A GW Ranking Approach for Facial Age Estimation

Onifade O. F. Williams and Akinyemi J. Damilola

Department of Computer Science, University of Ibadan, Ibadan, Nigeria.
olufadeo@gmail.com, akinyemijd@gmail.com

Abstract

In an effort to improve the accuracy of predicting human age from facial image, several algorithms have been proposed and tested on different datasets using various approaches. In this paper we propose a novel and intuitive approach called 'GW ranking' (an acronym for Group-Wise ranking) to age estimation from facial image. In our GW ranking approach, we first determine the age group into which a facial image belongs by comparing its features against the specific features of each age group and thereafter deriving inferences which enable us introduce an appropriate age-group-specific rank for determining the exact age. Although our GW approach is similar to and draws intuition from the listwise ranking approach used in Information Retrieval, our approach is slightly different from listwise ranking. Our results compare favourably with state-of-the-art algorithms in age estimation with a MAE of 1.32 on a combination of FG-NET and our locally collected FAGE databases. To the best of our knowledge, this is the first work to employ a GW ranking approach to age estimation and our results improve significantly over the state-of-the-art approaches.

Keywords: *Age Estimation; Age Rank; GW Ranking; Machine Learning; Computer Vision; Pattern Recognition*

1. Introduction

Age estimation from facial image has recently gained attention in the Computer Vision, Pattern Recognition and Image Processing research community partly due to its applicability in several real-world domains and to the difficulty of the task for machines. Humans do possess an innate ability early in life, to estimate the age of a person from his/her appearance [12], but this is not a very easy task for machines. Humans perform this task in a subjective manner that is largely related to the experience and exposure of the person estimating the age of another. However, it is noteworthy to state that, several factors – internal as well as external – have significant impact on the ageing of individuals. Factors such as eating habits, drugs, sickness, injuries, weather, genetic or hereditary factors, ethnicity, gender, etc. could cause variations in the pattern of aging of different individuals; this has it more challenging to find a unique solution to the Age estimation problem that will cut across all these factors and their variations.

Over the years, several approaches have been employed to make the computer combat the age estimation problem using an experimental dataset. The intent of research in age estimation is to propose a workable solution (either an algorithm or a model) that will be applicable in real-world applications. Some areas where age estimation could prove useful include Adaptive Computing Methodologies such as Age-Specific Human Computer Interaction (ASHCI) [1, 19, 5] in which we may wish to process users' requests based on their estimated ages. From our own point of view, a major motivation for this research is the fact that certain professions (Sports, Military etc.) require the knowledge of the actual age of individuals/professionals, therefore, a reliable means of verifying the ages of such professionals would be significant because it could be reduce the compromise in the ages supplied by these professionals thus reducing age falsification.

In this work, we propose a GW ranking approach to age estimation in which ages of facial images are estimated based on the inference derived from comparing each face across a group of facial images. Our significant contribution to the age estimation research is the intuitive GW ranking approach in which a test image is compared against a set of images of different ages but the same age group in order to determine the age group before determining the exact age of the image. This improves significantly in terms of speed and accuracy over previous ranking approaches which employ pairwise comparison against reference images. The rest of this work is organized as follows; section 2 discusses previous works in age estimation and their approaches. In section 3, we discuss our proposed methodology stating our approach of the GW ranking model and we present conclusion and future works in section 4.

2. Related Works

From our review of related works, we observed that previous research in age estimation can be organized into five categories based on the approach employed in the research [13]. The Anthropometric Models used in [6, 7] and [8] adopt knowledge from Facial Wrinkle Analysis and Craniofacial Research to model the growth (change in shape) of the face. This approach is however mostly suitable for young faces which still exhibit change in facial structure/shape during growth.

The second category is of those that employed 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 improved significantly on existing works due to the fact that aging factors could be personal to some extent. However, it fails to represent properly, images not represented (in terms of age, gender or ethnicity) in the training set, thus, to perform well, it required a large image training set with a wide range of age-separated images per subject.

Other research works approached Age Estimation as a classification problem [20, 5]. This research approach assumes that age labels are independent classes into which face images can be distinctly classified to result into a multi-class classification problem. The use of the Support Vector Machine (SVM) was significant to the success of this approach. However, the assumption that ages are independent is 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.

