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Individualised Model of Facial Age Synthesis Based on Constrained Regression

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Abstract **- Faces convey much information. Interestingly we humans have a remarkable ability of identifying, extracting, and interpreting this information. Recently automatic facial ageing (AFA) has gained popularity due to its numerous applications which include search for missing people, biometrics, and multimedia. The problem of AFA is faced with various challenges, including incomplete training datasets, unrestrained environments, ethnic and gender variations to mention but a few. This work presents a new approach to automatic facial ageing which involves the development of a person specific facial ageing system. A color based Active Appearance Model (AAM) is used to extract facial features. Then, regression is used to model an age estimator. Age synthesis is achieved by computing a solution that minimises the distance from the original face with the use of constrained regression. The model is tested on a challenging database of single image per person. Initial results suggest that plausible images can be rerendered at different ages, automatically using the AAM representation. Using the constrained regressor we are guaranteed to get estimated ages that are exact for an individual at a given age.**

Keywords **- Facial ageing, Age estimation, Age progression, Age synthesis, Constrained regression.**

I. Introduction

The ability to effectively conduct automatic face recognition is hindered by a number of factors, for example illumination variation, facial expressions, and many more. Facial ageing, being a function of shape and texture (e.g. wrinkles) also degrades the performance of face recognition systems [1].

Over the last decade, there has been a considerable amount of research in the area of facial ageing. This is due to its numerous practical applications which include forensics, gaming, and biometrics. Advancements in this area have been discussed in comprehensive reviews by [2], [3] and [4].

Although much work has been reported in the literature, the problem cannot be considered solved. This is due to complexities caused by multi-factor variations such as ethnicity, gender and other environmental factors.

One of the most obvious challenges of AFA is the fact that people have specific ageing patterns. It has been observed that some work in the literature develop models based on generalisation of facial variations. Also their experiments rely on the use of multiple images per subject, for training purposes. However, in real world scenarios such as international passports, and drivers' licenses, mostly single images of individuals are stored.

This work is aimed at developing individualised (person specific) age estimation and synthesis systems. Our contribution includes; the use of constrained regression for modelling, proposing improvement to Lanitis et al's [5] face synthesis method, as well as experimentation with only a single image per person.

II. Related work

Automatic Facial Ageing (AFA) can be categorised into estimation and synthesis, while the former computes the age or age group of individuals from their image, the latter re-renders the facial appearance with natural ageing effects [2]. Several techniques have been proposed in the literature for both problems. These can be categorised into three broad categories; geometric, textural, and appearance based methods.

Geometric techniques define facial features using distances and ratios [6], [7]. These methods work best for images of young people, because they mainly encode shape variations which are not significant in adulthood [2].

Texture models concentrate on extracting and manipulating intensity variations on the facial skin surface, specifically measurements of wrinkles have been used to classify ages [8]–[10], photo realistic aged faces have also been generated either by transferring wrinkles from old faces onto young faces, or via independent construction of skin models [11], [12]. The construction of 3D wrinkles has also been reported in the literature [13], [14]. However, wrinkles and skin deformation is actually not predominant in young people [2].

Appearance based approaches model both shape and texture variations simultaneously, [15] proposed an image based model that computes average faces for different age groups, then difference between the target age group and the current age group is computed and added to the subject's image. The same idea has been extended for unconstrained images by [16]. Age estimation and synthesis has also been achieved via the use of PCA to describe shape and texture variations [5], [17]–[21].

One method that has gained popularity among researchers [2], [19], [22] is that proposed by [5]. AAM was used to extract facial features then an ageing function that relates ages to the raw AAM parameters c was defined. By carefully choosing a regression function, the ages were estimated, additionally age synthesis was realised by computing a new set of c values. A number of AAM vectors were generated for each age in the training data and stored in a lookup table. In cases where there were several subjects having the same age, the average c vector corresponding to that age was computed and stored. In order to synthesize a new face, c values for the current and new ages were retrieved from the lookup table, and then their difference was added to the individual's original AAM parameters. The technique suffers from a number of limitations; it relies on adding or subtracting average values of c, this is actually not far from the method proposed in [15]. Firstly, adding averages can partially mask the identity of the subject. Secondly, being dependent on the lookup table, one cannot synthesize an age that is not in the training set.

