

# A MODEL OF CORRELATED AGEING PATTERN FOR AGE RANKING

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## **ABSTRACT**

*In this paper, we propose a framework for Age Estimation which uses a correlated ageing pattern to rank images and makes necessary inferences from the image ranks to estimate the exact age of images. We use AAM and LBP as complementary feature extraction techniques for extracting facial features in low dimensionality. Our correlated ageing pattern model learns the ageing patterns of different individuals across ages and uses these to determine an agerank for each image. Subsequently, the learned age rank of a reference image set is used to determine the ranks of test images in order to deduce relevant inferences for age estimation. Our approach is significantly different from the previous ranking approaches in that it determines age ranks that do not only represent the correlation of ages of different individuals but also the correlation of ageing patterns of different individuals. Our initial findings look promising with the intuitive manner with which we employ correlated ageing patterns.*

## **KEYWORDS**

*Age Estimation, Ageing Pattern, Age Rank, Ranking*

## **1. INTRODUCTION**

Human age estimation is a challenging task for humans as well as for machines. Although, humans possess the ability early in life to estimate the age of a person from his/her appearance [1], [2], the task is a subjective one which is largely based on the previous experience of the estimator. On the part of the estimated face image, several factors – external (eating habits, drugs, sickness, injuries, weather etc.) as well as internal (genetic or hereditary factors, ethnicity, gender) – could greatly cause variations in the pattern of aging of different individuals, thus making it more challenging to find a unique solution to the Age estimation problem. Therefore, whatever solution is to be proffered to the Age Estimation problem must be an adaptive one.

Human Age Estimation has recently received attention in the research community and as such, several approaches and insights have been developed over the years to combat the problem. It continues to gain research interest especially due to its wide application in Adaptive Computing Methodologies such as Age-Specific Human Computer Interaction (ASHCI) [3], [4], [5]. A major motivation for this research from our own point of view is the fact that certain professions (Sports, Military etc.) require the knowledge of the actual age of individuals/professionals, hence, a medium of verifying the ages presented in such professions will be invaluable as it could be able to reduce the compromise in the ages supplied by these professionals.

Some areas where this research could be applicable include the use of Automatic Vending Machines which could restrict a customer's purchase of alcoholic products based on the estimated age of the customer, National Youth Service Corps (NYSC) Scheme in which Nigerian Youth (below the age of 30 years) are sent to various states of the country to serve their Fatherland in their respective disciplines. The NYSC is also one of the primary motivations for this work as it will be very resourceful in reducing age falsification for participation in the scheme.

As much as this research area is gaining a wider span of interest and applicability, it is still a challenging research area that has left research gaps, particularly in terms of its accuracy. The accuracy of any prediction or estimation algorithm/system largely determines the extent to which it will be widely adopted in real-world applications. Hence, this work proposes a model for ranking images based on the correlation between the ages and the ageing pattern of individuals. Subsequently, the ranks of images can be determined and used to make relevant inferences for age estimation. Our significant contribution with this model is the correlation between the ageing pattern of different individuals and their ages which is used to determine the age rank of images. Possible applications of this model in real world domains include age estimation and age learning from facial image.

## 2. RELATED WORKS

From our analysis of previous works on age estimation, we deduced that they can be classified into five major categories based on the approach employed in the research. We have the Anthropometric Models [6], [7], [8] which adopt knowledge from Facial Wrinkle Analysis and Craniofacial Research for modeling the growth (change in shape) of the face. This approach is mostly suitable for young faces and often requires high resolution images with minimal head pose. Some other research approaches use the aging pattern of faces [9], [10], [11] by learning the aging pattern of individuals and trying to synthesize a facial image for this individual at some other ages not present in the training sample. This approach performed greatly especially due to the fact that aging factors could be personalized. However, its flaws are quickly exposed when it is applied to images not closely represented (in terms of age, gender or ethnicity) in the training set, thus it required a very large training set with a well-spread age distribution to perform well. The third category is of those which treat the Age Estimation problem as a classification problem. This research approach assumes the age labels to be independent classes into which face images can be classified thus resulting in a multi-class classification problem [12], [13], [14]. This approach also met with great success, especially due to the use of the Support Vector Machine; an excellent Machine learning algorithm for classification. Unfortunately, the assumption that ages are independent is, however, not too realistic. A person may have similar looks across different age classes and two different people might have, to some extent, similar facial features at the same age thus flawing the classification approach. Some other research approaches have handled age estimation as a regression problem in which the age labels are learned by a function which fits the face images to their corresponding estimated ages [15], [16], [17]. This is intuitive as the age labels are integers and their relationship with the ageing features, expressed as real numbers can be learn, but this is after some rigorous training. Support Vector Regression (SVR) has been very successful in this approach, thus researchers have applied several modifications of it to improve the model fitting function. The last category of research approaches in age estimation are those which treat the age labels as ordinal pairs and therefore calculate a rank for each face image which is compared against the set of already ranked images [18], [19], [20]. In this work, we employ this approach to age estimation but with an improvement over the existing rank-based frameworks.

