Iris Recognition And Degree of Freedom

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***Abstract*—Recognizing the imposter distribution as the indicator of information content of the iris biometrics, we show using ICE1 Exp1 data: 1. There exists an encoding methods whose degree of freedom (DOF) is more than three-times higher than that of Daugman. 2. A large DOF gives a better performance (True-Match-Rate (TMR = 1 – FRR (False-Reject-Rate)) at a very small False-Accept-Rate (FAR) of the order of 10^{-8} to 10^{-10} and permits more rotated irises (angle > 5 degrees) to be matched. 3. The information content of the iris has a uniform distribution along the polar angle direction but non-uniform along the radial direction of the iris. 4. DOF of the fixed mask matching is *linearly* proportional to the area of the mask. 5. Blur significantly affect DOF of the imposter distribution.**

***Index Terms*—Biometrics; Iris recognition; Binomial distribution; Identity verification; Information content.**

I. Introduction

DAUGMAN [1] proposed a method of encoding iris patterns into bit patterns, using quadrature 2D Gabor wavelets. He has shown that this phase information for the imposter distribution exhibits the Bernoulli trials of about 249 degrees of freedom (DOF) [2] independent of the database size and enables the decision about personal identity with high confidence. This abstraction from the iris pattern to the Bernoulli trials (which has only two parameters, DOF and the transition probability) for the imposter distribution is the revelation to the iris biometrics. Bit-pattern encoding scheme will share this abstraction of the imposter distribution not limited to the Daugman way. Other non-bit pattern encoding methods so far has not shown such a simple abstraction for the imposter distribution nor the database-size independence. The genuine distribution has eluded the characterization so far. In this paper, we focus on the imposter distribution and speculate on the genuine distribution.

Daugman [2] discussed the quality issues in terms of "ideal" and "non-ideal" imaging conditions. He declared that the imaging conditions do not affect the imposter distribution, but only the genuine distributions. In this paper, we argue against this declaration. It is generally accepted that iris biometrics is using the information embedded in the iris pattern which is revealed by near-infrared lighting. If we regard the imposter distribution as the Bernoulli trials encoded by an iris template creation, then it is a natural conclusion that DOF of the imposter distribution is the indicator of the information content encoded by iris template creation. That is, anything to affect the information content of iris will be revealed by DOF change. In particular, the smaller the information content is, the smaller the DOF is for the imposter distribution. We will show this fact repeatedly in different context by measuring DOF.

We can even make a stronger statement in how DOF changes. An interesting property of the binomial distribution is that for two independent random variables X and Y which has binomial distributions with degree of freedom N and M but the same probability p, then the sum of X and Y exhibits the binomial distribution with N+M and p. This means for the imposter distribution is that DOF of the iris matching for a fixed mask is *linearly* proportional to the mask area to the entire area if the random bits of iris template are distributed uniformly.

The genuine distribution has not been abstracted for modeling so far. We recognize that it should reflect the information content of the iris. If there are lots of information in the iris (or higher DOF in the imposter distribution), then the compared irises must be segmented exactly to get a perfect match. Therefore we expect the peak of genuine distribution to be slightly shifted to a larger value of the Hamming distance (HD) for a larger DOF encoding and the genuine distribution to be wider if the segmentation or the image conditions are not the same between the irises compared. On the other hand, if the number of bits to match is less (smaller DOF), then it is easier to match and thus the peak should shift toward the zero direction and the distribution will become narrower. This is the opposite to the imposter distribution where the loss of information leads to a wider distribution.

As soon as realizing consequences just mentioned, one must be very careful in compressing the iris images so that the full information content should not be reduced. That is, if compressed too much, one ends up a smaller DOF (wider imposter distribution) whose performance on the iris biometric is reduced. At this time, we have no way of knowing how much information iris pattern contains. We claims that the information is certainly larger than the Daugman encoding method produced. It should be noted that the Daugman encoding seemed changed because DOF listed in the patent [1] is 173. One must realize that when the two irises are matched against different angular rotation, then the imposter distribution shape will get modified. Daugman [2] modeled this by the "best of n" test of agreement from the binomial distribution described in Section III. It is important to measure the DOF of the imposter distribution without rotating against each other. This is usually not done when iris biometric performance is measured.