The fourth category includes research that treated age estimation as a regression problem by learning a function which fits the face images (facial features) to age labels [17, 18, 19]. This is intuitive as the age labels are integers and their relationship with the ageing features (which are expressed as real numbers), can be learnt, though 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 age estimation research which we refer to as the ranking approach treats age labels as ordinal pairs. Thus, a rank is calculated for each face image and then compared against a set of pre-ranked images [14, 15, 16]. Our GW ranking approach was motivated by this category of algorithms, so we will analyze existing works in this area in more details.

Yang et al. in [14] 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. They built pair-wise samples for the ranking model by organizing the age sequence according to individual ageing patterns within each subject. Thereafter, RankBoost [23], which employs a ranking model, was used with boosting learning to select relevant features. Following this, they used SVR with the Radial Basis Function kernel to estimate the age of a facial image. Chang et al. [15] applied a ranking model to age estimation arguing 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. In their work, they built a rank model using the relative order of age labels. Thus, 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 to guide the age prediction. Cao et al. in [16], proposed using 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 would reflect their slight differences as well as their common trends as regards to ageing.

In the above techniques, the authors performed pairwise comparison between images and individual images in their reference set, this is time consuming and it reflects more individual characteristics than characteristics common to a particular age group. In our proposed approach, we use age-group-specific characteristics to rank images, in order to reflect ageing features specific to each age group thus allowing the learning of GW ageing features.

3. Proposed Methodology

3.1 Overview of our Proposed Age Estimation Model

Estimating the age of humans from their facial image by mere observation of the face is somewhat difficult and subjective. Often, humans intuitively predict the ages of other people by performing a mental operation of relating the person with other persons whose ages are known and who appear to be in the same age group with the person in question. Humans do this quite naturally and unconsciously that they even use information such as the age of the person's friends, parents, children and sometimes the social status of such a person to determine his/her age. For humans, this task is relatively easy because it is an innate ability, but for machines, this is a difficult task; firstly because of the difficulty of obtaining such large amount of sensitive information about a single individual and secondly due to the rigour of making the computer understand and process such information. However, some amount of such information might be more helpful and intuitive for achieving a more accurate prediction of human age than a direct prediction from a single facial image.

Based on this notion, we propose a ranking approach which identifies and makes use of information specific to an age group to determine other subjects belonging to that age group before predicting the actual age of the subject. Thus, instead of ordinal pairs used in [14], we used what we called ordinal and homogenous image groups. We present an overview of our proposed model in figure 1 showing the processes involved in both the training and testing phases.

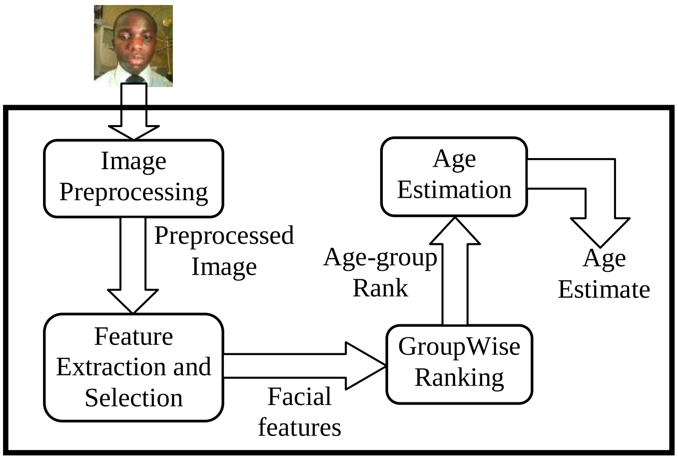

Figure 1. A General Overview of the Proposed Age Estimation Model

As in most face processing systems, in order to enhance our image analysis tasks, we pre-process our input images by converting them to grayscale, detecting the face and then cropping and resizing the detected face. Following the pre-processing, we perform feature extraction using Local Binary Pattern (LBP). LBP [27] is a powerful texture operator which is robust to illumination and grayscale changes and it also extracts image features with reduced dimensionality and low computational time. LBP coding and feature extraction is not the focus of this work; interested readers are referred to [21, 25, 27]. LBP has found success in Facial Age estimation and other computer vision tasks [24, 25]. The extracted LBP features are processed to obtain the rank of images in each age group and to construct an age-rank for each age group. The constructed age-rank is used to make inferences for estimating the age of each image in the age group. Using images from the publicly available ageing database, FG-NET [26] along with a locally built database FAGE (Facial-expression Age Gender Ethnicity), we were able to train and test our proposed algorithm.

