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Paper Authors

NALUKURTHI SUMALATHA

SV University, Tirupati, AP, India.

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ADAPTIVE DATA-DISTRIBUTION LEARNING APPROACH OF AUTOMATIC AGE ESTIMATION BASED ON FACIAL AGING PATTERNS

NALUKURTHI SUMALATHA
Academic Consultant, Dept of ECE, SV University, Tirupati, AP, India.
Email:nalukurthisumalatha@gmail.com

Abstract— As an essential and difficult trouble in pc imaginative and prescient, face age estimation is typically cast as a classification or regression trouble over a hard and fast of face samples with respect to numerous ordinal age labels, which have intrinsically go-age correlations across adjacent age dimensions. As a result, such correlations usually result in the age label ambiguities of the face samples. Namely, each face pattern is related to a latent label distribution that encodes the go-age correlation facts on label ambiguities. Motivated by means of this remark, we advocate a totally information-pushed label distribution studying approach to adaptively examine the latent label distributions. The proposed approach is capable of successfully coming across the intrinsic age distribution patterns for pass-age correlation analysis on the basis of the nearby context structures of face samples. Without any prior assumptions at the sorts of label distribution learning, our method is capable of flexibly version the pattern-particular context conscious label distribution homes by solving a multi-challenge problem, which mutually optimizes the obligations of age-label distribution mastering and age prediction for people. Experimental outcomes display the effectiveness of our technique.

Index Terms—Age estimation, subspace learning, label distribution learning.

1. INTRODUCTION

As an important and challenging problem, face age estimation has recently attracted considerable attentions [1]–[7] as it has a wide range of applications such as face identification [8] and human-computer interaction [9]. Typical approaches to age estimation focus on the following three issues: I) face feature representation; II) face context structure construction; III) age prediction modeling. For I), the face appearance is usually represented by various visual features, such as face texture features (LBP, Garbor, and AAM) [10]–[12], biologically inspired features (BIF) [13], and deep learning features [8], [13], [12]. the face context structure is often modeled by constructing a face affinity graph for subspace analysis, which aims to capture the intrinsic interactions among face samples in the face-related image feature or attribute space (e.g., gender and race . The key problem of age prediction modeling is how to effectively learn the mapping function (e.g., non-linear and hierarchical function) from low-level image features to high-level age labels.This paper proposes a subspace approach named AGES (Aging pattern Subspace) for automatic age estimation.

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Instead of using isolated face images as data samples, AGES regards each aging pattern as a sample. The basic idea is to model the aging patterns by a representative subspace. Each point in the subspace corresponds to one aging pattern. The proper aging pattern for a previously unseen face image is determined by the projection in the subspace that can best reconstruct the face image. Once the proper aging pattern is determined, the position of the face in the aging pattern will then indicate its age.

The rest of this paper is organized as follows: First, the related work is briefly reviewed in Section 2. Then, the concept of an aging pattern is introduced in Section 3. After that, the AGES algorithm is proposed in Section 4. In Section 5, the experimental results are reported. Finally, in Section 6, conclusions are drawn.

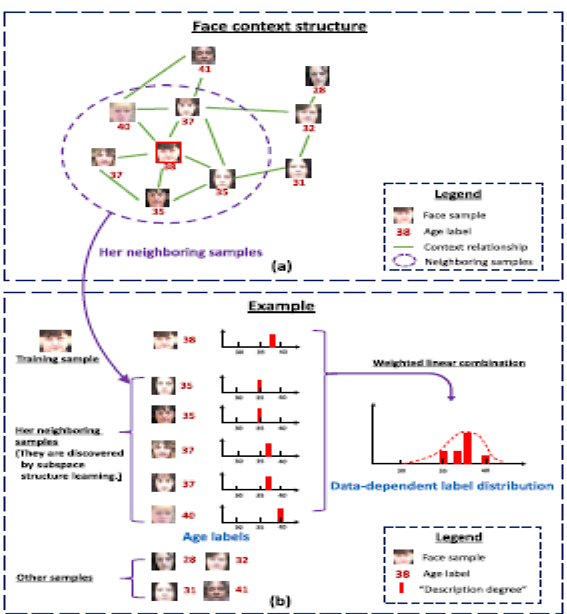

Fig.1: Proposed System for Age Patterns

2 RELATED WORK

There are some earlier works aiming to simulate the aging effects on human faces, which is the inverse procedure of age estimation. For example, Burt and Perrett [2] simulated aging variations by superimposing typical aging changes in shape and color on face images.