Due to the aforementioned problems, we propose a method that explicitly computes a particular solution of the ageing function using least squares optimization with a linear age constraint. It will be shown that this gives us the ability to synthesize ages that are not even in the training set. The proposed algorithm gives us a potential way of isolating ageing features from the facial identity. Additionally, state of the art work relies on the use of multiple images of a single subject for training purposes. However, in real world scenarios such as law enforcement mugshots, international passports, and drivers' licenses, only single images of people are stored. Hence our model will be tested on a "single image per person" training dataset.

III. METHODOLOGY

In this section we describe the extraction of facial features via the active appearance model that was first proposed by Cootes et al [23]. Additionally color information is encoded via the normalization technique proposed by [24]. Constrained regression is used to build a person-specific ageing model. Subsequently, we present our novel age synthesis method.

3.1 Features Extraction Using Color AAM

AAM is a statistically based template matching technique that captures shape and texture variability from a training dataset. A parameterised model is formed by using Principal Component Analysis (PCA) to combine shape and texture models thereby describing seen and unseen images [23]. Initially it was designed for greyscale images, however the technique has been extended to incorporate color information [24].

In this work, shapes are represented by a set of 79 landmarks defined in two dimensional space $\mathbb{R}^2$. Thus each face shape is described by a vector **x** of landmark coordinates given by,

$$\boldsymbol{x} = (x_1, x_2, \dots x_n, y_1, y_2, \dots y_n)^T \qquad (1)$$

In order to capture only the shape variations of the training images, translation, scale, and rotation variations were eliminated by alignment using the Generalised Procrustes Analysis (GPA). Having aligned the 2D vectors using GPA, the statistical shape model is built using PCA. Therefore, each shape **x**, can be approximated by a linear combination given by

$$\boldsymbol{x} \approx \overline{\boldsymbol{x}} + \boldsymbol{P}_x b_x \qquad (2)$$

where $\overline{\mathbf{x}}$ is the mean shape, $\mathbf{b}_x$ a set of shape parameters, and $\mathbf{P}_x$ the orthogonal modes of variation or "eigenshapes".

The texture model captures the variability of image pixels. This was previously achieved using the EigenFaces approach [25], although this lacks pixel to pixel correspondence across the training set as a result of person to person shape variations. With a view to tackling the stated problem, all face images are first aligned to a mean shape via warping, thus "shape-free patches" are created using piecewise affine method; a simple non parametric warping technique that performs well on local distortions [26].

In order to improve texture specificity, a number of researchers have extended the original AAM by incorporating RGB information [27], [28]. However, when dealing with color texture there is chromaticity variation in addition to the normal intensity variation [24]. It has been observed that these two variations are mixed within each of the three RGB color channels, and there is strong cross correlation between RGB channels thereby affecting performance [24]. While other color representations such as CIELAB have been considered in the past, the I1I2I3 color space [28] has been most successful [24]. This is because it uses PCA to decorrelate the RGB channels. The RGB to I1I2I3 transformation is given by,

$$I1 = (R + G + B)/3 \qquad (3)$$
$$I2 = (R - B)/2 \qquad (4)$$
$$I3 = (2G - R - B)/4 \qquad (5)$$

In the literature, global lighting effects are normalised by applying a scaling α and an offset β to the texture vector g [23]. The same technique is used to normalise each I1, I2, and I3 sub vector independently.