The FG-NET is a database of 1002 images from 82 different Caucasian subjects within the ages of 0-69 and the FAGE database contains 116 images of 86 indigenous Black/African subjects within ages 0-41. Our reason for using the FG-NET dataset is because of the wide range of age-separated images for each subject which makes it possible for our algorithm to learn certain ageing patterns which are relatively common to age groups. Our FAGE dataset was collected based on our observation of the unavailability of any facial ageing database of indigenous African faces. The black faces available in MORPH [28] are mostly African-American with a maximum age difference of about 4 years per subject and since the condition of living and weather are subtle factors responsible for individual ageing patterns [17, 19], we figured that the performance of an age estimation algorithm on the black faces in MORPH (faces of Africans in diasporas) may not provide accurate representation of the ageing of indigenous (home-based) African subjects. We present in Table 1, detailed analysis of the age distribution of facial images in both datasets.

3.2 GW Age Ranking Model

Object ranking is a popular approach used in Information Retrieval and it has recently found application in Facial Age estimation [14, 15, 16]. Previous age estimation research in which the ranking approach was used considered the pairwise ranking approach in which an image reference set was built using ordinal image pairs in which the rank of an image x_i is greater than that of its pair, x_{i-1}. Cao et al [16], however, improved their reference set by including what they called ‘consistent pairs’ which consisted of images of the same age. Thus, their own reference set consisted of both ordinal and consistent pairs. They constructed a reference set for all ages in the MORPH database using about 20 images for each age. We consider that comparison with such reference set could be computationally huge, considering the fact that we could have a large number of age labels (e.g. 0 – 69 as in FG-NET). More so, comparing individuals based on their exact ages could be misleading due to the closeness of individual age labels.

For instance, it is very likely to consider a 19 years old person as 17, 18 or 20 years, firstly because these ages are teenage/young adult ages and secondly because the age labels are close within a maximum range of 2 years, therefore, an image of age 19 can be incorrectly ranked as 17, 18 or 20.

Table 1. Age Distribution of facial images in FG-NET and FAGE

Age Distribution (years)	FG-NET		FAGE	
	Number Of Images	Percentage	Number Of Images	Percentage
0 – 12	482	48.10%	26	22.41%
13 – 16*	130	12.97%	27	23.28%
17 – 20*	118	11.78%	9	7.76%
21 – 24*	64	6.39%	22	18.97%
25 – 28*	51	5.09%	15	12.93%
29 – 32*	38	3.79%	11	9.48%
33 – 36*	36	3.59%	3	2.59%
37 – 40*	23	2.30%	2	1.72%
41 – 69	60	5.99%	1	0.86%
Total	1002	100%	116	100%

* Ages used for training and testing in the experiment.

This gives insight into the fact that each age can be relatively grouped into an age group which consists of images lying close to and around it and this is the basis of the GW ranking model. Our ranking approach draws some inferences from the listwise approach [3] used in Information Retrieval. However, GW ranking model is different in the sense that it derives ranks for each age group by learning the relationship between the ranks of individual objects/images in the group as opposed to the listwise approach which takes each list of object as an instance and ranks based on the relevance of the documents in the list to the given query.

We observe that humans often have a consistent look over a certain range of ages and from our findings, this range may be put at 3 to 5 years; this is explained by the number of years during which most identity documents are regarded as valid before expiry, our findings are also verified by our experiments presented in the following sections. Gaining insight from the aforementioned, our proposed model employs creation of ranks for images within the range of four years.