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Several attempts [4] have been discussed to characterize "qualities" on the performance using the Receiver-Operating-Characteristic (ROC) curve. Their prediction using quality metrics are qualitative in nature. We propose that any quality measure should be characterized by the change of DOF of the imposter distribution. In this way we can actually predict the performance for certain quality images as a whole. Here we show how two quality measures, coverage and blur, affect DOF of the imposter distribution in Sections V and VI.

Our discussion will be based on our results for ICE1 Experiment1 data [3] (Experiment2 results are similar), even though they are several issues regarding the data qualities and acquisitions (See Appendix).

II. DOF and Iris Templates

It is enough to show that there exists an bit-pattern encoding method of an iris which has a larger DOF that that of Daugman. We developed a way of encoding iris using a polar-unwrapped image following the ANSI-INCITS 379-2004 Iris Image Interchange Format standard *without* using the Daugman Gabor-2D filter. As Daugman [2] showed, the way of getting the DOF is to measure the imposter distribution without rotations and regard it to be the Binomial distribution B(N, p) where *N* is the DOF and *p* is the probability : mean for number of successes = Np and variance = Np(1-p). Since we are interested in the *sample* proportion (the count of successes divided by the number of observations), we calculate N and p from the imposter HD distribution by $N = \mu(1-\mu)/\sigma^2$ where μ is the mean and σ is the standard deviation of the imposter distribution. Figure 1 is our encode result for NIST ICE-1 Experiment 1 for imposter distribution.

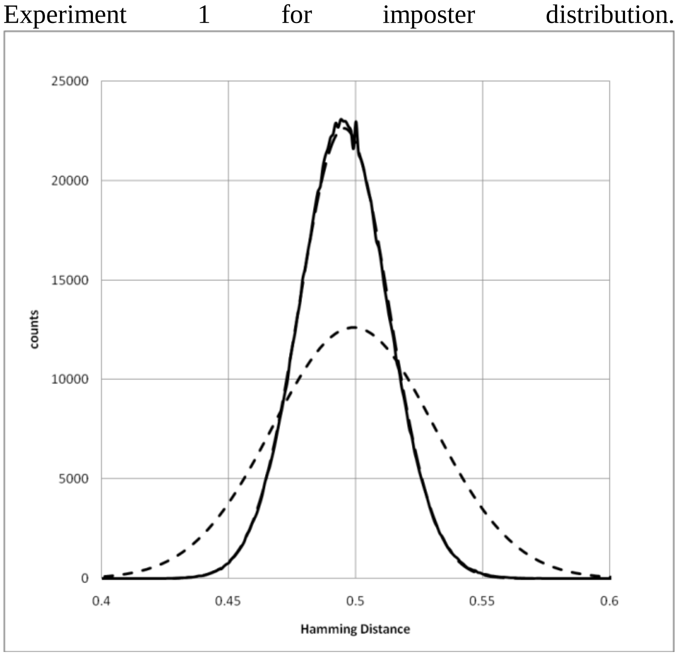


Fig. 1. The imposter distribution and two binomial distributions "normalized" for the size of the database. The solid curve corresponds to the imposter distribution with our encoding. The long-dashed curve is the binomial distribution with N=801 and p=0.4953. The short-dashed line is the binomial distribution of Daugman [2] with N=249 and p=0.499.

As you can see, the binomial distribution fits very well. Note that the DOF is 801. The binomial distribution is normalized so that the total area is 1,002,386. Our distribution has a slight shift from 0.5 which indicates the slight correlation on the transition rate. Note that the higher DOF is, the sharper the imposter distribution is. Ma et al. [5] also obtained a narrower imposter distribution (i.e. larger DOF) in CASIA Iris Database of 2,297,019 comparisons, using a 1-D wavelet encoding. Unfortunately, we cannot confirm that this non-public database exhibits the same behavior as ICE1 data does and these authors did not provide the value for DOF. We are sure that there are multiple encodings which provide larger DOFs than that of Daugman. We encourage readers to search an encoding scheme, since we are not sure what is the largest DOF is for iris biometrics.

