

A Linear Regression Analysis of the Effects of Age Related Pupil Dilation Change in Iris Biometrics

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Abstract

Medical studies have shown that average pupil size decreases linearly throughout adult life. Therefore, on average, the longer the time between acquisition of two images of the same iris, the larger the difference in dilation between the two images. Several studies have shown that increased difference in dilation causes an increase in the false non-match rate for iris recognition. Thus, increased difference in pupil dilation is one natural mechanism contributing to an iris template aging effect. We present an experimental analysis of the change in genuine match scores in the context of dilation differences due to aging.

1. Introduction

Like every part of the human body, the eye is subject to aging effects [1]. The effect of aging on the size of the pupil was first studied by Birren [2], and he observed that the size of the pupil tends to decrease as one ages. A further study by Winn *et al.* [3] which accounted for various illumination levels also found that as we age our eye's pupil size decreases linearly as a function of age under all illumination levels. A smaller study by Bitsios *et al.* [4] found that the pupil's reflexive response time due to change in illumination levels also decreases. The results of these studies should inform the general understanding of how iris recognition works, and particularly how aging and pupil dilation interact.

Several studies [5, 6, 7] have found that an increased difference in pupil dilation between two images of the same iris is correlated with an increase in the false non-match rate (FNMR). Researchers [8, 9, 10, 11, 12, 13] have also shown that an increase in the time lapse between two images of the same iris is correlated with an increase in the false non-match rate. However, the studies that examined pupil dilation differences and those that examined template aging have not previously taken into account the fact that

average pupil dilation changes due to the natural aging of the eye. In this paper, we use two iris matching software packages, VeriEye [14] and IrisBEE [15], to generate match data that we use to model (1) average pupil dilation as a function of age, and (2) genuine match score as a function of difference in dilation. Thus we explore how the natural aging of the eye, in particular the decrease in average pupil size with age, links studies on pupil dilation difference affecting the FNMR with studies reporting a template aging effect.

2. Related Work

Several studies in the medical literature have examined the effects of age on the pupil [2, 3, 4]. Winn *et al.* [3] conducted a study involving 91 subjects who ranged in age from 17 to 83. They examined pupil size under several different illumination levels. They found that, for each illumination level, the pupil size decreased linearly with age. An earlier study by Birren [2], did not control for varying illumination levels, and found a nonlinear decrease in pupil size with age. A more recent study by Bitsios *et al.* [4], in addition to finding that the average pupil size decreases linearly with age, also found that the response time of the pupil due to a change in illumination level also diminishes with age.

The studies which show that the average pupil size decreases as we age help to explain the observed increase in FNMR of iris recognition due to both differences in pupil dilation and template aging. Hollingsworth *et al.* [5, 6] found that as the difference in pupil dilation grows so too does the FNMR. Additional studies into this effect and ways to mitigate its impact were reported by Grother *et al.* [7] and by Ortiz and Bowyer [16]. Iris template aging has a similar impact on iris biometric systems.

Iris biometric template aging was initially studied by [8, 12] in which each of the authors found that as the time difference between an enrolled iris template and a corresponding probe template increased so did the probability

of a false non-match. Further investigation into this observation was made by Fenker *et al.* [9, 10] with a larger sample set, with a similar result. A more recent study by Czajka [13] examined template aging over three different iris matchers, Neurotechnology’s VeriEye, SmartSensors’ MIRLIN, and their own iris matcher referred to as BiomIrisSDK. Czajka found evidence of iris template aging in the case of each of the three iris matchers, and suggested that the aging effect was more noticeable in the results from more accurate matchers. Each of the authors studied how elapsed time between probe and gallery template acquisition affect the performance in terms of match detection at a given threshold. These studies however, did not attempt to model the behavior of time difference and match scores. The research by Sazonova *et al.* [11] does model the behavior of match scores and time differences in a template comparison.