The statistical texture model is constructed by applying PCA to the data from each of the normalised I1, I2, and I3 channels. The texture of each image can then be approximated using three linear equations (one for each I1, I2, I3) expressed below

$$\boldsymbol{g}_{i1} \approx \overline{\boldsymbol{g}_{i1}} + \boldsymbol{P}_{i1} \boldsymbol{b}_{i1} \qquad (6)$$

$$\boldsymbol{g}_{i2} \approx \overline{\boldsymbol{g}_{i2}} + \boldsymbol{P}_{i2}\boldsymbol{b}_{i2} \quad (7)$$
$$\boldsymbol{g}_{i3} \approx \overline{\boldsymbol{g}_{i3}} + \boldsymbol{P}_{i3}\boldsymbol{b}_{i3} \quad (8)$$

where $\mathbf{P}_{i1}$, $\mathbf{P}_{i2}$, and $\mathbf{P}_{i3}$ are the orthogonal modes of variations, and b_{i1}, b_{i2}, and b_{i3} the texture parameters for I1, I2, and I3 respectively.

Our Color AAM is a single model that combines the shape and three texture models. Since the shape and color models can be described using the set of model parameters $\mathbf{b}_x$, $\mathbf{b}_{i1}$, $\mathbf{b}_{i2}$, and $\mathbf{b}_{i3}$ respectively, this combined model is then built by concatenating the four vectors

$$\boldsymbol{b}_{com} = \begin{pmatrix} \boldsymbol{W}_k\, \boldsymbol{b}_x \\ \boldsymbol{b}_{gi1} \\ \boldsymbol{b}_{gi2} \\ \boldsymbol{b}_{gi3} \end{pmatrix} = \begin{pmatrix} \boldsymbol{W}_k\, \boldsymbol{P}_x^T(\boldsymbol{x} - \overline{\boldsymbol{x}}) \\ \boldsymbol{P}_{i1}^T(\boldsymbol{g}_{i1} - \overline{\boldsymbol{g}_{i1}}) \\ \boldsymbol{P}_{i2}^T(\boldsymbol{g}_{i2} - \overline{\boldsymbol{g}_{i2}}) \\ \boldsymbol{P}_{i3}^T(\boldsymbol{g}_{i3} - \overline{\boldsymbol{g}_{i3}}) \end{pmatrix} \quad (9)$$

where $\mathbf{W}_k$ is a diagonal matrix of weights used to compensate for the difference in magnitude between the units of shape and texture models. PCA is then applied to the new vector $\mathbf{b}_{com}$ to remove any correlation that may exist between the shape and textures. This results in an appearance model given by,

$$\boldsymbol{b}_{com} = \boldsymbol{P}_{com}\boldsymbol{c} \quad (10)$$

$\mathbf{P}_{com}$ is a matrix of eigenvectors, and c the appearance parameter that controls all 4 models (shape and color), having zero mean.

$$\boldsymbol{P}_{com} = \begin{pmatrix} \boldsymbol{P}_{com\_x} \\ \boldsymbol{P}_{com\_i1} \\ \boldsymbol{P}_{com\_i2} \\ \boldsymbol{P}_{com\_i3} \end{pmatrix}. \quad (11)$$

Due to the linear nature of the appearance model, the shape and textures can be expressed in terms of **c** [23].

3.2 Facial Ageing

AAM parameters c used as facial features are used to model an ageing function which can then be used for age estimation, furthermore the ageing function will play an important role in our novel approach for age synthesis.

Ageing Function

It has been observed that facial appearance consistently changes with age. Since AAM models both face shape and texture variations, then the AAM parameters c capture ageing variations [5]. Consequently, an ageing function can be defined relating age to vectors of AAM parameters [5].

$$age \approx f(\boldsymbol{c}) \quad (12)$$

Regression methods have been used in the literature to relate the AAM parameters to a person's age [5], [29], [30]. There are many types of regression analysis depending on the distribution of the response variable. These include linear, inverse, logarithmic, logistic, quadratic, and cubic models. In our work we start by assuming a simple linear model given by,

$$age = \alpha + \boldsymbol{\beta}^T\boldsymbol{c} \quad (13)$$

where α is the intercept also called an offset, and **β** a vector of regression coefficients. Equation (13) can be used to get an estimated age for an individual provided the vector c has been computed from the AAM. To get the best fit for the linear relationship described by (13) we wish to choose α and **β** to minimize the error,

$$\sum_{i=1}^{N} |age_i - (\alpha + \boldsymbol{\beta}^T\boldsymbol{c}_i)|^2 \quad (14)$$

where N is the number of images in the database. A person specific model is obtained by forcing (14) to pass through the appearance parameter $\mathbf{c}_i$ of a particular individual by using a linear constraint expressed as,

$$age_i = \alpha + \boldsymbol{\beta}^T\boldsymbol{c}_i \quad (15)$$

Using the constrained approach, we are guaranteed to get the exact age of subject "i" if we plugged in his/her appearance parameter c into the age estimation function.