III. Database size independence of DOF

We divided the ICE1 Exp1 database into two in the middle of the listing of files and calculated DOFs and compared them.

The results are: N=801, p=0.4953 for the whole database, N=825, p=0.4949 and N=788, p=4953 for half the database. The mean is 805 and the stddev is 18.7. Thus we confirm the Daugman observation that DOF is independent of the datasize even though our encoding method differs from him.

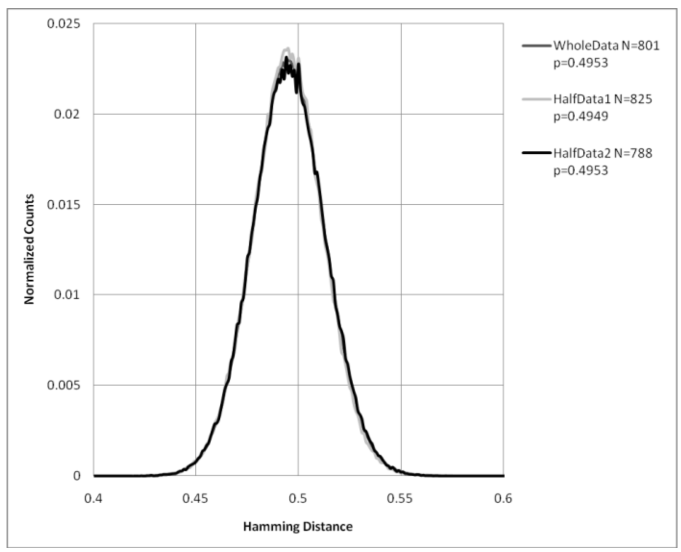


Fig. 2. The database size independence of DOF.

IV. Implication of a large DOF

By identifying the imposter distribution without rotation as the binomial distribution, we can make predictions without looking at the database. In particular, the shape of the imposter distribution gives the false-accept-rate (FAR): Given the threshold in the Hamming Distance (HD), FAR is calculated the cumulative percentage of the imposter distribution below the threshold as shown by Daugman [1] as shown in Figure 3.

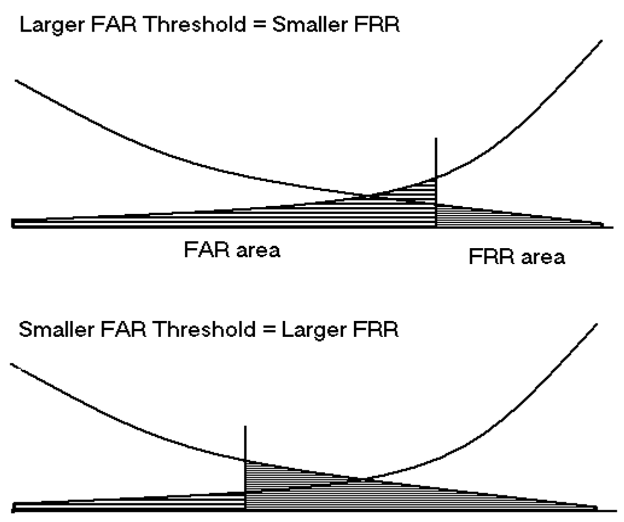


Fig. 3. The relation between FAR and FRR. The smaller the threshold for FAR, the larger FRR is. One also notice that when the motion of the threshold is small, the increase in FRR is small.

We can calculate FAR for various thresholds by knowing DOF (N) and probability p of a binomial distribution, $B(N, p)$. Here are the values for N=249 (Daugman) and N=801 (us) with or without rotation using the explicit binomial distributions. In order to make our predictions realistic, we used the Daugman shift equation for the shifted imposter distributions, i.e. the probability of m shifted false match $f_m(x)$ and its cumulative distribution $F_m(x)$ are given by corresponding non-shifted ones, $f_0(x)$ *and* $F_0(x)$:

$$f_m(x) = m f_0(x)[1 - F_0(x)]^{m-1} \qquad (1)$$

$$F_m(x) = 1 - (1 - F_0(x))^m \qquad (2)$$

where $F_0(x) = \int_0^x dy\, f_0(y)$. The meaning of shift=7 is +/- 3 rotation along the angular direction of the template whose size is 256 (i.e. 360/256 = 1.41 degrees per shift or up to +/- 4.22 degrees rotation). The shift of 21 is +/- 14 degrees. By finding threshold values for FAR values, 10^{-6}, 10^{-8}, and 10^{-10}.(binomial distribution has discrete values of x and thus we pick the closest x for those FAR values), we have the following table I and II.