In [18], Yang et al. used Harr-like features to represent the face and then used a combination of a ranking model and personal aging pattern to reduce the dimensionality of the feature set obtained.

Pair-wise samples were built for the ranking model by organizing the age sequence according to individual ageing patterns within each subject and RankBoost [21], which employs a ranking model with boosting learning, was used to select relevant features, thereafter, they used SVR with the Radial Basis Function kernel to estimate the age of a facial image. Chang et al. [19] also applied a rank-based framework to age estimation with an intuition that it is easier to estimate the age of a subject by comparing his face with the faces of other people whose ages are known. Their work used the relative order of age labels to build a rank model. To avoid exhaustive comparison with all face images in the database, they only used a subset of the database (80 images) to build the rank model which was used as a reference for comparison with test images. For each image compared against the set of ranked images, the age estimation problem is eventually reduced to a binary classification problem and a combination of binary decisions is used to make inferences which guide the age prediction. Cao et al. in [20], proposed a Ranking SVM for human age estimation by building a set of images used as a reference set to which images are compared before they are then classified into their corresponding age labels. They improved upon the ranking model of Yang et al. by including what they called ‘consistent pairs’ (images of the same age) in their reference set. Also, based on the intuition that Humans age differently, they ranked images of the same age such that they reflect their slight differences as well as their common trend, but these differences do not reflect the true variation in the ageing pattern of these individuals because it is not derived based on a trend of ageing patterns along ages.

### 3. PROPOSED METHODOLOGY

#### 2.1. Age Estimation Framework

Our proposed ranking approach makes intuitive improvements on the existing ones by employing the correlation between individual ageing patterns for determining age ranks. The generic processes involved in our proposed model are the major processes involved in face processing but with different techniques.

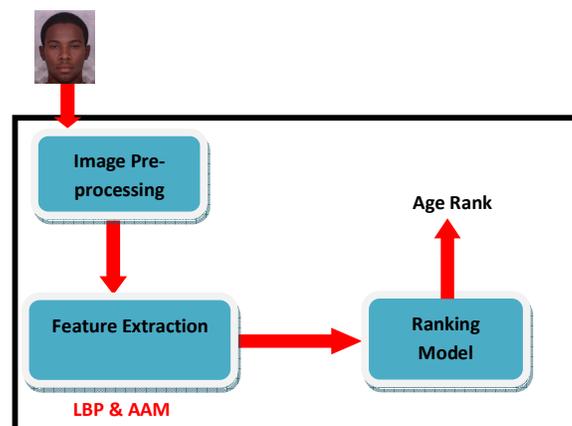


Figure 1: A General Overview of the Age Ranking Framework

The processes shown in figure 1 are involved in both the training and testing phases. As in most face processing systems, in order to improve performance, there will be need to pre-process our input images by first converting them to grayscale, detecting the facial part of the images and then cropping this facial part. Thus after pre-processing, the image is expected to contain just the face which is sufficient to provide the necessary facial features required for face representation. Feature extraction is to be carried out by Local Binary Pattern (LBP) and Active Appearance

Model (AAM). LBP [22] is a powerful texture operator which is robust to illumination and grayscale changes, but more importantly, it extracts image features with reduced dimensionality and low computational time. For each pixel in an image, LBP extracts pixel information from by computing a binary code from its neighbouring pixels. It has found success in many face processing tasks including facial age estimation [23], [24]. AAM [25], known for appearance modeling, is an extension of the Active Shape Model (ASM) [26] which represents shape and contour features in a single appearance model. AAM uses annotated facial landmarks to model the contours/shape of the face and constructs a shape free patch of the face which it later uses to create a texture model. By learning the correlation between these two face models; AAM is able to create a single representation of the face which represents both its shape and contour.

