# An Iterative Search based Technique to Find or Predict Older Face Images of a Child

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## ABSTRACT

The major variations in the appearance of human faces is because of age changes. Due to many lifestyle issues, it is difficult to precisely predict how individuals may look in older years. This work aims to develop a technique for predicting older face images from a given childrens face image. This method requires only one input face image of a child and produces different age progressed images of the child at different target ages. This technique might be very helpful to find the missing children. In this method we have proposed a technique to find or construct a synthesize older face images from a given face image dataset. In the proposed work the FG-NET image dataset has been classified with different age groups of face images. Age groups are named by AgeGroup IDs 10-14, 15-19,. . . , 50-54. For a given child image we have applied an iterative approach to find the face images in higher age groups. At the first step an input of a child image of age that is below of the first age group has been taken and searched that image in the face dataset of higher age group. If the face is found, then the founded image is considered as the target image at that age group and that new face is searched in the next higher aged group data set. If it is not found, then a synthesized mean image is constructed with the input image and the founded nearest image. The same technique is repeated until the construction of the oldest (of age 50-60) synthesized image computation is completed. Here age group 50-60 has been considered as the oldest image in the experiment. In this way the older images of all the respective age groups can be found. Here PCA face recognition algorithm is used for searching an image from a given dataset.

## Keywords

Synthesize Image, Age Progression, Future Image Prediction, Face Image Modeling, Missing Children

## 1. INTRODUCTION

Predicting older face image of a child has become an important topic with many practical applications. Prediction of such older image can be used for many other applications, such as biometrics, cosmetology, forensic art, and searching for missing children.

In this work, we study the various technique of age progression where most of the techniques were applied for missing children searching. As per the report of the U.S. Department of Justice, there are over almost 790,000 children who are younger than 18 reported missing every year [1]. These children were kidnapped/lost when they were at the age of 18 years or less, as these missing children grow up their faces may seem to be quite different from the images given by their parents. Thus, if a missing child cannot be found soon, the changes in face often makes it a difficult to find the child. So if we can predict or search successful older images then it would be very helpful to the society.

Another problem that can be solved is updating employee databases. Several companies have employee records with photographs of the employees stored in their database. After a certain number of years, the employees have to update their photographs to match their current appearance. Automatic techniques such as ours might eliminate the need for this, by automatically updating the entire database with gradually predicted older images of employees [3].

At present some expert painters are used in many missing children cases to construct synthesized older images of the child based on some heritability factors found in parents, siblings and, in some cases, grandparents. The future faces created by these professionals are not unique and dependent on dissimilar drawings of painters. Based on the thinking of these painters, the paintings may affect their interpretation of the source face data. These process takes time, and its significantly harder to produce a perfect image.

The technique to construct synthesized older face images of a child can run on a standard computer and takes about 30 seconds to generate images for one face. Our proposed method to construct synthesized older face images of a child has several advantages. Primarily, it is an automatic system that does not depend upon the expertise of a sketch painter to create aged photographs. It saves both the time and money of users of this system, since it produces the output within minutes. Secondarily, it is based on a simple and clean theoretical foundation with the clearly stated limitations and algorithm breaking points. Thirdly, from a single image of the subject the system can perform the synthesis. Lastly, the synthesized faces are visually realistic.

## 2. RELATED WORKS

Since human faces alter with age, therefore facial aging properties are recognized mainly to the growth of craniofacial and skin related deformations associated with the introduction of wrinkles and decrease of muscle strength [21, 5]. Specially, the craniofacial (craniofacial is a medical term that relates to the bones of the skull and face) growth (human face shape) is the most noticeable effect from birth to adulthood. Including the growth of the face size, nose, eyes, mouth and skull, and the growth of the chin and cheek, each type of growth affects the facial appearance. Although there are many changes in facial skin over time, the skin change is more indirectly proportional to the craniofacial growth, such as skin color changes, growth of mustache etc.