Later,Tiddeman et al. [5] extended this work by adopting a wavelet based approach to add high frequency information to the age progressed images. O'Toole et al. [5] described how aging variations can be made by applying a standard facial caricaturing algorithm to the 3D models of faces. Hutton et al. [9] proposed a dense surface point distribution model for expressing the shape changes associated with growth and aging. Hill et al. [7] presented a statistical approach to age face images along the "aging direction" in a face modelspace. Scandrett et al. [12] constructed a statistical model in which historical, familial, and average growth tendencies of a peer group can be incorporated. Ramanathan and Chellappa [9] proposed a craniofacial growth model that characterizes growth related shape variations observed in human faces during young ages. Although these works did not attempt age estimation, they did reveal some of the important facts in the relationship between age and face. Some other work tried to partly reveal the mapping from face to age. For example, Ramanathan and Chellappa [8] proposed a method for face verification across age based on a Bayesian classifier. Zana et al. [8] proposed a face verification algorithm in polar frequency domain which is robust against aging variation. Shi et al. [3] studied how effective are landmarks and their geometry-based approach for face recognition across ages. Kwonand da Vitoria Lobo [11] proposed an age classification method based on well-controlled high-quality face images, which can classify faces

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into one of the three groups (babies, young adults, and senior adults). Zhou et al. [11] presented a boosting-based algorithm for image-based regression (IBR). Although the algorithm was designed for the general purpose of IBR, it can be well applied to the problem of age estimation. The first true age estimation algorithm was proposed by Lanitis et al. [13]. In their work, the aging pattern is represented by the aging function: age ¼ fðbÞ, where b is the vector of the face model parameters and f is defined as a quadratic function. During the training process, a quadratic function is fitted for each individual in the training set as his/her aging function. To determine the suitable aging function for a previously unseen face image during age estimation, they proposed four different ways. Among the methods that do not rely on the external "lifestyle profiles," the Weighted Appearance Specific (WAS) method achieved the best performance.

Later, Lanitis et al. [12] compared their quadratic aging function method with several conventional classification methods in age estimation. The algorithms were tested in the single layer mode as well as in three hierarchical modes. As expected, all classifiers performed better in the hierarchical modes because the hierarchical structures handle the face image clusters separately according to the age groups or the appearance or both. Among them, the Appearance and Age Specific (AAS) method achieved the best performance.

However, according to the experimental results, the quadratic aging function did not show remarkable superiority over the conventional classifiers in the overall performance. The aging function-based approaches regard age estimation as a conventional function regression problem without special design for the unique characteristics of aging variation. This limitation prevents them from obtaining more satisfying results. In detail, there might be four weaknesses in such approaches. First, the formula of the aging function is empirically determined. There is no evidence suggesting that the relationship between face and age is as simple as a quadratic function. Second, the temporal characteristic cannot be well utilized by the aging function. The dependent relationship among the aging faces is mono directional, i.e., the status of a certain face only affects those older faces. However, the relationship revealed by the aging function is bidirectional: Any changes on a particular face will change the aging function, hence affecting all other faces. Third, the learning of one person's aging pattern is solely based on the face images of that person. Although people age in different ways, there must be some commonality among all aging patterns, i.e., the general trend of aging. Such commonality is also crucial in age estimation, especially when the personal training data is insufficient. Fourth, the aging function for the previously unseen face image is simply a linear combination of the known aging functions, rather than being generated from a certain model of aging patterns. All of these problems can be solved, from a new point of view, by the AGES algorithm. Changes start from the very beginning: data representation.

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3 AGING PATTERN

The aging function-based methods regard age estimation as a conventional classification problem: The data are the face images, the target is their age labels. According to the personalized characteristic, each image I should have one more label other than its age label age, i.e., its personal identity. If the problem is to be solved by supervised techniques like LDA (Linear Discriminant Analysis), then the algorithm must deal with the multilabel data, which is alone a problem in machine learning.