N=249	No rotation		
FAR	1.35E-06	1.04E-08	1.90E-10
Threshold	0.349	0.321	0.301
Delta	0.028	0.020	
N=249	Shift = 7		
FAR	1.31E-06	1.55E-08	9.60E-11
Threshold	0.337	0.313	0.289
Delta	0.024	0.024	
N=249	Shift=21		
FAR	9.61E-07	9.22E-09	1.16E-10
Threshold	0.329	0.305	0.285
Delta	0.024	0.020	

Table I. Threshold dependencies on FAR for N=249.

N=801	No rotation		
FAR	1.34E-06	1.43E-08	1.17E-10
Threshold	0.412	0.397	0.383
Delta	0.015	0.014	
N=801	Shift=7		
FAR	1.06E-06	1.22E-08	1.23E-10
Threshold	0.404	0.391	0.378
Delta	0.014	0.012	
N=801	Shift=21		
FAR	1.00E-06	9.73E-09	1.38E-10
Threshold	0.400	0.387	0.376
Delta	0.013	0.011	

Table II. Threshold dependencies on FAR for N=801.

Note that the threshold shift between two order of magnitude in FAR is around 0.024 for N=249 and 0.013 for N=801. Observing that the genuine distribution has the similar shape for both N=249 and 801, we see the following: the decrease in the true match rate (1 – FRR) is much smaller for the larger DOF imposter distribution when FAR is changed by the same order of magnitude. That is, the larger DOF encoding will yield a straighter-line behavior under the ROC performance curve. Conversely, the smaller DOF encoding will yield the faster drop in the true match rate when FAR gets smaller.

As emphasized by Daugman [2], the requirement of operating in one-to-many "identification" mode are vastly more demanding than operating merely in one-to-one "verification" mode due to the fact that the probability of making at least one false match when searching a database of N unrelated patters is $P_N = 1 - (1 - P_1)^N$ where $(1 - P_1)$ is the probability of not making a false match in single comparisons, or $P_N \approx N P_1$ for small P_1. Therefore, having a larger DOF encoder of iris image will yield a much better performance in "identification" mode. Figure 4 is the qualitative picture of what we just discussed.

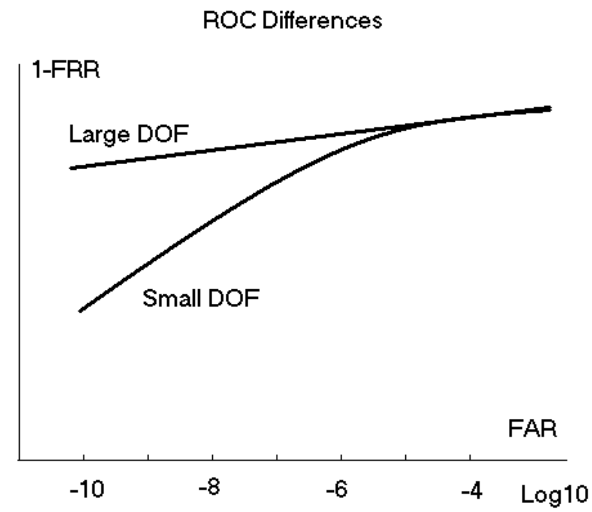


Fig. 4. ROC performance difference between a large DOF vs a small DOF imposter distribution.

Another merit of having a larger DOF is the tolerance of more rotated irises to be matched. For N=249, FAR=10^{-6} threshold changes from 0.337(shfit=7) to 0.329 (shift=21). Meanwhile for N=801, FAR=10^{-6} threshold changes only from 0.404 (shift=7) to 0.400 (shift=21). Again this shift is twice as much for N=249. The drop in 1-FRR is bigger for N=249.