First a reference image set is constructed from a subset of the image dataset; the reference set is organized according to age groups and a rank is calculated by learning the relationship between the ranks of individual images in the age group. Based on the observed relationship of image ranks, an age-rank is constructed for each age group. Subsequently, inferences are made from the ranks for estimating the ages of the training and test images. In estimating the age of a test image, a learned ranking function, as presented in equation (13), is used to first determine the age-group to which the age belongs, thus reducing the amount of possible deviation from the ground truth age during age prediction. Having derived the age group of an image an age predictor is trained to determine the exact age of the subject. As shown in figure 2, our reference set (a subset of the images in the databases used) can be simply described as a matrix of images in which images in each row belong to the same age group and those in each column belong to the same individual. The essence of using images of the same individual along the columns is to also reflect individual ageing patterns while learning the age rank of each age group. Images surrounded by dotted lines are substitutes for missing images of the particular subject in that column. The images in figure 2 are from the FG-NET and FAGE databases; the images on the last column are from FAGE while the rest are from FG-NET.

In a bid to present enduring and adaptable model, we present below a rigorously defined mathematical formulation for our proposed GW ranking approach.

Definition 1: Given a list of objects (in this case, facial images), X and an outcome space Y (of age labels), we state the following definitions.

$$X = \{x_1, x_2, \ldots, x_n\} \quad (1)$$

$$Y = \{y_1, y_2, \ldots, y_m \mid \forall y_i > y_{i-1}\} \quad (2)$$

Suppose we can define a particular subset of X as

$$X_i \subset X \quad (3)$$

Such that X_i contains objects (images) belonging to a particular age group specified by an age range, ρ. We therefore wish to define k such subsets of X as follows.

$$X_1 \cap X_2 \cap \ldots \cap X_k = \emptyset; \ \forall X_j \subset X \quad (4)$$

Equation 3 shows that each X_j is a distinct subset of X and thus each $x_i \in X$ belongs to exactly one X_j. Therefore, we can state the following equation

$$\forall x_i \ \exists X_j \ x_i \in X_j, i = 1,2, \ldots, n; j = 1,2, \ldots, k \quad (5)$$

Consequently, Y can also be partitioned into k disjoint subsets according to the age range, ρ, as follows:

$$Y_1 \cap Y_2 \cap \ldots \cap Y_k = \emptyset; \ \forall Y_j \subset Y \mid cardinality(Y_j) = \rho \quad (6)$$

Such that each image $x_i \in X_j$ maps to a corresponding Y_j

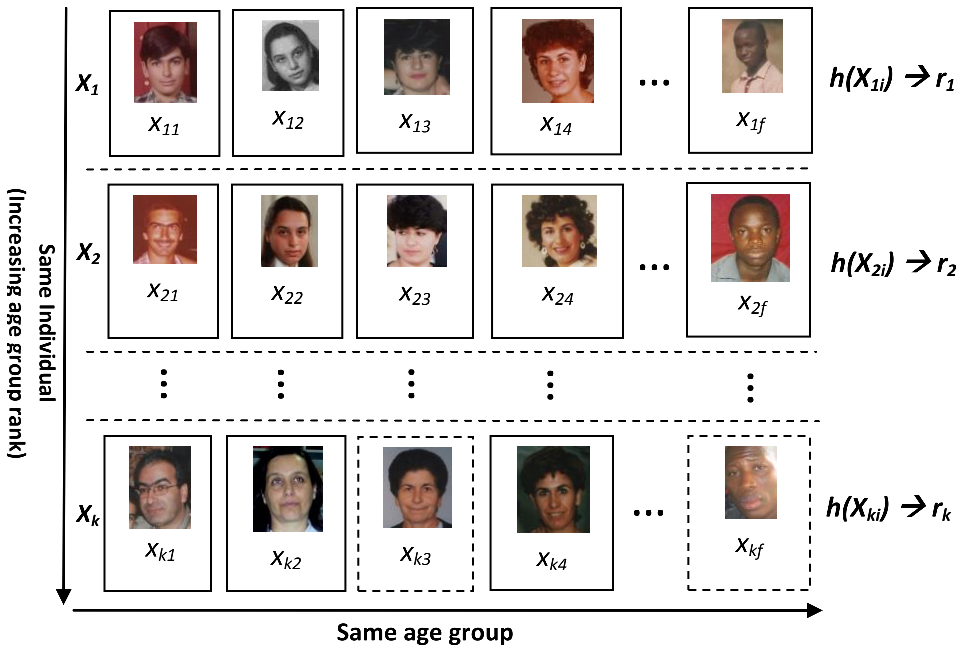

Figure 2. Generic Framework for GW Age-Ranking Model

Definition 2: Suppose there is an arbitrary function *agegroup(.)* which maps each subset of X to its corresponding subset in Y. Then we can write