Age Synthesis

As stated earlier, the use of an ageing function was first proposed by [5]. Having modelled the ageing function in equation (13), the age for an individual can be synthesized by first computing a new set of raw AAM parameters. This is supposed to be achieved by computing the inverse expressed as,

$$\boldsymbol{c} = f^{-1}(age) \quad (16)$$

Lanitis et al [5] used the lookup table approach (discussed in section 2). In our approach we choose a solution which minimizes the distance from the original face. We first simplify equation (13) by subtracting the offset from both sides of the equation,

$$age' = age - \alpha = \boldsymbol{\beta}^T \boldsymbol{c} \quad (17)$$

Since $\boldsymbol{\beta}$ is not invertible, a particular solution can be computed using the Moore-Penrose pseudoinverse

$$\hat{\boldsymbol{c}} = \boldsymbol{\beta}^{\dagger} age' \quad (18)$$

Equation (18) implies that, every $\hat{c}$ computed for a certain age will have the same value irrespective of the individual. In linear algebra, suppose a transformation T (e.g. projection) applied to two vectors $\mathbf{c}_1$ and $\mathbf{c}_2$ results in the same vector $\mathbf{c}_p$ expressed as

$$T\boldsymbol{c}_1 = \boldsymbol{c}_p \quad (19)$$

$$T\boldsymbol{c}_2 = \boldsymbol{c}_p \quad (20)$$

Subtracting the two equations (19) and (20) above, results in

$$T(\boldsymbol{c}_1 - \boldsymbol{c}_2) = 0 \quad (21)$$

Thus we have a nonzero vector $\mathrm{T}(\mathbf{c}_1 - \mathbf{c}_2)$ whose image is zero, this implies that the two projections differ by an element in the null space of T [31]. In our representation, since AAM parameters of two individuals having the same age differ by some value, we can conveniently say that each person's AAM parameter contains two components; the "age component" ($\mathbf{c}_{age}$) that is computed as a projection using (18) and an identity component (c_{id}) which lies in the null space of $\boldsymbol{\beta}^{\dagger}$, this is expressed as,

$$\boldsymbol{c}_{individual\_now} = \boldsymbol{c}_{age} + \boldsymbol{c}_{id}. \quad (22)$$

To compute the AAM parameter $\mathbf{c}_{new}$ for a new age, we first use equation (22) to get the identity component $\mathbf{c}_{id}$, then using equation (18) the age component for the new age can be computed. The sum of these two values results in a $\mathbf{c}_{individual\_new}$ i.e. the AAM parameters for that individual at a new age, this can summarised in algorithm 1 below.

Algorithm 1 Age Synthesis

[1] Given the raw AAM parameters $\mathbf{c}_{\text{individual\_now}}$ at the current age
[2] Compute the age component $\mathbf{c}_{\text{age\_now}}$ at current age, using equation (18)
[3] Calculate the person's identity component
$\mathbf{c}_{\text{id}} = \mathbf{c}_{\text{individual\_now}} - \mathbf{c}_{\text{age\_now}}$
[4] Compute the age component for the new age using equation (18) $\mathbf{c}_{\text{age\_new}}$
[5] Sum the result in 3 and 4 to get the raw AAM parameters at new age
$\mathbf{c}_{\text{individual\_new}} = \mathbf{c}_{\text{age}_{\text{new}}} + \mathbf{c}_{\text{id}}$
[6] Reconstruct the face using $\mathrm{c}_{\text{individual\_new}}$

Because $\boldsymbol{\beta}^T\boldsymbol{\beta}^{\dagger}$ is an orthogonal projector, $\mathbf{c}_{\text{individual\_new}}$ minimizes

$$\left|\boldsymbol{c}_{individual\_now} - \boldsymbol{c}_{individual\_new}\right|^2 \quad (23)$$

Using this constraint coupled with the constrained model, we are guaranteed that $\mathbf{c}_{\text{individual\_new}}$ does not alter $\mathbf{c}_{\text{i}}$ for an individual when the correct age is used as the target age.