Unfortunately the ICE1 Exp1 has only 1 million matchings and thus cannot go beyond 10^{-6}, but we confirmed this straight line behavior for *undisclosed* iris data by those people who used our encoding/matching SDK.

V. Information Distribution in Iris

If we believe that the DOF for the imposter distribution is the indication of information content of encoded iris, then it is natural to ask about how the information is distributed in the iris. Because we have a larger DOF encoder, we can answer more definitely about this question than a smaller DOF encoder can provide, since the results will be noisy. We will show that the information on the iris is distributed uniformly angularly. We have a slightly less conclusive data on the radial information content.

In order to ask this question, we created several masks for matching to get the DOF value for each mask. As discussed in Appendix A, many images have lower coverage value than 70% and thus we put the 50% mask always to calculate the DOF for the imposter distribution. First we compared the 25% masks, one with upper part not masked and another with the bottom part not masked as depicted in Figure 5.

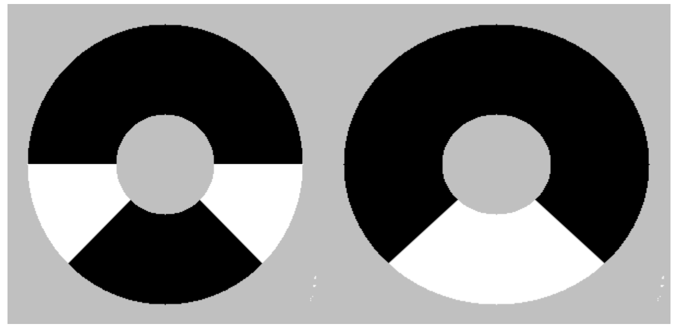


Fig. 5. Two masks of 25% coverage.

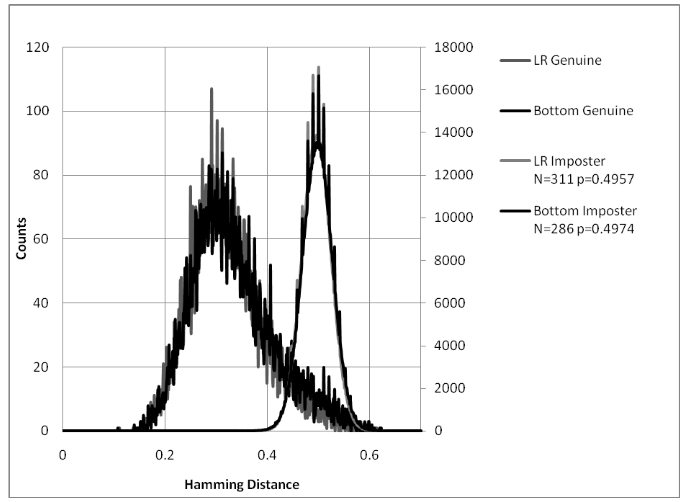


Fig. 6. Genuine and imposter distributions for two 25 % masks.

First we observe in Figure 6 that DOFs for the imposter distribution (311 and 286) agree within 8 % (mean 298.5 stddev 17.7). Second the genuine distribution overlaps nicely. Note also that the genuine distribution has the anti-correlation which goes beyond 0.5 when not rotated to match.

Encouraged by this result (the iris information is equally distributed between the two regions, we divided the region further into 12.5% of the coverages shown in Figure 5.

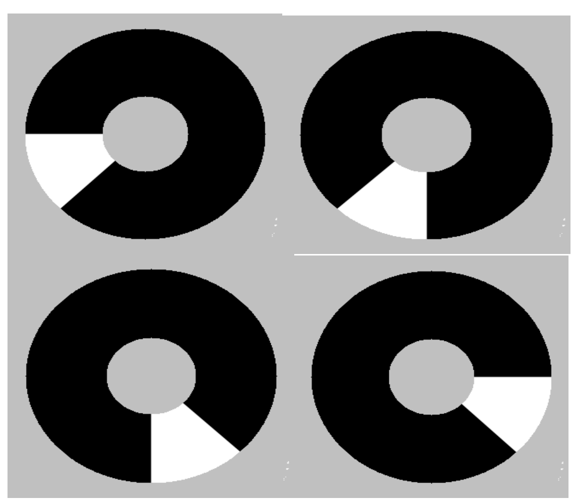


Fig. 7. Four different 12.5% masks to obtain DOFs.