The authors of [11] studied the behavior of genuine match scores in terms of template aging as a linear regression model. In their models, the independent variable was elapsed time (in days) between probe and gallery template acquisition and the dependent variable was match score. They analyzed genuine match scores from two different iris matchers, VeriEye and Iris-BEE. They found that Iris-BEE’s fractional Hamming distance tended to increase linearly with increase in time lapse. Analogously, they found that VeriEye’s similarity score tended to decrease linearly with increase in time lapse. They also suggested that the effect was more noticeable when the analysis was restricted to a higher-quality subset of the images.

Fairhurst and Erbilek [17] consider age-related factors that affect iris biometrics. They found that when accounting for errors in segmentation, aging effects are seen more as a function of the changes in pupil dilation size as one ages. They state [17] "...dilation of the pupil (specifically, the dilation ratio) decreases with age and this increases the attainable recognition performance." so two images of an older person, both taken when the person is older, may each show more of the iris by having low dilation, and thereby give a better match than two images of the same person both taken when the person was younger. But matching an older to a younger image would not be better. Their study provides the initial link to examine and model template aging effects in the context of dilation changes due to age.

In this paper, we link the results from the medical literature on how pupil size changes with age [2, 3, 4], with the results from the iris recognition literature on difference in pupil dilation causing an increase in FNMR [5, 6, 7], in order to better understand one underlying cause of an iris template aging effect [8, 9, 10, 11, 12, 13]. We perform this analysis through the use of linear regression models for both the effect of age on dilation, and the effect of dilation difference on fractional Hamming distance scores and VeriEye

match scores for genuine comparisons. Figure 1 provides a graphical summary of past research into template aging, dilation difference, and medical studies of the change of pupil dilation over time.

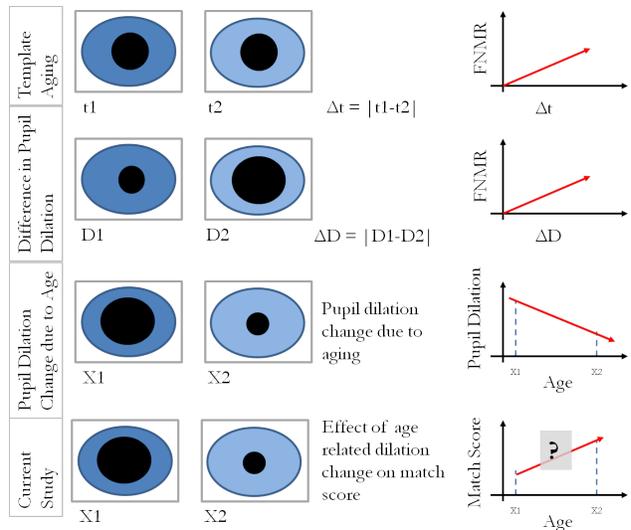


Figure 1. Outline of past work leading up to this current study

3. Data and Software

The image data used in this study was collected between 2008 and 2011 using the LG IrisAccess 4000 camera. The dataset contains 955 unique subjects with a combined total of 49936 eye images (left: 25160, right: 24776). In terms of age, the dataset contains representative samples from the ages of 18 to 64. Figure 2 shows the distribution of image samples per age of the subject at the time of acquisition. We note that the number of subjects declines substantially for ages greater than 25 years.