IV. Experiments

We trained the model described in section 3.1 using 228 images obtained from two high quality controlled image databases. Firstly, HQFaces [32]: a database of 97 pairs of siblings' facial images, all photographed under the same lighting conditions; the subjects are Caucasian, ranging from 13 to 50 years of age, out of which 43% are female. For the purpose of our experiments, 148 frontal non smiling images were collected from this database. Secondly, The Dartmouth Children's Faces Database [33]: Contains 80 images of Caucasian children ranging from the ages of 6 to 16 years, with 1:1 gender ratio. Each subject was photographed under two lighting conditions, five angles, and displaying eight facial expressions. For the purpose of our work only those frontal images with neutral expression were picked. All 228 images were cropped to 340 × 340 pixels in order to reduce images size as well as computational cost.

The linear regression model described by equation (13) was built using the first 20 elements $(\mathrm{c}_1, \dots \mathrm{c}_{20})$ of the AAM parameters $\mathbf{c}$. This selection was made with the goal of fitting the model using a small number of predictors, in order to avoid the problem of over fitting. As a guide to our choice of these first 20 elements of **c**, the cumulative variance of the eigenvalues of our AAM model was plotted as shown on Fig. 1. The Fig. shows that the first 20 eigenvectors account for over 75% of the variance.

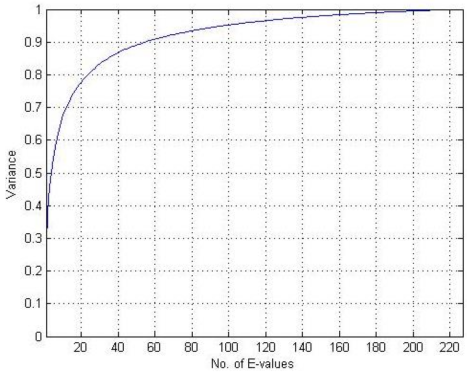


Fig. 1: Percentage variation accounted for by AAM eigenvectors, first 20 eigenvectors account for 77% variation

Evaluation of the age estimation model, was performed using K-Fold-Cross-Validation (K = 25). Within twenty five (25) successive iterations, the data comprising 228 images was split into two; training and test data. First the regression model was computed using the training subset, then the test data were used to cross validate the model. The performance measures used are Mean Absolute Error (MAE) and Cumulative Score (CS), expressed as,

$$MAE = \sum_{i=1}^{N} | age' - age |/N, \qquad (24)$$

$$CS(m) = N_{abs\_error \leq m} / N \times 100\% \qquad (25)$$

where age' is the estimated age and the ground truth age is "age", N number of test images, and $N_{abs\_error \leq m}$ is the number of images on which the system makes absolute error not higher than m years. Experimental results for MAE and CS are shown on Table 1 and Fig. 2 respectively.

Table 1: MAEs of age estimation experiments

Test-set	**MAE**
Best	2.99
Median	5.27
Worst	7.86

Out of the 25 test sets, the best i.e. the one with least error had MAE of 2.99 years. Table 1 also shows the MAE of the median set. The worst set had MAE of 7.86 years, this is primarily because the test set contained outlier ages. Considering automatic age estimation systems reported in the literature, [34] proposed a locally adjustable robust regressor (LARR) that outperformed other state of the art systems. The MAE of our best test set is about 41% ((5.07 – 2.99)/5.07) lower than Guo et al's [34] best result. However, it is not a surprise that our result was better, because we used controlled frontal images and color texture normalization. It is worth noting that a better comparison would be to perform our experiments using the same image database they used.