Our choice of AAM and LBP is based on the fact that they have achieved significant success in previous face processing tasks including facial age estimation. More importantly, we chose to use the two techniques as complementary techniques so that the results obtained from both techniques can be compared to arrive at more accurate age estimates. Due to the relatively low dimension of features extracted by the two techniques mentioned above (when compared to other techniques such as Gabor and Haar features), using them concurrently is not as expensive as one would expect. LBP features can be collected into histograms of length 256 or less and AAM features could extract 68 landmark features. Taking advantage of multi-core processors, we consider that the concurrent use of these techniques is worth the expected age estimation results. Our proposed Feature Extraction technique is explained in details in figure 2.

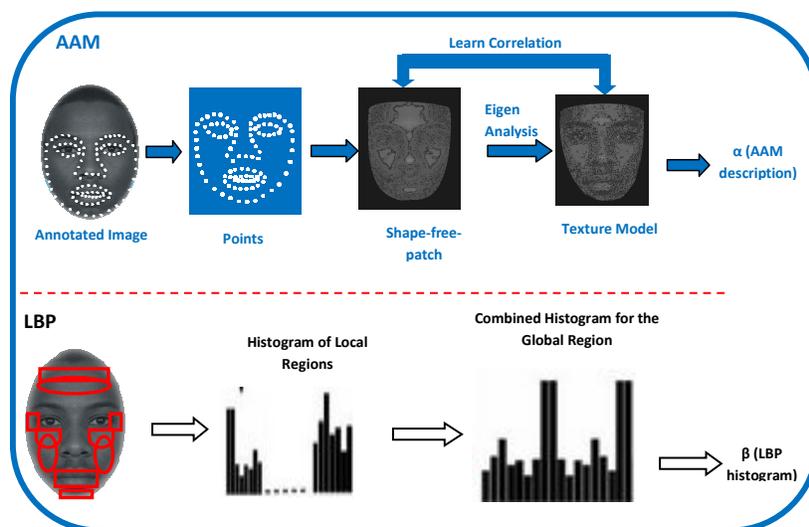


Figure 2: Feature Extraction and Selection using AAM, LBP and LARS

### 3.2. Proposed Ranking Model

Our usage of the ranking approach is based on its intuitive nature in helping to learn the correlation between the ages of images. The faces of two different people at the same age may not look completely similar, however, they possess similar characteristics common to their age; at the same time, the pattern of ageing of different individuals is personalized and thus different across different individuals. For instance three people of age 17 each; are of the same age but might reflect different ageing patterns. Although, they are different individuals, we expect that their different ageing patterns should also reflect certain traits common to their age (e.g. initial appearance of facial hair). Thus, inferences can be made from the correlation between individual ageing patterns along each age for determining the ranks of individuals and these inferences can be used to enhance age estimation.

We present mathematical formulations for our proposed model below

Definition 1: Given a set of image,  $X$  and an outcome space,  $Q$  (in this case, age labels) and a set of ranks  $R$ , we have the following definitions:

$$X = (x_{1j}, x_{2j}, \dots, x_{mj} \mid A j = 1, 2, \dots, m) \quad (1)$$

$$Q = \{q_{1j}, q_{2j}, \dots, q_{mj} \mid A q_i > q_{i-1}, j = 1, 2, \dots, m\} \quad (2)$$

$$R = \{r_{1j}, r_{2j}, \dots, r_{mj} \mid A r_{ij} > r_{i-1j}, j=1,2,\dots,m; r \in \mathbb{R}\} \quad (3)$$

Definition 2: For the given definition above, we wish to find a space of ranking functions,  $H$ , a mapping of images to ranks, such that each  $h(.) \in H$  is a function which appropriately ranks  $X$ .

$$H = \{h(.)\} \quad (4)$$

$$h(.) = X \rightarrow R \quad (5)$$

We expect  $h(.)$  to construct  $R$  such that there is a one-to-one mapping between  $Q$  and  $R$  and that each rank in  $R$  appropriately represents its corresponding age in  $Q$ . However, the age labels in  $Q$  are integers while the ranks are real values in order to capture the variations in ageing patterns along ages (this is further illustrated in the following definitions and equations).