$$\forall X_j \exists Y_j \; agegroup(X_j) \rightarrow j; \; \forall j = 1,2,\dots,k \tag{7}$$

Definition 3: We remember that Y is the outcome space (of age labels) and that each

$$Y_j \subset Y \tag{8}$$

contains age labels in Y that belong to the same age group and therefore are assumed to have the same (age-group) rank (note that the range of ages which determine the age groups can be chosen arbitrarily, in our experiment, we have used a range of 4 years). Therefore, we can define an age group-specific ranking function given a set R of ranks. For now, we will abstract our ranking function as *rank(.)*

$$R = \{r_1, r_2, \dots, r_k \mid r_j \in \mathbb{R}\} \tag{9}$$

$$\forall Y_j \exists r_j \; rank(Y_j) \rightarrow r_j; \; \forall j = 1,2,\dots,k \tag{10}$$

Thus, from (7), we can map each subset of X, i.e. (3) to a rank $r_j \in R$ as follows:

$$\forall X_j \exists r_j \; rank(X_j) \rightarrow r_j; \; \forall j = 1,2,\dots,k \tag{11}$$

Therefore, each image in each X_j has exactly one r_j according to (5)

$$\forall X_j \exists r_j \; rank(x_i) \rightarrow r_j; \; x_i \in X_j \; \forall i = 1,2,\dots,n; j = 1,2,\dots,k \tag{12}$$

So far, we have used *rank(.)* as an abstraction of our ranking function, but we will now provide adequate definitions for our proposed GW ranking function.

Definition 4: Suppose we have a space H of ranking functions defined as follows

$$H = \{h(.)\} \tag{13}$$

Thus, we can redefine (12) as

$$h(x_i) \to r_j;\ \forall\, x_i \in X_j \,\&\, r_j \in R, i = 1,2,\ldots,n, j = 1,2,\ldots,k \tag{14}$$

Our goal therefore is to find an *h(.)* with the least error/loss on ranking so that the error on ranking images into their age groups can be minimal (in our experiments, this was achieved through an empirical study of the performance of different learners for age ranking). This is necessary so that the possibility of deviation from ground truth age can be reduced even before the age estimation is carried out. Thus, we define the loss/error on ranking as $\mathcal{E}_r$

$$\varepsilon_r = \frac{\Sigma|\overline{r_j} - r_j|^2}{N} \tag{15}$$

$\overline{r_j} = predicted\ rank\ (expected\ to\ lie\ close\ to\ the\ actual\ rank\ values) r_j = actual\ rank\ in\ R$

$N = Number\ of\ observations$

4. Experiments

In our experiments, we tested our proposed model on a combined dataset consisting of the publicly available FG-NET and our locally collected FAGE dataset. We constructed each age group using ρ=4 (from equation (6)), and used 12 images from different subjects in each age group; therefore, we had 7 different age groups (13-16, 17-20, …, 37-40). Training and testing were performed on images of subjects within the ages of 13 to 40 years based on our observation that this age range reflects the most active periods of human life; thus age-related crimes are more likely at this ages than lower and higher ages. However, the proposed model can be applied to estimate ages on a wider range of ages – this would simply involve having more age groups to spread across the intended ages.

In ranking facial images, we compared the performance of ensemble learning on three different sets of values which we will refer to in this paper as types of rank; (Type 1) the rank of reference age groups (Type 2) the standard deviation of reference age groups and (Type 3) a product of the standard deviation of each image and the median of its respective age group. Thus, the function h (as in definition 4) was learned using LSBoost [2] (a weak ensemble learner) because of its ability to fit regression ensembles while minimizing least squares error which is close to the mean squared error defined as our loss/error on ranking (ε_r) in equation (15).