The approaches to find the older images generally classified into anthropometry-model-based methods, AAM (Active Appearance Models) based [5] methods and landmark-based methods. The surveys of some existing approaches can be found in [19, 20, 11]. Normally anthropometry-model-based techniques are used to determine the facial aging with a face model controlled by a high-dimensional parameter vector. Lin et al. implemented anthropometric data from [10] to produce a statistical growth function which was used to simulate the aging process of 3-D graphic models for a Caucasian boy, an African-American boy and an Asian boy, respectively [2]. Also Ramanathan and Chellappa [20] projected a craniofacial growth model to guess the development of the human face under the age of eighteen years old. Again Ariyarathne and Dharmarathne modelled a same method to predict the age progression [7]. They have developed an aging model to simulate the facial changes with age progression of children who are below 18 years of age. They were working in the anthropometric statistical data of 2,325 Caucasian people collected by Farkas [10] to differentiate the variations of facial landmarks. Then the variation of every pixel in the entire image was founded based on the variations of the landmarks with an interpolation method to nonlinearly warp the input image. In this method for any large age differences between the source image and the target image, the computed results of interpolated nonlinear warping with facial landmarks will be inaccurate. Also in this method many multiple factors such as ethnicity, gender and age group affect facial aging transformation. They only considered the face images of males to develop their model.

The methods with AAM-based [5] techniques are developed based on the active appearance models. Lanitis et al. described how the effects of aging on facial appearance can be explained using learned age transformations and presented experimental results to show that practically accurate estimates of age can be made for unseen images [5]. They have developed their method on the basis of statistical face model [13], [4] which allows compact and reversible coding of face images. Also Suo et al. projected a multi-resolution AAM based technique which groups the face images in the same age group by using a hierarchical and-or graph to account for the large variations of facial structures [14, 16, 15]. In this method, Suo et al. modelled the aging procedure as a dynamic Markov, to predict older aging faces which provides suitable results for predicting older aging faces, but this method is not able to handle the age progression problem for children [13]. Again Luu et al. included the AAM and the support vector regression (SVR) to learn the aging function in their technique [17]. In this method a training database is used to construct standard feature vectors at different ages. Then the difference between siblingss feature vector and the standard feature vector are used to adjust the input feature vector. Finally, the resulting feature vector is converted into a photo with the inverse AAM. However, their proposed method can be applied with only one sibling photo, and if the sibling does not look like the subject or input child image the prediction result is not so reliable.

In the landmark-based approaches, the construction of the growth function model of the face shape is defined with a set of facial landmarks. The facial landmark points can be determined either manually [2, 22, 12, 8, 23] or automatically [18]. Using PCA technique Hill et al. generate a shape model and a texture model, and the proposed method is used to predict the face orientation and expression [8].

Cheng-TA S [9], et al. has proposed a 3D Age Progression Prediction technique using a facialcomponent based FAPP (Face Age Progression Prediction) method. In this method for a given image of a child, they first extract facial components, such as eyes, nose, mouth and the face shape of the child. For every facial components of the input child image, similar facial components are extracted from different children in a training database, then using that growth curves the predicted the facial components of the missing child.

## 3. PROPOSED METHODS

The work is carried out in this paper are described in the Method 1 and 2. After doing some experiments with Method 1 we modified it and is called Method 2 for better results.

### 3.1 Method 1

At first we have prepared a data set of different images of ages from 10 to 55. All images have been properly aligned with the authors algorithm which has been found in [6]. For a given image $S_i$, we find the nearest image $S_{i+1} = Nearest(S_i, AgeGp_{i+1})$ from the set of given images of (i+1)-th age group $AgeGp_{i+1}$. Where $AgeGp_i$ is a set of face images of ages $[10 + i \times 5, 14 + i \times 5]$ where $i = 0, 1, \dots, 10$. We have considered the age of oldest image is as of 64 years old and for which $i = 10$ is the upper limit and similarly the lowest age of a face image is of 10 years old for which $i = 0$ is the lower limit. To find the nearest image we compute minimum distance $D_{i+1} = PCA\_Edistance(S_i, AgeGp_{i+1})$, which can be found from the distance metric of PCA algorithm. To find the similarity of two different aligned facial images, we have used the Euclidean Distance and PCA technique. After getting the values of $D_i$ we select $S_i$ for which $D_i$ is the minimum. If $D_i$ is greater than the given threshold value $\theta$ we compute mean $M_i$ which is the mean image of $S_i$ and $S_{i-1}$. And this $M_i$ is considered as the predicted face image of $i^{th}$ age group. Thus in the $k^{th}$ step we get the predicted images $S_1, S_2, \dots, S_k$ of age groups $i = 1, 2, \dots, k$. The process of the proposed method has been discussed in the following steps with the help of an examples and summarized in the algorithm 1. The proposed algorithm has been explained with an example as shown in different steps as given below.