Yang et al. [18], Chang et al. [19] and Cao et al. [20] all used pair-wise ranks of images for comparison with test images. This reduces the substantiality of information available for making inferences about the age to be estimated. Cao et al [20] ranked images using a reference set containing ordinal and consistent pairs (images of different individuals of the same age), however, they abandoned the ageing pattern of individuals, an important factor which facilitated the success of many age estimation algorithms [9],[10],[11],[1]. Although, they provided a variation between the ranks of images of different individuals for each age, the use of images of the same individual in our model allows us to properly represent this variation as a true difference between the ages of individuals.

For our proposed model, we use a subset of the image database as a reference set (with known ranks) and organize it such that individual ageing patterns can be learned along different ages. In organizing our reference set, we maintain sets of images of the same individuals at different ages for learning the ageing pattern of each individual and arrange these sets in a dimension that groups together, images of different individuals at the same ages. Thus we have a matrix of images with the rows corresponding to images of different individuals at the same ages and the columns corresponding to the images of the same individuals at different ages, the images in our reference set are labeled with ground-truth ages so that their age ranks are pre-determined relative to their true ages. Mathematically,

Definition 3: suppose we have a particular individual  $x$ , with  $n$  different images and an arbitrary individual  $w$ ; then for  $j$  such individuals and a function  $age(.)$  which returns the age of an individual, we define the set  $\chi$  as follows;

$$\chi = \{x_{i,j} \mid age(x_{i,j}) > age(x_{i-1,j}) \text{ and } age(x_{i,j}) = age(w_{i,j-1}), A i = 1,2,\dots,n, j= 1,2,\dots,m; x \neq w\} \quad (6)$$

For individuals with missing images at certain ages, in order to complement the row of same ages, we fix in images of other individuals belonging to the same age and gender.

Definition 3: Thus, for a test image  $x_{i,j}$  such that  $age(x_{i,j})$  is greater than an age  $k$  (chosen arbitrarily) in  $Q$ ,  $R$  is divided into two subsets,

$$R_1 = \{r_{i,j}, q_{i+1,j}, \dots, q_{km}\} \quad (7)$$

$$R_2 = \{q_{k+1,j}, q_{k+2,j}, \dots, q_{nm}\} \quad (8)$$

Where  $R_1$  is the set of ageranks less than or equal to the rank of the test image  $x_{i,j}$  and  $R_2$  is the set of ageranks greater than the rank of the test image.