We observed that the first type of rank (Type 1) gave the least error on rank learning; therefore, according to our goal of obtaining the least ranking error, we used Type 1 rank to predict ranks for images in our experiment. Based on the predicted ranks, LSBoost was also used as the age learner on 80% of the training set while the remaining 20% (partitioned randomly by cross validation) was used for testing. The age learner is not discussed in details because it is not the focus of our proposed GW Age Ranking model; interested readers can consult [2] for details about LSBoost and ensemble learning. To further examine the performance of our proposed model on age learning, we used 4-fold cross validation for training and evaluating the performance of the age learner.

We evaluated the performance of age estimation using GW age ranking using two standard metrics; Mean Absolute Error (MAE), which is the average absolute difference between predicted and ground truth ages and Cumulative Score (CS), which is the percentage of images for which the estimation error falls below or equal to a particular error level. MAE is calculated as $MAE = (|\hat{y} - y|) / N$, where $\hat{y}$ is the predicted age, y is the ground truth/actual age and N is the number of observations while CS is calculated as $CS = ((|\hat{y} - y|) \leq L / N) X 100\%$, where L is the chosen error level and all other parameters remain as previously defined. Table 2 shows the error on ranking for the different types of ranks experimented while table 3 shows a comparison between the Mean Absolute Error (MAE) obtained using our approach and existing age estimation algorithms. Figure 3 shows the error/loss on age learning at the training and testing phases. The plot in figure 3 shows estimation error in years against the number of training cycles (trees) – as shown in the plot, an estimation error of less than 2 years was already obtained in less than 200 training cycles; however, best results were obtained for 1000 training cycles. Figure 4 shows the Cumulative Score (CS) for different age estimation algorithms.

Table 2. Error/loss on ranking

Type of Rank used	Minimum & Maximum values	Range of Values	Loss on Ranking
Type 1	0.0067, 0.0588	0.0074	0.0000145
Type 2	147.3475, 176.8391	4.2129	6.4688
Type 3	18725.79, 106931.73	12600.85	13632564.1

Table 3. Comparison of MAE on FG-NET & FAGE

Algorithm	Dataset	**MAE** (years) / **Testing approach**
RankBoost [14]	FG-NET	5.67 / 4-fold CV
Rank [15]	FG-NET	5.79 / 20% of dataset
OHRank [29]	FG-NET	4.48 / 20% of dataset
RUN [4]	FG-NET	6.95 / LOPO
C-lsLPP [22]	FG-NET	4.38 / LOPO
GW Ranking	FAGE & FG-NET (combined)	**1.32 / 20% of dataset**
GW Ranking	FAGE & FG-NET (combined)	**2.38 / 4-fold CV**