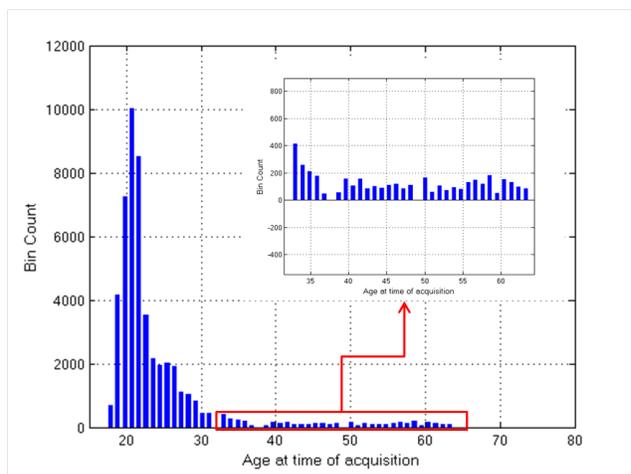


Figure 2. Histogram of eye image samples per age

Each eye image in the dataset is processed using VeriEye [14] and IrisBEE [15]. VeriEye is a commercial iris matcher created by Neurotechnology [14] that achieved good performance in the NIST IREX study [7]. The IrisBEE software is a modified version of iris biometrics due to Daugman [18, 19, 20] and Wildes [21]. IrisBEE is based on an implementation first described by Masek [22] and improved and updated by Liu [15]. Both VeriEye and IrisBEE provide information regarding pupil dilation.

VeriEye gives a measure of pupil dilation named "PupilIrisRatio" within its metadata for each iris template created. IrisBEE requires the measure of dilation to be computed from the found segmentation information. For IrisBEE, the pupil dilation ratio metric described in [5] is used. The pupil dilation ratio is defined as the ratio of the pupil radius R_p to the iris radius R_i (R_p/R_i) Where R_p and R_i are determined in the segmentation phase of IrisBEE.

There was no documentation regarding how VeriEye's "PupilIrisRatio" is computed. Therefore we compared dilation ratios from IrisBEE spanning the range from dilated to constricted to the corresponding "PupilIrisRatio" calculated by VeriEye. As a reference, the dilation ratios calculated using IrisBEE range in value from 0.15 (constricted) to 0.73 (highly dilated). The corresponding range in the dilation measure used by VeriEye is seen to vary from 37 to 174. Figure 3 is a scatter plot of VeriEye's "PupilIrisRatio" and the dilation ratio calculated from IrisBEE, showing good agreement between the two metrics.

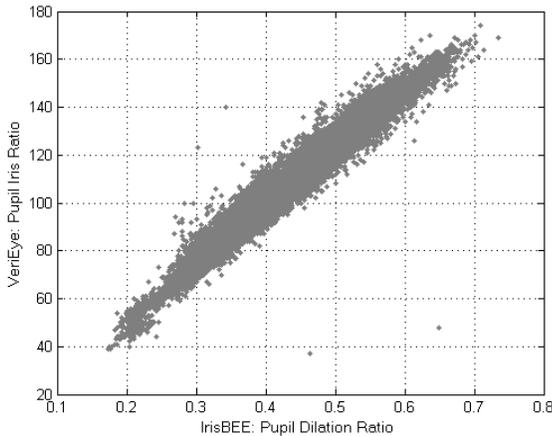


Figure 3. Scatter plot of VeriEye's PupilIrisRatio and the dilation ratio from IrisBEE

We first analyze the relationship between pupil dilation and age in our dataset. Our result follows the general pattern of analogous studies in the medical literature [2, 3, 4]. Our approach to measuring pupil dilation differs from that in [2, 3, 4], in that it is based on IrisBEE segmentation information from an eye image and the reported dilation data from VeriEye. Also, subjects in the medical studies [2, 3, 4]

may have been screened on conditions of normal eye function, or use of medications, whereas such restrictions were not enforced in collecting the iris recognition images. However, the overall pattern of results shown in Figure 4 and Figure 5 follows that which appears in [2, 3, 4].

The metric used for comparing two iris templates also differs between VeriEye and IrisBEE. IrisBEE uses the fractional Hamming distance (FHD) [18, 19]. The FHD is defined as the number of disagreeing bits in two iris codes (templates) divided by the total number of bits compared, accounting for occlusions through each of the iris template's masks. Thus a small FHD provides evidence that the two images are of the same iris, and a large FHD provides evidence that the two images are of different irises. However, the metric reported by VeriEye is a similarity score in which a large value corresponds to match and a low value to a non-match.