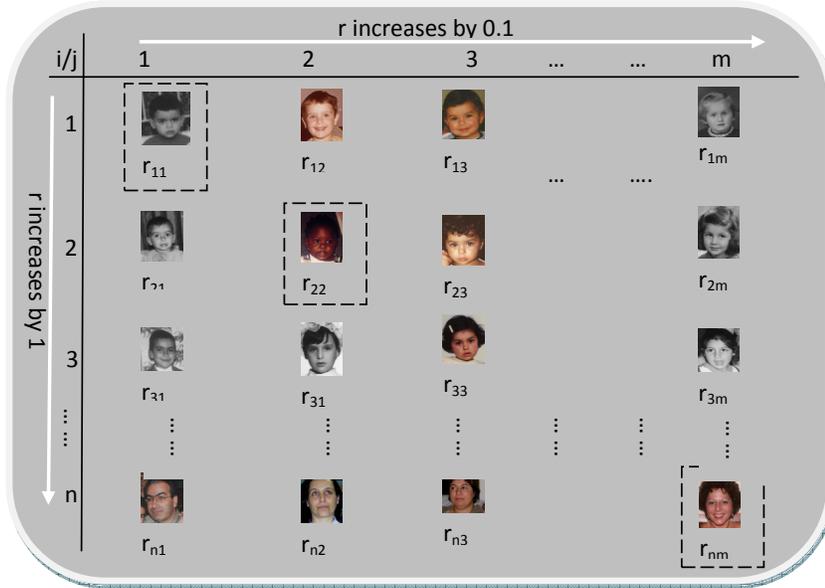


Figure 3: Proposed Correlated Ageing Pattern Ranking Model

Subsequently, the problem is reduced to a binary classification where we only need to compare the rank of  $x_{i,j}$  with the ranks of images in either  $R_1$  or  $R_2$  and by an iteration of such binary classifications, we are able to further reduce each sub-problem to a smaller one until the appropriate rank of  $x_{i,j}$  is found.

Inspired by the work of Li and Lin [27] in stating an equation for calculating the rank of a data set in an ordinal regression problem for the purpose of binary classification, we define our ranking equations. For each test image in  $X$ , we compare the rank of the image against the ranks in  $R$  (comparing against  $d$  different individuals in each age, and  $d$  is less than the number of images in an age) until the test image is found to be less than or equal to the range of ranks of a particular row (of ages)  $i$ ; we then compare along rows  $i-1$ ,  $i$  and  $i+1$  until the rank of the test image satisfactorily falls within a range of ranks in one of these ages. The essence of this kind of comparison is to cater for the relative correlation in between neighbouring ages and to ascertain that an image truly belongs to the age to which it is ranked.

Definition 4: For each image  $x_{ij}$ , and an arbitrarily chosen  $k$ , we assume a rank comparison function  $f(x_{ij}, k)$ , a threshold  $d$  and then calculate its rank as follows:

$$r_{ij} = 1 + \sum_{k=1}^{k-1} g\left(\sum_{j=1}^d f(x_{ij}, k)\right) \quad (9)$$

Where

$f(x_{ij}, k) = \Phi$  if the rank of  $x_{ij}$  is greater than  $k$  and  $0$  otherwise ( $\Phi = 1/m$ )

$g(.) = 1$  if the inner summation is equal to  $(d \times \Phi) \pm \phi$  otherwise it is equal to  $0$ . (In our model, we chose  $\Phi = 0.1$  and  $\phi = 0.05$  with an assumption that there are 10 images for each age).

Thus, the age ranks of images for each age differs from those of images in neighboring ages by an approximate value of  $1$  while images within the same age differ in rank by  $0.1$ . Thus individual ageing patterns are reflected within each age but the ranks of images in each age are still kept within the same range.

As shown in our model in figure 3, images surrounded with dashed lines are substituted for those individuals whose images for that particular age are not present in the dataset used. As mentioned earlier, we used images of the same gender. Each  $r_{ij}$  denotes the rank of the labeled image. This approach is superior to the ranking models discussed earlier in that it utilizes the correlation between aging patterns across different individuals alongside the discriminative features within the same age while maintaining relative similarities within the ages. For the purpose of illustration, we have used images from the popular FG-NET [28] database and our locally collected FAGE database in constructing the model shown in figure 3. FG-NET is a database of 1002 images of 82 different individuals with ages ranging from 0-69 years. Due to the wide range of age separated images for each individual in this database, we considered it suitable for use with our proposed model.

### 3. CONCLUSION

The intuitive approach used to construct our ranking model in this paper is based on the fact that, if the rank of facial images can be determined relative to the ages to which they belong, we can provide inferences for estimating exact ages more accurately. Thus, we have embedded in our model, a correlation between individual ageing patterns as well as a relative discrimination between ages. With the use of AAM and LBP for feature extraction, age estimation algorithms will find our proposed model applicable for estimating ages more accurately by using the age estimates of features extracted using both techniques to determine a more exact age estimate for a given image. With the intuition employed in our proposed model, it will be possible to reduce the Mean Absolute Error (MAE) and increase the Cumulative Score (CS) (the two mostly used benchmarks in age estimation) of most age estimation algorithms thus producing age estimation algorithms that compare favourably with (or even performs better than) human prediction and the state-of-the-art algorithms in age estimation.

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