**Step 1:** To find an older aged images of a given childs face image, we used age groups 10-14, 15-19, ..., 50-54. In the following figure 2, the child image $S_0$ is chosen to find its older face images. In the second column images $D_1, D_2, D_3, \dots$ are shown from the database whose ages are in the age group of 10-14 years, and the set of this age group images are represented by $AgeGp_1$. We compute the minimum distance $d_1$ with the source image $S_0$ from the set of given images of $AgeGp_1$. We get the image $S_1 = Nearest(S_0, AgeGp_1)$ which is nearest to $S_0$ , and which has been considered as the predicted or founded older face image of $S_0$ at the age group of 10-14 years. At the end of step 1 we get $S_1$ of age 10-14, and will be considered as the input in the step 2. The process of the first step is shown in figure 1 with an example.

**Step 2:** As mentioned in figure 3 the same technique has been applied to get the predicted or to find older face image of $S_1$ (where $S_1$ is obtained in step 1) at the age group of 15-19 years. Here we compute the minimum distance $D_1$ of the source image $S_1$ from the set of given images of $AgeGp_2$. We get the image $S_2 = Nearest(S_1, AgeGp_2)$ which is nearest to $S_1$. This $S_1$ has

**Algorithm 1- An Iterative Search Based Technique to Find or Predict Older Face Images of a Child.**

**Method 1**

1. Objective/Result
   a. Find/recognize older face images of a child from datasets of different age groups.
   b. Or produce synthesize mean older face images if older face is not recognised in the dataset.
2. Training Database
   a. AgeGp[1-n], n numbers of different age groups in the datasets. $AgeGp_i$: set of face images of ages $[10 + i \times 5, 14 + i \times 5]$.
3. Input $S_0$
4. For i=1:n
   a. $S_i$ = Nearest Image of $S_{i-1}$ and $AgeGp_i$
   b. $D_i$=PCA_Edistance($S_{i-1}$, $AgeGp_i$)
   c. If($D_i$<θ) where θ is a threshold to measure the distance of similar image, then
      i. $S_i$ is the exact nearest image of $S_{i-1}$ at i-th age group.
   d. Otherwise
      i. $S_i$ is not exact but nearest image of $S_{i-1}$ at i-th age group.
      ii. $M_i = (S_{i-1}+S_i)/2$, mean of $S_{i-1}$ and $S_i$
      iii. $S_i = M_i$, input for next iteration.
   e. End-if
5. End-for
6. Outputs $S_i$, i=1, 2, … n are the predicted images of $S_0$ in the i-th age groups.

Fig. 1. Algorithm of method 1

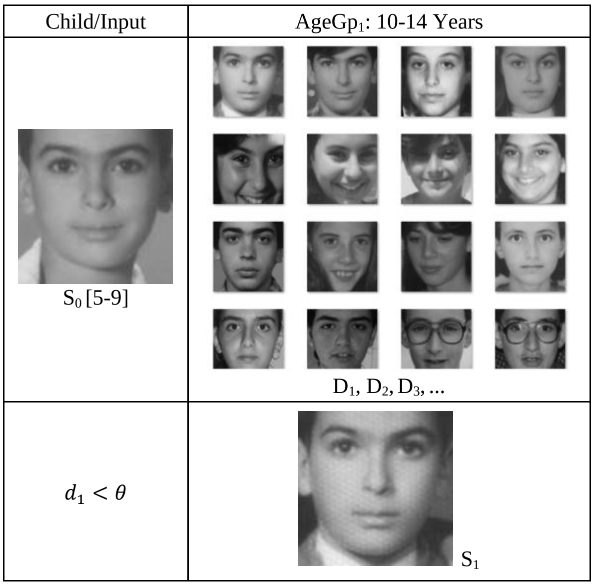



Fig. 2. Method-1, Step-1: $S_i = Nearest(S_{i-1}, AgeGp_i)$

been considered as the predicted or founded older face image of $S_0$ & $S_1$ at the age group of 15-19 years. And finally, we get predicted images $S_1$ and $S_2$ of age groups 10-14 and 15-19 respectively at the end of step 2. In this step $S_2$ will be considered as the input in the step 3 and the same technique has been applied to get the image $S_4$ of age group 20-24.