Amazingly we have DOFs 154, 157, 145, 155 with mean 152.7 and stddev 5.32. Note that the DOF for mask 25% is just twice as big. Again both the imposter and the genuine distributions overlay nicely. We interpret this fact as the information content of the iris being equally distributed in polar angle direction. We should be able to do for the upper half if we had the iris database without eyelid or eyelash obstructions as explained in Appendix.

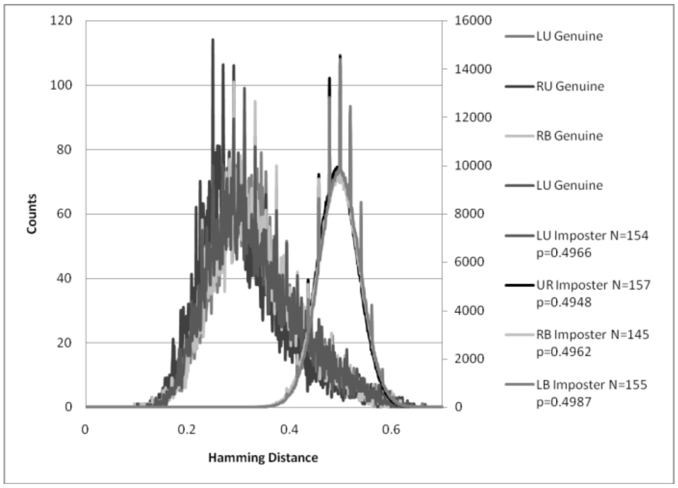


Fig. 8. Genuine and imposter distributions for four 12.5% masks.

We did a similar measurement for the 50% mask to obtain DOF = 557, which is slightly less than 150x4 = 600. If we had a fully opened iris database, we would have obtained DOF = 150x8 = 1200.

Encouraged by the results so far, we looked at the radial information content of the iris. We employed the masks along the radial directions depicted in Figure 9:

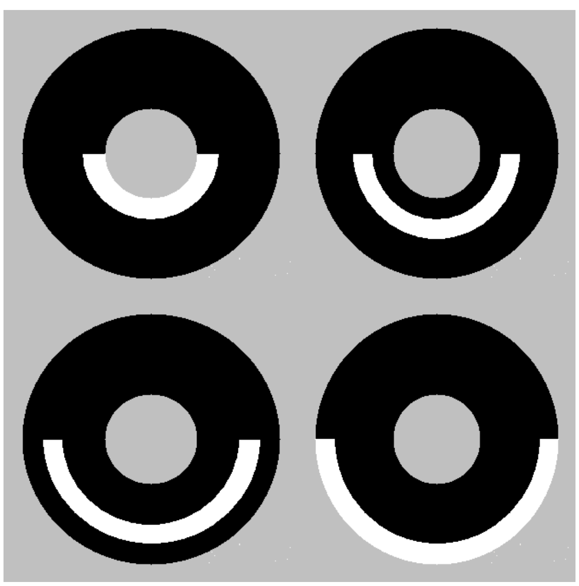


Fig. 9. Four different 12.5% masks to obtain radial dependency of DOF.

To our surprise, there are significant differences in DOFs for imposter distribution: 228, 138, 151, and 170 with mean 172 and stddev 39.7. Note also that genuine distributions are significantly different. If we regard DOF as the information content, then the inner most region has the largest information next to the outer most region. We like to discuss the significance of the differences in genuine distributions in future.