Along with the calculation of the IrisBEE's fractional Hamming distance and VeriEye's similarity score we use each software's metric of dilation and calculate the absolute value of the dilation difference. Letting D_A and D_B denote the measures of dilation for eye image A and eye image B , the difference in dilation used is simply $\Delta D = |D_A - D_B|$.

For each pair of same-eye images, we calculate the IrisBEE dilation difference and match score and the VeriEye dilation difference and match score. We omit pairs of images acquired on the same acquisition day. In total there were 1,003,807 match instances. The following section uses linear regression models to analyze dilation in terms of age and match scores in terms of dilation difference.

4. Linear Regression Models

We model the relationship of age and dilation to estimate the expected amount of dilation change due to aging. We then model the relationship between fractional Hamming distance and measured dilation difference. The two models are then used to estimate the impact that changes in dilation due to aging have on match scores for genuine match comparisons. For each of the linear models we examine the statistical significance of the estimated intercept and slope. In particular, we follow the traditional analysis of linear models in that the null hypothesis for the estimated parameters is that there exists no linear relationship between the observed data and its covariates. In the context of this analysis, the null hypothesis is that the estimated slope is zero. Therefore a small p-value indicates that there is evidence to reject the null hypothesis in favor of the alternative which is that a linear relationship exists. For a review of applied regression models see [23, 24].

4.1. Age and Pupil Dilation

Let Y_D denote the dependent variable of pupil dilation and X the independent variable of age of the subject at the

time of acquisition. The corresponding linear regression model to be estimated has the following form:

$$Y_D = \beta_0 + \beta_1 X. \quad (1)$$

Given the paired raw data observations for pupil dilation and age (see Figure 4 and Figure 5) we find the corresponding estimates $\hat{\beta}_0, \hat{\beta}_1$ under the least squares formulation. The results along with respective 95% confidence intervals (CI) and p-values for VeriEye data can be found in Table 1, and for IrisBEE in Table 2.

Table 1. PupillIrisRatio and age linear model parameter estimates

Parameter	Estimate	95% CI	p-value
$\hat{\beta}_0$	121.7370	[121.2367, 122.2373]	*
$\hat{\beta}_1$	-0.7438	[-0.7634, -0.7242]	*

* p-values less than $1e^{-15}$

Table 2. Dilation ratio and age: linear model parameter estimates

Parameter	Estimate	95% CI	p-value
$\hat{\beta}_0$	0.4914	[0.4894, 0.4935]	*
$\hat{\beta}_1$	-0.0029	[-0.0030, -0.0029]	*

* p-values less than $1e^{-15}$

The adjusted R-square values were found to be 0.1 and 0.0933 for the linear models of the VeriEye and IrisBEE data respectively. Plots of the data and estimated regression line are seen in Figure 4 and Figure 5.

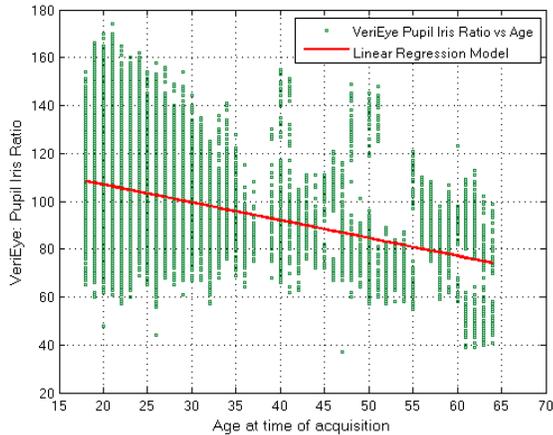


Figure 4. Dilation in terms of age of person at time of acquisition

4.2. Match Score and Dilation Difference

Let Y_{score} denote the dependent variable corresponding to the metric used for comparing two iris templates. For