**Step 3:** In figure 4 after applying the same technique we get the minimum distance $d_1$ which is greater than of our predefined thresh hold value $\theta$ and therefore we compute mean $M_3$ as the mean image

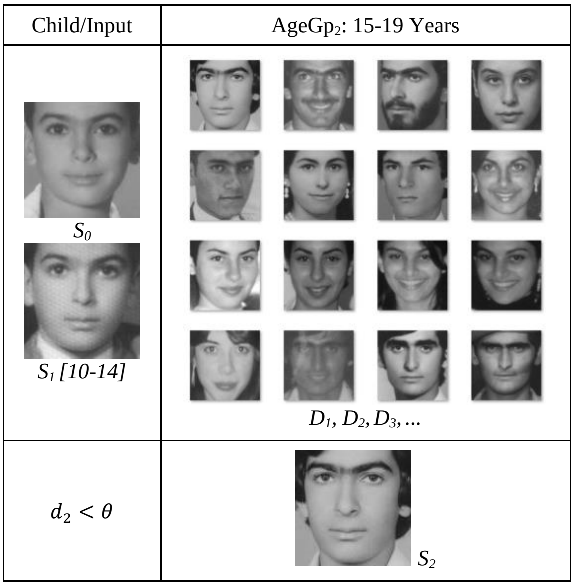
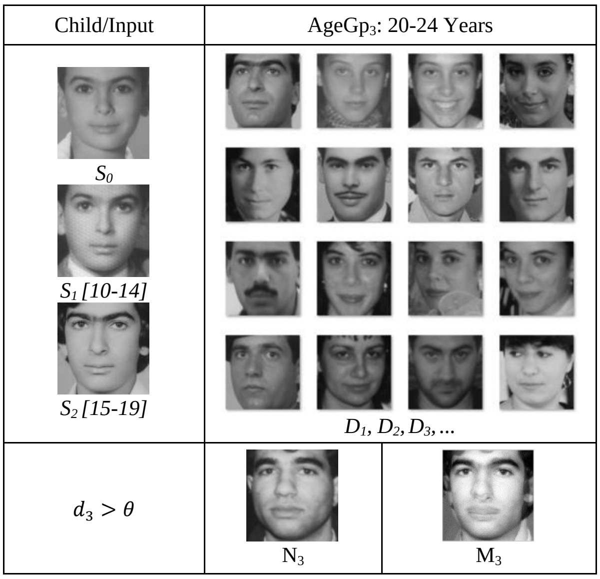



Fig. 3. Method-1, Step-2: $S_i = Nearest(S_{i-1}, AgeGp_i)$




$$s_k = \begin{Bmatrix} N_k, \ if\ D_k = nearestDist(S_{k-1}, AgeGp_k) < \theta \\ M_k = Mean(S_{k-1}, N_k), \ otherwise \\ K=1, 2, \dots, 9 \end{Bmatrix}$$

$S_3 = M_3 = Mean(S_2, N_3)$

Fig. 4. Method-1, Step-3

of $S_2$ and $S_3 = Nearest(S_2, AgeGp_3)$, where image $S_3$ is the nearest to $S_2$. In this case image $M_3$ has been considered as the predicted older face image of $S_0$, $S_1$ and $S_2$ at the age group of 20-24 years. And similarly, at the end of step 3 we get $S_1$ and $S_2$ and $S_3 = M_3$ of age groups 10-14, 15-19 and 20-24 respectively, and $S_3$ will be considered as the input in the step 4. The same technique has been applied until we get all $S_k, k = 1, 2, \ldots, n$, where $n = 10$ is the last age group number and Sk is the predicted face images in different age groups.
This method has been summarized in the algorithm Algorithm 1. The result of this method is shown in figure 7. In this experiment if we compare the predicted/founded images with the original image of source in different age groups of age 10-14, 15-19, ..., 50-54, we get only 33% correct images in older ages.
In this experiment if we compare the predicted or founded images with the original image of source in different age groups of age 10-14, 15-19, ..., 50-54, we get only 33% correct images in older ages. The success rate of this method is not as good as our expectation.

### 3.2 Method 2

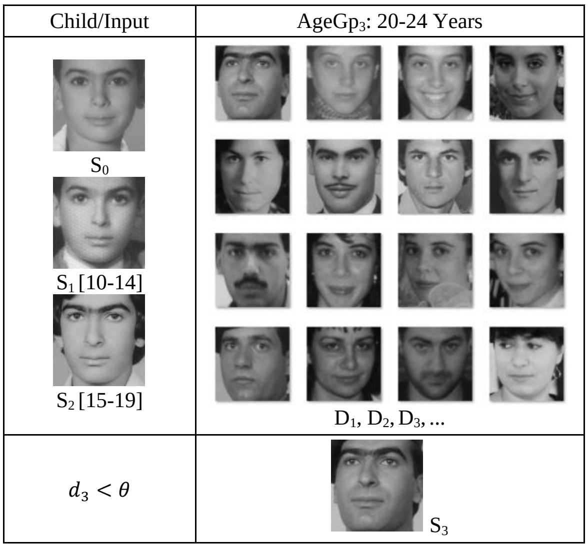
To improve the success result rate, we have proposed Method 2 where the technique to find $S_k$ for input $S_{k-1}$ has been modified as below.