On the other hand, if all of these labels can be integrated into the data representation, then the multilabel problem can be transformed into an unsupervised learning problem. Thus, we propose a data representation called Aging Pattern, which is the basis of AGES. A formal definition is given as follows:

Definition 1. An aging pattern is a sequence of personal face images sorted in time order.

The keywords are "personal" and "time." All face images in an aging pattern must come from the same person and they must be ordered by time. Take the aging pattern shown in Fig. 1 as an example. Along the t axis, each age (0-8) is allocated one position. If face images are available for certain ages (2, 5, and 8), they are filled into the corresponding positions. If not, the positions are left blank.

If all positions are filled, the aging pattern is called a complete aging pattern; otherwise, it is called an incomplete aging pattern. Before the aging pattern can be further processed, the face images in it are first transformed into feature vectors. Obviously, aging is a process related to both the shape and the texture of face. Thus, the Appearance Model [4] is used as the feature extractor, whose main advantage is that the extracted feature combines both the shape and the intensity of the face images. Fig. 1 gives an example of the vectorization of the aging pattern, where b2, b5, and b8 represent the feature vectors of the face images at the ages 2, 5, and 8, respectively.

By representing aging patterns in this way, the two labels ageðIÞ and idðIÞ are naturally integrated into the data without any preassumptions. Each aging pattern implies one ID, each age is fixed into a position in the aging pattern, and the position is ordered according to time. Consequently, the personalized and temporal characteristics can be well utilized. As long as the aging patterns are well sampled, a proper model of aging patterns can be learned and the learning process is unsupervised. However, this brings two other challenges: 1) During training, the learning algorithm applied to the aging patterns must be able to handle highly incomplete training samples and 2) during age estimation on test data, the most suitable aging pattern as well as the most suitable position in that aging pattern must be selected for an unknown face image. The next section mainly tackles these two problems.

4 THE AGES ALGORITHM

4.1 Aging Pattern Subspace

A representative model for the aging patterns can be built up by the information theory approach of coding and decoding. One widely adopted technology is using PCA [10] to construct a subspace that captures the main variation in the data set.

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The projection in the subspace is computed by

$$y = \mathbf{W}^{\mathrm{T}}(x - \mu),$$

where _ is the mean vector of x andWT ¼W_1 is the transpose of W, which is composed by the orthogonal eigenvectors of the covariance matrix of x. The difficulty is that the aging pattern vector x is highly incomplete. Based on the characteristics of aging patterns, an EM-like algorithm is proposed here to learn a representative subspace.

Suppose the training set has N aging pattern vectors D={x1; . . . ; xN}. Any sample in this set can be written as xk ¼ {xak; xm},where xak are the available features and xmk are the missing features

of xk. Suppose the transformation matrix isW, the projection yk of xk in the subspace can be calculated by (1) and the reconstruction of xk is calculated by

$$\hat{x}_k = \mu + \mathbf{W}y_k.$$

It is well known that standard PCA can be derived by minimizing the mean reconstruction error (residuals) of the data set D in the subspace [10]. With the presence of the missing features xmk , the goal is changed into finding aWthat minimizes the mean reconstruction error of the available features

$$\overline{\varepsilon}^a = \frac{1}{N}\sum_{k=1}^{N}(x_k^a - \hat{x}_k^a)^{\mathrm{T}}(x_k^a - \hat{x}_k^a).$$

In case the number of missing features in different instances is highly uneven, (3) should be normalized by the dimensionality of the missing part. This is equivalent to a preprocess of dividing each instance by its missing dimensionality. The FG-NET Aging database used in this paper has a similar number of missing features in each aging pattern; thus, there is no significant difference observed in the experiments with/without the normalization.