A more comprehensive analysis is given by Cumulative Scores (CS). Fig. 2 is a comparison of CS at error levels 0 to 10 years for the best, median, and worst test sets.

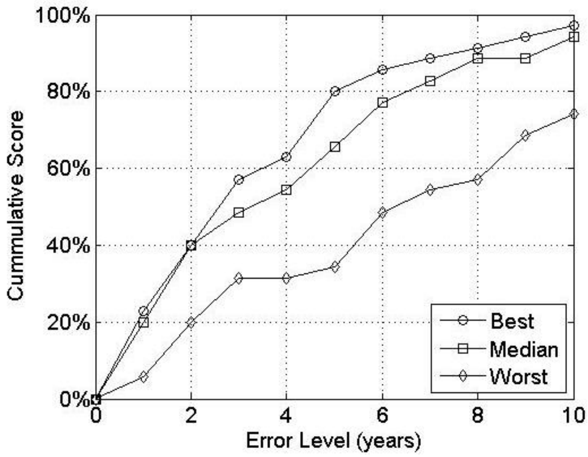
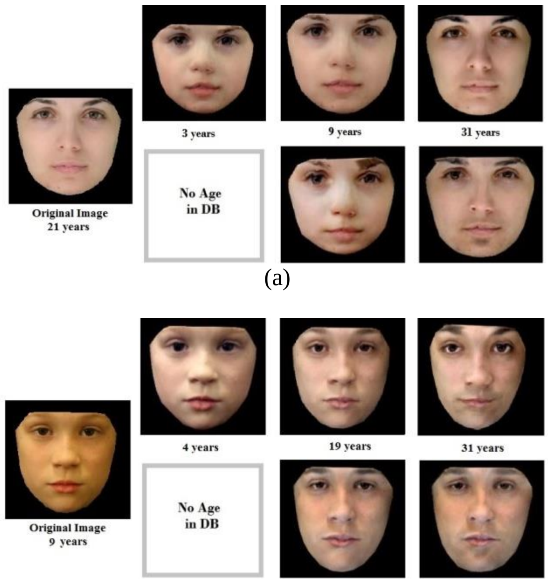


Fig. 2: CSs for Best, Median, and Worst sets, at error levels from 0 -10 years

It is evident that 80% of the images in the “best set” had error level not higher than 5years. Furthermore, it can be observed that over 60% of the images in the best and median sets have error levels not higher than 5 years.

In order to conduct experiments on age synthesis using our new approach, person specific ageing functions were modelled and inverted. This was achieved by forcing the age estimation model to pass through the known individual with a constrained regression. A comparison of synthesized ages using our technique (i.e. top row in Fig 3 (a) & (b)) and Lanitis' [5] method (bottom row of Fig 3 (a) & (b)) is shown on Fig. 3. An obvious advantage of the new method is the ability to compute AAM parameters for any age, including those that are not in the training set and those for non-integer ages. Secondly the method has provided a potential way of extracting age invariant features. Finally, the model guarantees that the input face will not be altered when the target age is set as the true age for a pre-selected individual.



(a)

(b)

Fig. 3: Age Synthesis results, single images on the left of 3(a) and (b) are the real images. Images on top were rendered using our new method. Those on the bottom row were obtained using [5]'s method.

V. CONCLUSION

In this paper we have presented the initial results of a piece of research aimed at synthesizing person specific facial ageing from a database with single image per person. This work is relevant to practical applications in forensics, biometrics, multimedia communication, and human computer interaction, where automatic facial ageing has attracted the interest of researchers recently. We have developed a constrained regression model for age estimation, this linear constraint forces the model to pass through specific face parameters, thus we are guaranteed to estimate correct ages for a pre-selected known face using our model. Our novel age progression method is an advancement on the lookup table technique proposed by [5]. The proposed age synthesis technique, is able to synthesize ages that are not even in the training set. Secondly the method has presented a potential way of extracting age invariant facial features. Additionally, using constrained regression to individualise the model, helps in retaining person's identity even after age progression. The reported literature has proposed models that rely on the use of multiple images of a single subject for training purposes, this is evident from the most popular benchmark ageing databases. However, in a real world scenario (e.g. law enforcement mugshots, and international passports) only a single image per person is stored, thus we have conducted our experiment on a challenging database of non-repeating images.