1. If minimum distance $D_i$ <= thresh-hold value $\theta$
   a. $S_i = Nearest(S_{i-1}, AgeGp_i)$
2. Otherwise
   a. $S_i' = Nearest(\forall S_k, AgeGp_i), 0 \le k < i$
   b. $D_i = PCA\_Edistance(S_i', AgeGp_i)$
   c. If $D_i > \theta$
      $S_i' = Mean(S_i, S_i', \forall S_k), 0 \le k < i$
   d. End-if
   e. $S_i = S_i'$
3. End-if

To find an older aged images of a given childs face image, we used age groups 10-14, 15-19, ..., 50-54 as similar to method 1. In this method modification is done in $4(c - e)$ of algorithm 1 of method 1. All other experimented steps are described in the figure 5. To describe this method, we have completed the experiment with the same input image and same database and aged group as described in method 1. In this experiment the result to get $S_1$ and $S_2$ of age 10-14 and 15-19 is same as described in step 1 and step 2 respectively of method 1. In step 3 of method 2, we get the minimum distance $D_3$ which is greater than of our pre-defined thresh hold value and therefore we compute $S_3$ as following:

$N_i$= *Nearest*($S_{i-1}$, $AgeGp_k$), $i$=[1, k-1]
$S_k$=$Mean_k$=$Mean(N_i)$, $i$=[i, k-1]
Here, $k$=3, and
$N_1$= *Nearest*($S_0$, $AgeGp_3$)
$N_2$= *Nearest*($S_1$, $AgeGp_3$)
$S_3$=$Mean_3$=$Mean(N_1, N_2)$

At the end of this step 3, we get $S_1$, $S_2$ and $S_3$ of age 10-14, 15-19 and 20-24 respectively, and $S_3$ will be considered as the input in the next step 4. The result of step 3 is shown in the 5. The same technique has been applied until we get all $S_k$ where $k = 1, 2, \ldots, n$, where n is the last age group number and it is considered as the predicted face images in the respective age groups.
The result of this method has been described with the help of an example which is shown in figure 6. In this experiment if we compare the predicted/founded images with the original image of source in




$S_3$=*Nearest* ([$S_0$, $S_1$, $S_2$], $AgeGp_3$)

Fig. 5. Method-2, Step-3 [Step- 1 & 2 are same as mentioned in Figure 2 & 3]

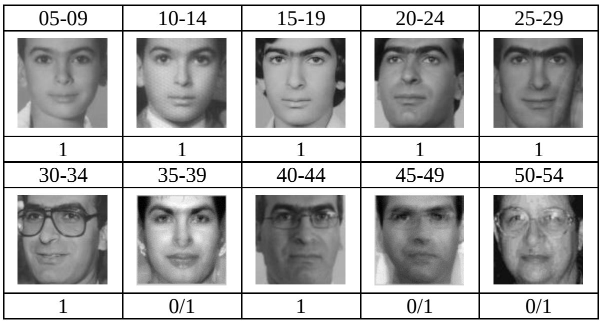



Fig. 6. Experimental result of method 2: Predicted or Nearest Images of 001A in different age groups, result is 1 for matching with original, 0 for not matching and 0/1 for non-availability of original image

different age groups of age 10-14, 15-19, ..., 50-54, we get 83% correct images in older ages of the given child image, which is much better than the method 1. The comparative results are discussed in the following sections.

## 4. EXPERIMENT AND ANALYSIS

We have done our experiment with 30 different inputs for both the methods 1 & 2. For testing our result, we have used FG-NET (Face and Gesture Recognition Network) Aging Database. The database is a publicly available, which is having a number of subjects at different ages. This database contains 1002 images from 82 different subjects with ages ranging between new-born to 69 years old subjects. The specifications of the FG-NET dataset are as shown in Table 1. The comparative result of these method 1 & 2 is shown in figure 7, 8 & 9.