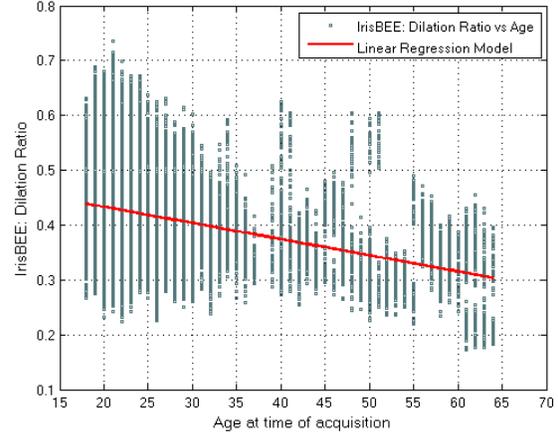


Figure 5. Dilation in terms of age of person at time of acquisition

IrisBEE Y_{score} is a distance measure while for VeriEye Y_{score} is a similarity score. We denote ΔD the independent variable to be the absolute value of the dilation difference between two eye images. Thus the corresponding linear regression model to be estimated has the following form:

$$Y_{score} = \alpha_0 + \alpha_1 \Delta D. \quad (2)$$

The model estimates $\hat{\alpha}_0, \hat{\alpha}_1$, respective 95% confidence intervals (CI) and p-values are reported in Table 3 (VeriEye data) and Table 4 (IrisBEE data). Figure 6 and Figure 7 display the estimated linear regression model for the VeriEye data and IrisBEE data respectively. The adjusted R-square values for each model are 0.074 and 0.083 for the VeriEye and IrisBEE data respectively.

Table 3. VeriEye similarity score and difference in pupil dilation: linear model parameter estimates

Parameter	Estimate	95% CI	p-value
$\hat{\alpha}_0$	1127.9499	[1126.7261, 1129.1737]	*
$\hat{\alpha}_1$	-12.0041	[-12.0872, -11.9210]	*

* p-values less than $1e^{-15}$

Table 4. Fractional Hamming distance and difference in pupil dilation: linear model parameter estimates

Parameter	Estimate	95% CI	p-value
$\hat{\alpha}_0$	0.1133	[0.1131, 0.1134]	*
$\hat{\alpha}_1$	0.3971	[0.3945, 0.3997]	*

* p-values less than $1e^{-15}$

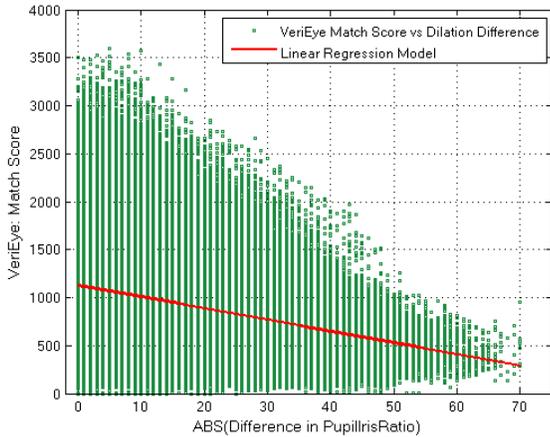


Figure 6. Linear regression of VeriEye similarity score and dilation difference

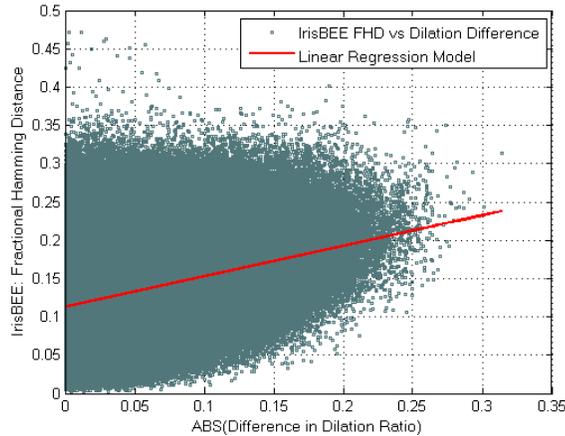


Figure 7. Linear regression of IrisBEE FHD score and dilation difference

4.3. Composite Model

To estimate how aging acts through pupil dilation to affect the fractional Hamming distance and VeriEye's similarity score, we first find the difference in pupil dilation in terms of the estimated regression model for age and dilation. Once found, it is used as an input to the estimated model of match score and dilation difference for the respective iris matchers. This creates a composite model accounting for change in genuine match score with age. A brief derivation and results are given in this section.