In our future work the performance of our new model will be evaluated using benchmark databases. It will also be compared to state of the art algorithms. While AAM is able to model deformable objects, its linear nature fails to represent the appearance of intricate objects, for example in our synthesized faces. We intend to investigate a way of modelling this nonlinear features as well as incorporating more constraints into the model.

References

[1] Z. Akhtar, A. Rattani, A. Hadid, and M. Tistarelli, "Face Recognition under Ageing Effect: A Comparative Analysis," in *Image Analysis and Processing–ICIAP 2013*, 2013, pp. 309–318.

[2] Y. Fu, G. Guo, and T. Huang, "Age Synthesis and Estimation via Faces : A Survey," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 32, no. 11, pp. 1955–1976, 2010.

[3] N. Ramanathan, R. Chellappa, and S. Biswas, "Age progression in Human Faces : A Survey," *J. Vis. Lang. Comput.*, vol. 15, no. 1, pp. 3349–3361, 2009.

[4] C. Fernandez, I. Huerta, and A. Prati, "A Comparative Evaluation of Regression Learning Algorithms for Facial Age Estimation," *FFER conjunction with ICPR, Press. IEEE*, 2014.

[5] A. Lanitis, C. Taylor, and T. Cootes, "of Aging Effects on Face Images," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 24, no. 4, pp. 442–455, 2002.

[6] Y. H. Kwon and V. Lobo, "Age classification from facial images," *Proc. IEEE Conf. Comput. Vis. Pattern Recognit. CVPR-94*, pp. 762–767, 1994.

[7] N. Ramanathan and R. Chellappa, "Modeling Age Progression in Young Faces," *2006 IEEE Comput. Soc. Conf. Comput. Vis. Pattern Recognit. - Vol. 1*, vol. 1, pp. 387–394, 2006.

[8] J. Hayashi, M. Yasumoto, H. Ito, and H. Koshimizu, "Method for estimating and modeling age and gender using facial image processing," *Proc. Seventh Int. Conf. Virtual Syst. Multimed.*, pp. 439–448, 2001.

[9] H. Takimoto, M. Yasue, F. Minoru, and A. Norio, "Robust gender and age estimation under varying facial pose," *Electron. Commun. Japan*, vol. 91, no. 7, pp. 32–40, 2008.

[10] S. E. Choi, Y. J. Lee, S. J. Lee, K. R. Park, and J. Kim, "Age estimation using a hierarchical classifier based on global and local facial features," *Pattern Recognit.*, vol. 44, no. 6, pp. 1262–1281, Jun. 2011.

[11] S. Mukaida and H. Ando, "Extraction and manipulation of wrinkles and spots for facial image synthesis," *Sixth IEEE Int. Conf. Autom. Face Gesture Recognition, 2004. Proceedings.*, pp. 749–754, 2004.

[12] Y. Shan, Z. Liu, and Z. Zhang, "Image-Based Surface Detail Transfer," *IEEE Comput. Graph. Appl.*, vol. 24, no. 3, pp. 30–35, 2004.

[13] A. Mehdi, R. Qahwaji, H. Ugail, and M. Abdullah, "Construction of 3D Facial Wrinkles using Splines," in *Fourth International Conference on Information Technology*, 2009.

[14] Y. I. N. Wu and N. M. Thalmann, "A plastic-visco-elastic model for wrinkles in facial animation and skin aging," in *Second Pacific Conference on Computer Graphics and Applications, Pacific Graphics*, 1998, pp. 201–214.

[15] M. Burt and D. Perrett, "Perception of age in adult Caucasian male faces: Computer graphic manipulation of shape and colour information," in *Proceedings of the Royal Society of London. Series B: Biological Sciences*, 1995, pp. 137–143.