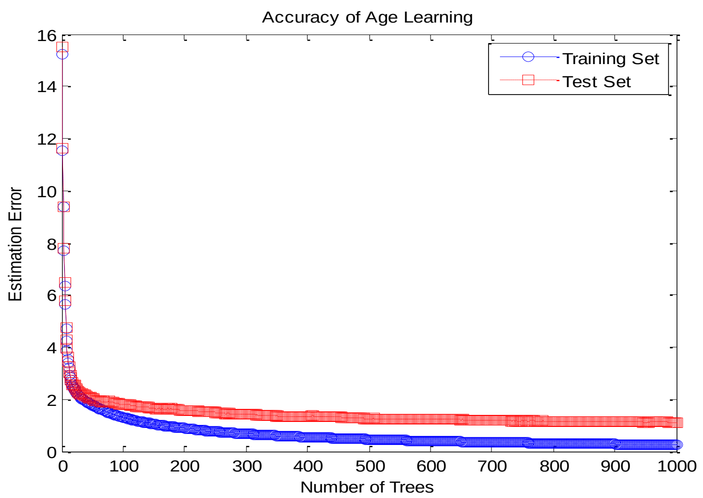

Figure 3. MAE on Age Estimation training and testing

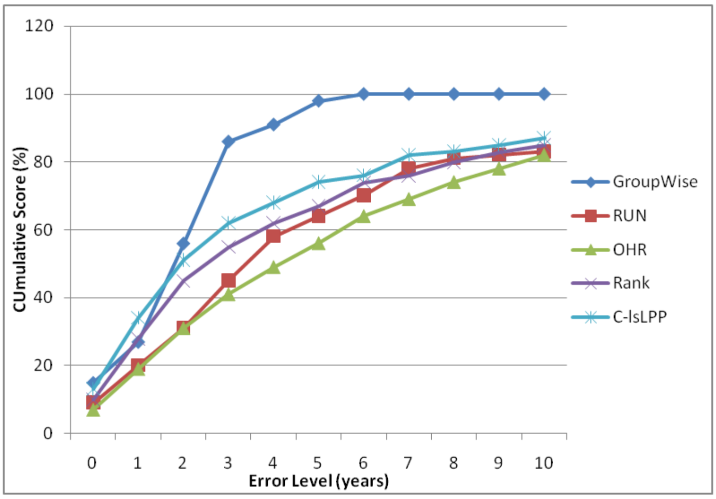

Figure 4. Age Estimation Cumulative Score on FG-NET & FAGE

From the tables and figures, it is clear that our algorithm significantly outperforms many state-of-the-art approaches. The Cumulative Score shows about 27% of images have estimation error less than or equal to 1 year and 100% have error less than 6 years. This achieves the highest accuracy compared to other algorithms considered. Also, to the best of our knowledge, our work achieves the lowest MAE on the FG-NET database using an independent test set constituting 20% of the dataset used. Using, 4-fold cross validation, the mean square loss on training even indicates a lower error level.

5. Conclusion

The above research results show that our proposed GW ranking approach improved age estimation significantly over existing state-of-the-art approaches. We have demonstrated the performance of this approach on the publicly available FG-NET dataset and our locally collected FAGE dataset. With the GW rank, we were able to achieve a MAE of 1.32 years using 20% (cross validation partition) of the dataset for testing and MAE of 2.38 years. Our experiments on a combined database of subjects from two different ethnicities also indicate good generalization of our approach across different ethnicities. However, in future works, we hope to test this approach on a larger dataset and a wider range of ages using the popular leave-one-person-out (LOPO) technique.

6. Acknowledgment

We appreciate Computer Science department, University of Ibadan and the International School Ibadan, Nigeria for granting permission to obtain the facial images of their students for the collation of our FAGE dataset. We also appreciate Andreas Lanitis for providing us with the FG-NET dataset for this work.

References

[1] G. Guo and G. Mu, “Simultaneous dimensionality reduction and human age estimation via kernel partial least squares regression,” in Proc. IEEE Computer Vision and Pattern Recognition (CVPR), 2011, pp. 657–664.

[2] T. Hastie, R. Tibshirani, and J. Friedman, Elements of statistical learning - data mining, inference and prediction, Springer, 2008.

[3] Z. Cao, T. Qin, T.-Y. Liu, M.-F. Tsai, and H. Li, “Learning to rank: From Pairwise Approach to Listwise Approach,” in Proc. 24th International Conference on Machine Learning, 2007, pp. 1–8.

[4] S. Yan, H. Wang, T. S. Huang, Q. Yang, and X. Tang, “Ranking with uncertain labels,” in Proc. IEEE International Conference on Multimedia and Expo, 2007, pp. 96–99.

[5] A. Lanitis, C. Draganova, and C. Christodoulou, “Comparing different classifiers for automatic age estimation,” IEEE Trans. System Man, Cybernetics Part B Cybernetics, 34(1), pp. 621–628, 2004.

[6] Y. H. Kwon and V. Lobo, “Age classification from facial images,” Computer Vision and Image Understanding, 74(1), pp. 1–21, 1999.

[7] W. Horng, C. Lee, and C. Chen, “Classification of age groups based on facial features,” Tamkang J. Sci. Eng., 4(3), pp. 183–192, 2001.

[8] N. Ramanathan and R. Chellappa, “Face verification across age progression age progression in human faces,” IEEE Trans. Image Process., 15(11), pp. 3349 – 3361, 2006.