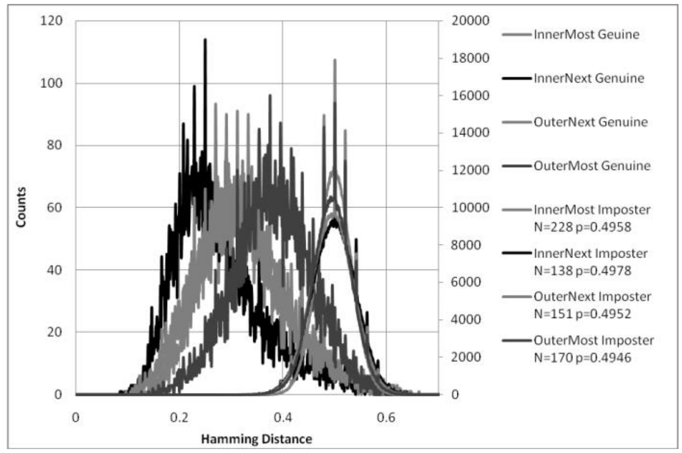


Fig. 10. Four radially-different 12.5% masks genuine and imposter distributions.

VI. Blurred Images and DOF

Now we discuss the effect of image blur on DOF. We employ a very simple model of blur, using different width of Gaussian filter. That is, we apply a Gaussian filter on the images and then do the matching on the filtered images. Applying a Gaussian filter is equivalent of changing the MTF (Modular Transfer Function) of the acquisition lens in that the frequency content is changed. Thus the Gaussian filtered image is simulating a bad acquisition system or out-of-focus acquisition. We have the following results with g=1, 5, 10, and 15 where g is the radius of Gaussian filter, e.g. g=1 corresponds to a 3x3 Gaussian filter.

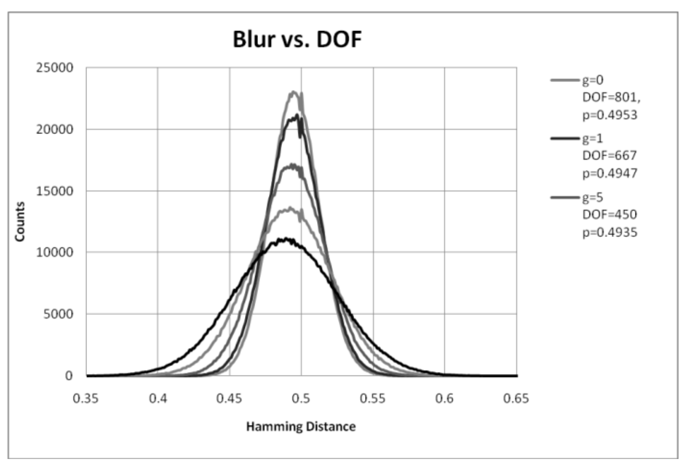


Fig. 11. The effect of blur on DOF. Images are filtered by Gaussian filter with radius g=1, 5, 10, and 15.

The DOFs are 801 (g=0), 667 (g=1), 450(g=5), 282(g=10), and 186(g=15). It is interesting to note that the probability gets smaller for increasing gauss filter radius. We believe that this is due to the long range correlation introduced by the filter.

VII. Conclusions

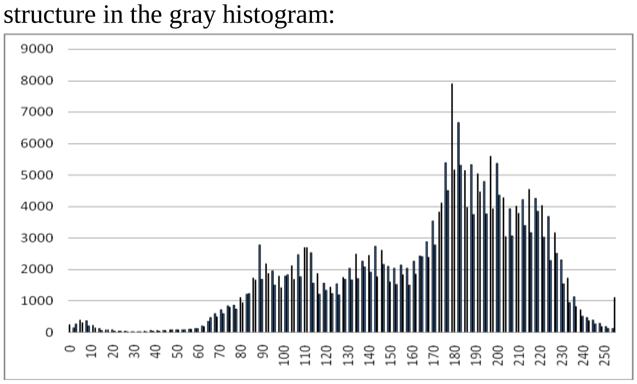
Using ICE1 Exp1 data, we demonstrated the importance of DOF of the imposter distribution on the iris biometric performance. Obviously what we demonstrated must be repeated on other iris databases. In particular, we look for an encoding method which has a large DOF in the imposter distribution in order to have a better matching performance in small FAR. We may use different encoding for different purpose: one-to-one verification uses a smaller DOF encoding and identification uses a larger DOF encoding. We demonstrated that the iris information is equally distributed along the polar angle direction, but not along the radial direction. We noted the inner most region had the highest DOF (the outer most region was the next highest).