When initializing, xmk is replaced by the mean vector calculated from other samples whose corresponding features are available. Then, standard PCA is applied to the full-filled data set to get the initial transformation matrix W0 and mean vector _0. In the iteration i, the projection of xk in the subspace spanned byWi is estimated first. Since there are many missing features in xk, the projection cannot be computed directly by (1). Note that the aging patterns are highly redundant; it is possible to estimate yk only based on part of xk [4], say xak . Instead of using inner product, yk is solved as the least squares solution of

$$[\mathbf{W}_i(^a_k)]y_k = x_k^a - [\mu_i(^a_k)],$$

. Then, standard PCA is applied to the updated data set to get the new transformation matrix Wiþ1 and mean vector _iþ1. The whole process repeats until the maximum iteration _ is exceeded or "a is smaller than a predefined threshold _. The convergence of this algorithm is proven in the Appendix.

During the training process of AGES, the missing faces in the training aging patterns can be simultaneously learned by reconstructing the whole aging pattern vectors through (2). Fig. 2 shows some typical examples of the “full-filled” aging patterns when AGES is applied to the FG-NET Aging Database [4]. For clarity, only the faces in the most changeable age range from 0 to 18 with two year increments are shown. Since remarkable variations other than the aging effects exist in the FG-NET Aging Database and the feature extractor does not treat them separately, some generated faces present noticeable variations in expression, pose, or llumination. These variations can be dealt with, as will be discussed in Section 5, by applying LDA to the Appearance Model parameters. It can be seen that the learned faces inosculate with those real faces very well in the aging patterns. Thus, this learning algorithm can also be used to simulate aging effects on human faces. The process of the learning algorithm is actually a process of interaction between the global aging pattern model and the personalized aging patterns. As mentioned in Section 2, although different people age in different ways, the commonality (modeled by the subspace) of all aging patterns is also crucial for age estimation, especially when the aging patterns are highly incomplete.

In each iteration, the missing part of the personal aging pattern is first estimated by the current global aging pattern model. Then, the global model is further refined by the updated personal aging patterns. In this way, the commonality and the personality of the aging patterns are alternately utilized to learn the final subspace.

4.2 Age Estimation

The aging pattern subspace is a global model for aging patterns, each of which corresponds to a sequence of age labels. But, the task of age estimation is based on a single face input and expects a single age output. This section will describe how this can be done with the aging pattern subspace. Given a previously unseen face image I, its feature vector b is first extracted by the feature extractor. Recall the two steps of age estimation mentioned in Section 1. The first step is to find a proper aging pattern for I. Note that each point in the subspace corresponds to one aging pattern. Thus, the proper aging pattern for I can be selected through finding a point in the subspace that can best reconstruct b, i.e., minimizing the reconstruction error. However, without knowing the position of I in the aging pattern, which should be determined in the second step, the reconstruction error cannot actually be calculated. Thus, I is placed at every possible position in the aging pattern, getting p aging pattern vectors zjðj ¼ 1 . . . pÞ by placing b at the position j in zj. Noting that b is the only available feature in zj, the projection yj can be estimated by (4), and the reconstruction error can be calculated by

$$\varepsilon^a(j) = (\boldsymbol{b} - \boldsymbol{\mu}_{(j)} - \mathbf{W}_{(j)}\boldsymbol{y}_j)^{\mathbf{T}}(\boldsymbol{b} - \boldsymbol{\mu}_{(j)} - \mathbf{W}_{(j)}\boldsymbol{y}_j),$$

where µj is the part in µand Wj is the part in W that corresponds to the position j. Then, the projection yr that can reconstruct b with minimum reconstruction error over all of the p possible positions is determined by

$$r = \arg\min_j(\varepsilon^a(j)).$$

Thus, the suitable aging pattern for I is zr. Step 2 afterward becomes trivial because r also indicates the position of I in zr. Finally, the age associated to the position r is returned as the estimated age of I. As a byproduct of age estimation, the whole aging pattern vector can be reconstructed as Wyr, which can be used to simulate faces at different ages of the subject in I. During the age estimation process of AGES, the proper aging pattern for the test image is generated based on both the aging pattern subspace and the face image feature. The subspace

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defines the general trend of aging, and the face image feature represents the personalized factors. By placing the feature vector at different positions, candidate aging patterns specified to the test face are generated. Among these candidates, only one is consistent with the general aging trend, which can be detected viaminimum reconstruction error by the aging pattern subspace. At the same time, the position of the test image in that aging pattern can be determined.