[16] I. Kemelmacher-Shlizerman, S. Suwajanakorn, and S. M. Seitz, "Illumination-Aware Age Progression," *2014 IEEE Conf. Comput. Vis. Pattern Recognit.*, pp. 3334–3341, Jun. 2014.

[17] C. M. Hill, C. J. Solomon, and S. J. Gibson, "Aging the human face-A statistically rigorous approach," in *The IEE International Symposium on Imaging for Crime Detection and Prevention, 2005*, 2005, no. 7, pp. 89–94.

[18] C. M. Scandrett (née Hill), C. J. Solomon, and S. J. Gibson, "A person-specific, rigorous aging model of the human face," *Pattern Recognit. Lett.*, vol. 27, no. 15, pp. 1776–1787, Nov. 2006.

[19] E. Patterson, A. Sethuram, M. Albert, and K. Ricanek, "Comparison of synthetic face aging to age progression by forensic sketch artist," in *International Conference on Visualization, Imaging, and Image Processing*, 2007, pp. 247–252.

[20] X. Geng, Z. Zhou, S. Member, and K. Smith-miles, "Automatic Age Estimation Based on Facial Aging Patterns," vol. 29, no. 12, pp. 2234–2240, 2007.

[21] X. Geng, Z.-H. Zhou, Y. Zhang, G. Li, and H. Dai, "Learning from facial aging patterns for automatic age estimation," *Proc. 14th Annu. ACM Int. Conf. Multimed. - Multimed. '06*, p. 307, 2006.

[22] Y. Wang, Z. Zhang, W. Li, and F. Jiang, "Combining Tensor Space Analysis and Active Appearance Models for Aging Effect Simulation on Face Images.," *IEEE Trans. Syst. Man. Cybern. B. Cybern.*, vol. 42, no. 4, pp. 1107–1118, Mar. 2012.

[23] T. F. Cootes, G. J. Edwards, and C. J. Taylor, "Active Appearance Models," in *In Computer Vision—ECCV'98*, 1998, pp. 484–498.

[24] M. C. Ionita, P. Corcoran, and V. Buzuloiu, "On Color Texture Normalization for Active Appearance Models," *IEEE Trans. Image Process.*, vol. 18, no. 6, pp. 1372–1378, 2009.

[25] M. A. Turk and A. P. Pentland, "Face recognition using eigenfaces," *Proceedings. 1991 IEEE Comput. Soc. Conf. Comput. Vis. Pattern Recognit.*, p. fr eigenfaces1, 1991.

[26] C. a. Glasbey and K. V. Mardia, "A review of image-warping methods," *J. Appl. Stat.*, vol. 25, no. 2, pp. 155–171, Apr. 1998.

[27] G. Edwards, T. F. Cootes, and C. J. Taylor, "Advances in active appearance models," in *The Seventh IEEE International Conference on Computer Vision*, 1999, pp. 137–142.

[28] P. Martins, "Active Appearance Models for Facial Expression Recognition and Monocular Head Pose Estimation," 2008.

[29] A. Lanitis and P. O. Box, "Evaluating the Performance of Face-Aging Algorithms," 2008.

[30] G. Guo, Y. Fu, T. S. Huang, and C. R. Dyer, “Locally Adjusted Robust Regression for Human Age Estimation,” *2008 IEEE Work. Appl. Comput. Vis.*, pp. 1–6, Jan. 2008.
[31] L. Hogben, Ed., *Handbook of linear algebra*. CRC Press, 2006.
[32] T. F. Vieira, A. Bottino, A. Laurentini, and M. De Simone, “Detecting siblings in image pairs,” *Vis. Comput.*, pp. 1–13, 2013.
[33] K. a. Dalrymple, J. Gomez, and B. Duchaine, “The dartmouth database of children’s faces: Acquisition and validation of a new face stimulus set,” *PLoS One*, vol. 8, no. 11, pp. 1–7, 2013.
[34] G. Guo, Y. Fu, T. S. Huang, and C. R. Dyer, “Locally Adjusted Robust Regression for Human Age Estimation,” *2008 IEEE Work. Appl. Comput. Vis.*, pp. 1–6, Jan. 2008.