[9] M. R. Gandhi, “A method for automatic synthesis of aged human facial images,” Masters’ thesis, McGill University, Canada, 2004.

[10] X. Geng, Z. Zhou, and K. Smith-miles, “Automatic age estimation based on facial aging patterns,” IEEE Trans. Image Process., 29(12), pp. 2234–2240, 2007.

[11] M. Tsai, Y. Liao, and I. Lin, “Human face aging with guided prediction and detail synthesis,” Multimed. Tools Appl., 2013.

[12] G. Guo and T. S. Huang, “Human age estimation using bio-inspired features,” in Proc. IEEE Conference on Computer Vision and Pattern Recognition, 2009, pp. 112–119.

[13] O. F. W. Onifade and J. D. Akinyemi, “A model of correlated ageing pattern for age ranking,” in Proc. Fourth International Conference on Computer Science and Information Technology, 2014, vol. 4, no. 2, pp. 477–485.

[14] P. Yang, L. Zhong, and D. Metaxas, “Ranking model for facial age estimation,” in Proc. International Conference on Pattern Recognition, 2010, pp. 3408–3411.

[15] K. Chang, C. Chen, and Y. Hung, “A ranking approach for human age estimation based on face,” in Proc. International Conference on Pattern Recognition, 2010, pp. 3396–3399.

[16] D. Cao, Z. Lei, Z. Zhang, J. Feng, and S. Z. Li, “Human age estimation using ranking svm,” in Proc. 7th Chinese Conference, CCBR, 2012, vol. 7701, pp. 324–331.

[17] K. Ricanek, Y. Wang, C. Chen, and S. J. Simmons, “Generalized multi-ethnic face age-estimation,” IEEE BTAS, 2009.

[18] Y. Fu and T. S. Huang, “Human age estimation with regression on discriminative aging manifold,” IEEE Trans. Multimed., 10(4), pp. 578–584, 2008.

[19] G. Guo, Y. Fu, C. R. Dyer, and T. S. Huang, “Image-based human age estimation by manifold learning and locally adjusted robust regression,” IEEE Trans. Image Process., 17(7), pp. 1178–1188, 2008.

[20] Y. Tang and B. Lu, “Age classification combining contour and texture feature,” in Proc. 17th International Conference on Neural Information Processing, 2010, pp. 493–500.

[21] T. Ojala, M. Pietikäinen, and M. Topi, “Multiresolution gray-scale and rotation invariant texture classification with local binary patterns,” IEEE Trans. Pattern Anal. Mach. Intell., 24(7), pp. 971–987, 2002.

[22] W. Chao, J. Liu, and J. Ding, “Facial age estimation based on label-sensitive learning and age-oriented regression,” Pattern Recognit., 46(3) 2013, pp. 628–641, 2013.

[23] Y. Freund and R. E. Schapire, “An efficient boosting algorithm for combining preferences,” J. Mach. Learn. Res., 4, pp. 933–969, 2003.

[24] Z. Yang and H. Ai, “Demographic classification with local binary patterns,” in Proc. International Conference on Biometrics, 2007, pp. 464–473.

[25] C. Shan, S. Gong, and P. W. Mcowan, “Facial expression recognition based on local binary patterns : a comprehensive study,” Image Vis. Comput., 27(6), pp. 803–816, 2009.

[26] FG-NET Ageing Database. Available at http://sting.cycollege.ac.cy/~alanitis/fgnetaging/index.htm. Accessed June, 2013

[27] M. Pietikäinen, “Local binary patterns,” Scholarpedia, 5(3), pp. 9775 doi:10.4249/scholarpedia.9775, 2010.

[28] K. Ricanek Jr. and T. Tesafaye, “MORPH: A longitudinal image database of normal adult age-progression”, in Proc. IEEE 7th International Conference on Automatic Face and Gesture Recognition, 2006, pp 341-345.

[29] K. Chang, C. Chen, and Y. Hung, “Ordinal Hyperplanes Ranker with Cost Sensitivities for Age Estimation,” in Proc. IEEE Conference on Computer Vision and Pattern Recognition, 2011, pp. 585 – 592.