Using the model Y_D and found estimates $(\hat{\beta}_0, \hat{\beta}_1)$ for age and dilation given in Equation 2 we can determine the form of dilation difference in terms of changes in age. We let X_1 and X_2 be ages such that $X_2 > X_1$, the corresponding pupil dilation estimates from the regression model are Y_{D1} and Y_{D2} respectively. Using the absolute value of the dilation difference ΔD we find the following,

$$\begin{aligned} \Delta D' &= |Y_{D1} - Y_{D2}| \\ &= \left| \hat{\beta}_1 (X_1 - X_2) \right| \end{aligned} \quad (3)$$

We use $\Delta D'$ as input for the estimated regression model of Y_{score} to estimate how a change in age in years $|(X_1 - X_2)|$ affects the match score. Specifically we find the following,

$$\begin{aligned} Y_{score} &= \hat{\alpha}_0 + \hat{\alpha}_1 \Delta D' \\ &= \hat{\alpha}_0 + \hat{\alpha}_1 |\hat{\beta}_1| |(X_1 - X_2)| \end{aligned} \quad (4)$$

Thus the factor $\hat{\alpha}_1 |\hat{\beta}_1|$ gives the rate of change of match score per unit change in years. See Table 5 for the computed factor $\hat{\alpha}_1 |\hat{\beta}_1|$ for VeriEye and IrisBEE observations and respective linear models.

Table 5. Composite Model

Composite Regression Model	$\hat{\alpha}_1 \hat{\beta}_1 $
VeriEye	-8.9286
IrisBEE	0.0012

Thus we see that for both VeriEye and IrisBEE there is a measurable degradation in match score due to dilation difference caused by aging effects.

5. Conclusions and Discussion

In this study we found that dilation changes due to age have a measurable effect on the match score for genuine match comparisons. In particular, there is an increase in fractional Hamming distance in terms of the size change of the pupil due to age effects as seen in the IrisBEE data. Similarly there is a decrease in similarity score of the VeriEye data as we observe dilation differences grow due to aging. We modeled the effects of age and pupil dilation size as seen in previous studies. In addition, we modeled the behavior of the match score and difference in pupil dilation.

A composite model was derived from the two estimated models to account for the pupil dilation change due to age. From the composite model we showed the rate at which the FHD increases as well as the rate at which VeriEye's similarity score decreases due to pupil dilation change in terms of aging. In each of the estimated models we found the parameter estimates and results to be statistically significant. Thus the degradation of the match score will lead to an increase in the false non-match rate if the effect of aging on pupil size is not accounted for by some aspect of the iris biometric system.

The most direct way to account for effects of age related pupil dilation difference is to control the pupil size at the time of acquisition and enrollment. Accounting for pupil dilation can be accomplished in a number of ways. Ortiz and Bowyer [16] enroll subjects' eye images based on their

pupil dilation statistics. The IrisGuard [25] sensor controls for large pupil dilations by activating a set of visible lights to reduce the pupil dilation level. Both approaches can be used to minimize the difference in pupil dilation during enrollment and image acquisition.

Our study examined a linear regression model for match score behavior in terms of pupil dilation difference. Future research could examine a multiple linear regression model that accounts for a myriad of differences in eye images. Such differences can include the following: pupil dilation difference, template aging, illumination variations, and frequency component differences. Modeling the various factors that contribute to match score degradation may provide insights into how improve iris recognition performance.

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