Table 1. FG-NET Aging Database

| | | |
|---|---|---|
| Total number of images | 1002 | |
| Number of subjects | 82 | |
| Number of images per subject | 6 – 18 (on average 12 images/subject) | |
| Minimum age | 0 | |
| Maximum age | 69 | |
| Image Type | JPG images, color or grey scale images | |
| Image Resolution | Variable- approximately 400x500 | |
| Conditions (typical conditions encountered on images from the database) | Illumination | Varying |
| | Pose | Varying |
| | Expression | Varying |
| | Beards | Yes |
| | Moustaches | Yes |
| | Spectacles | Yes |
| | Hats | Yes |

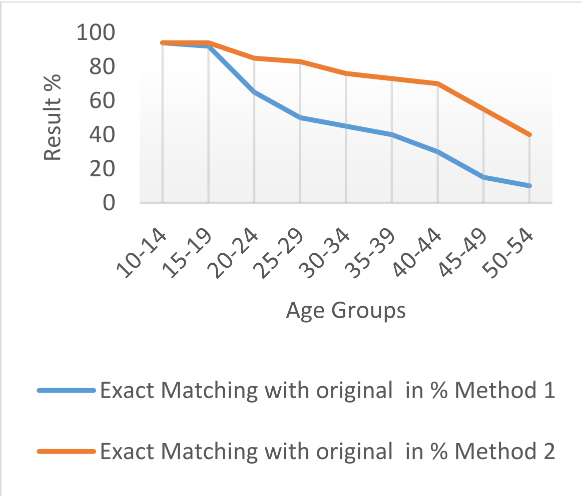



Fig. 7. Comparisons of Method 1 & 2 with exact match.

## 5. CONCLUSION AND FUTURE WORK

Our main goal of this research focused on the face shape changes. So we have considered the facial shape changes with elderly aging progression. The next step of the research is to extend the same application to add wrinkles, face texture variations, hair and eye line color changes with age progression. This next approach to improve this technique where it may one day replace forensic artistry where familial data is critical. Future efforts revolve around improving the texture rendition of this approach and the use of gender weighted biasing for familial data. Also in the next approach we can find/develop the better methods to find the nearest image which is one of the key feature of this work.
In this work, some difficulties occur due to finding the growth model of the whole face from a small familial database and also because of the smaller size of age grouped image database. If we can increase the numbers of images in the age grouped image database, then we can expect more accurate result to find synthesized older face images of a given child face image. Also the results of this technique highly depends upon on the searching methods to find the nearest images.

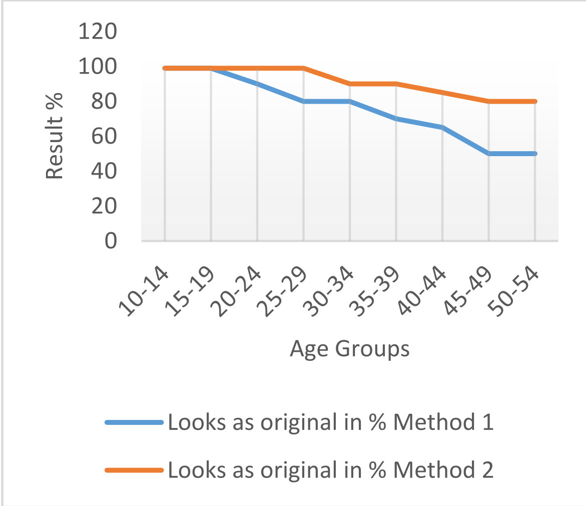



Fig. 8. Comparisons of Method 1 & 2 with feedback system.

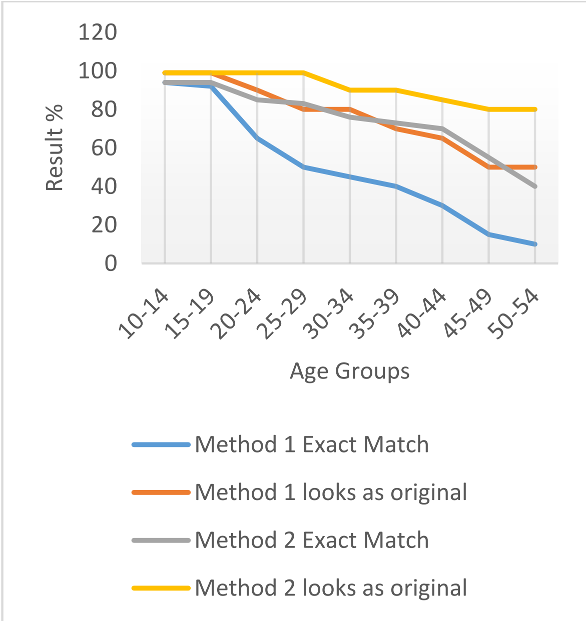



Fig. 9. Comparisons of Method 1 & 2

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