging patterns that take into account the possible effect of external factors and the definition of facial representations that include discriminatory but at the same time age invariant features.

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