5.AGING EFFECTS SIMULATION AND FACE RECOGNITION

As mentioned in Section 4.2, given a face image, AGES can be used to simulate face images at different ages. Besides the direct applications of aging effects simulation, such as aging missing children, it can be used for face recognition systems across ages.For each subject in the FG-NET Aging Database, 10 pairs of face images are randomly selected, the first one as "gallery" face and the second one as "probe" face. Usually, there is remarkable age difference between them. Given a probe face, the objective of aging effects simulation is to generate a face image at the age of the gallery face. Some typical results of the simulation by AGES are shown in Fig. 6. As can be seen that the simulated faces look quite similar to thereal faces (the gallery faces), only with slight difference in pose, illumination, or expression. It is noteworthy that, for the first probe face, the simulated face looks relatively more different from the gallery face. This might be because the gallery face wears glasses, which is impossible to predict based on the 4-year-old probe face. To evaluate the simulation quantitatively, the difference between images is calculated as the Mahalanobis Distance (MD) between the Appearance Model parameters. The average MD from the original probe faces to the gallery faces is 18.83, while that between the simulated faces to the gallery faces is 11.92, which reveals that the simulation makes the probe faces more similar to the gallery faces.If one gallery face from each subject (82 subjects in the FG-NET Aging Database) is selected and composes a database, then each probe face can be recognized by this database. The most common implementation is to calculate the similarity between a probe face and each gallery face in the database, then recognize the probe as the person in the most similar gallery image. Here, the Mahalanobis Distance is used again as the similarity measure. Also, we use the same 10 gallery-probe pairs selected from each subject in the aging simulation experiment. Note that the gallery set and the probe set are both selected randomly and they do not have intersection. Each time, the gallery face in one pair from each subject is used to build a database and the probe face in that pair is used to constitute a test set corresponding to the database. In total, 10 gallery databases and 10 corresponding probe sets are composed. One face recognition test is performed on each pair of them. The average recognition rate of the 10 tests without aging simulation is 14.39 percent. If the probe face is first simulated by AGES to the age of the gallery face, then the average recognition rate can be improved to 38.05 percent. Of course, the assumption that the ages of both the probe and the gallery faces are known before the recognition is

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sometimes unsatisfactory. One possible way to solve this problem is to simulate the whole aging pattern from the gallery/probe face and recognize the "probe aging pattern" based on the database of the "gallery aging patterns."

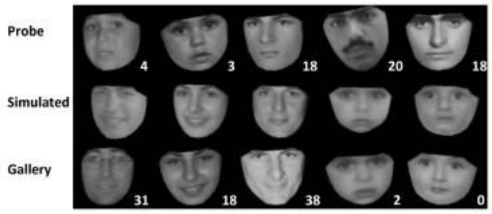

Fig. 2. Typical examples of aging effects simulation by AGES. The ages are marked at the right-bottom corner of the images.

6 CONCLUSION

This paper proposes an automatic age estimation method named AGES, which improves our earlier work [5]. It is interesting to note that, at least under the experimental configuration in this paper, the performance of AGES is not only significantly better than that of the state-of-the-art algorithms, but also comparable to that of the human observers.

The current preprocessing method in AGES relies on many landmark points in the face images, eventually these landmarks should be determined by applying automatic land marking algorithms like [3]. Moreover, the current preprocess does not retain the information about the outer contour size of the face. However, face size varies across ages, especially during formative years.

Hence, as future work, taking the size and shape of the face contour into consideration might significantly improve the accuracy of AGES, especially for age estimation on children's faces. Besides age estimation, AGES can be utilized in other computer vision tasks. For example, with the ability to simulate facial aging effects, AGES can be used for face recognition across ages, which has been tested in the experiment. More generally, pose and illumination variations are always troublesome in computer vision systems.

Similar to AGES dealing with images at different ages, images under different pose and illumination conditions can be treated as a whole (analogous to an aging pattern). This idea has been explored in face recognition, known as the "Eigen Light-field" [6], [30]. In order to model the light-field, a "generic training data set" is required in such works, which contains face images under all possible pose and illumination conditions. But, this is not always available in reality.

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