Appendix

Why ICE1 data is not ideal?

After receiving the ICE1 data from NIST, we realized several issues with the data. Obviously these artifacts benefit the algorithm made to work with these images. However these artifacts will affect accurate segmentations of iris, which leads to a wose ROC performance than a better database can exhibit.

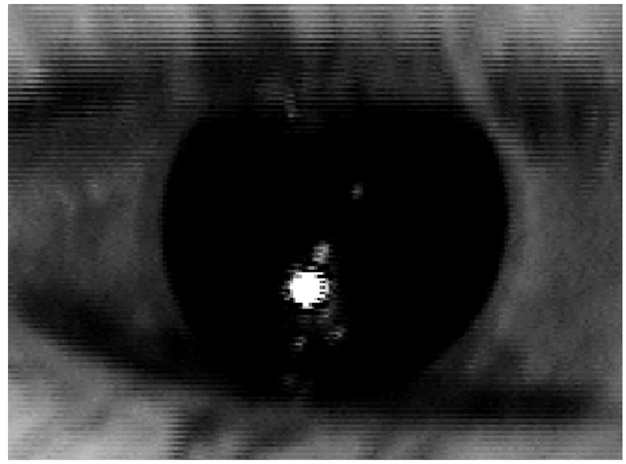
1. The gray scale is manipulated in that you can see not all gray values are present between 0 and 255. Interestingly the pupil area is mostly 0 but not consistently. This indicates that some sort of preprocessing is done on acquired images on LG 2200. Here is the grey value of image 287810_243007 which you see the tooth-like structure in the gray histogram:



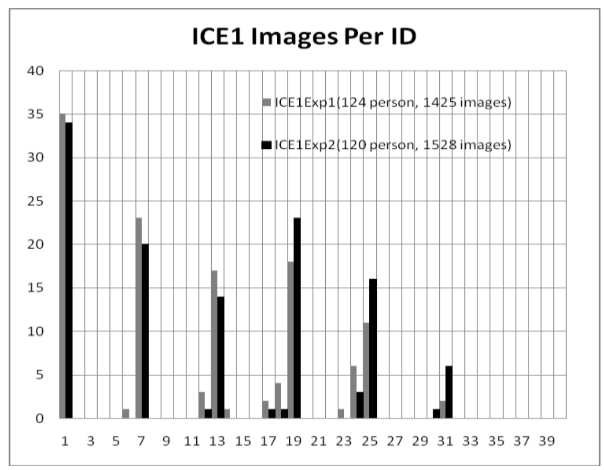
Here is the first few gray value counts:
250 0 144 266 0 386 298 0 369 210 0 226 142 0
Every third gray value is absent.

It turned out that this behavior applies to all images in ICE1 Exp1. The purpose is unknown to us, but the Iridian/LG must use this property.

2. Many images have interlaced artifacts, i.e. even lines and odd lines have shifts. For example, the image 291472_246587 is the following:

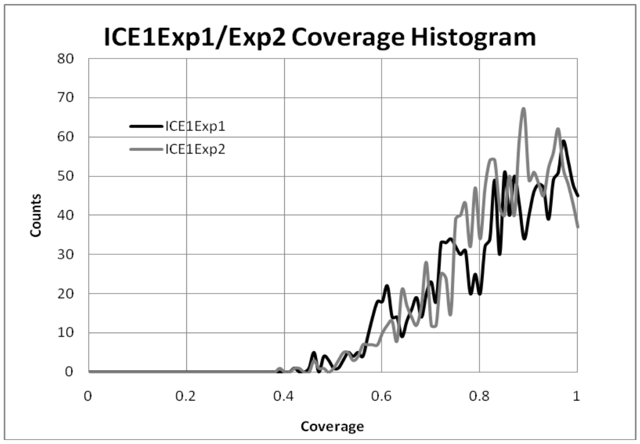


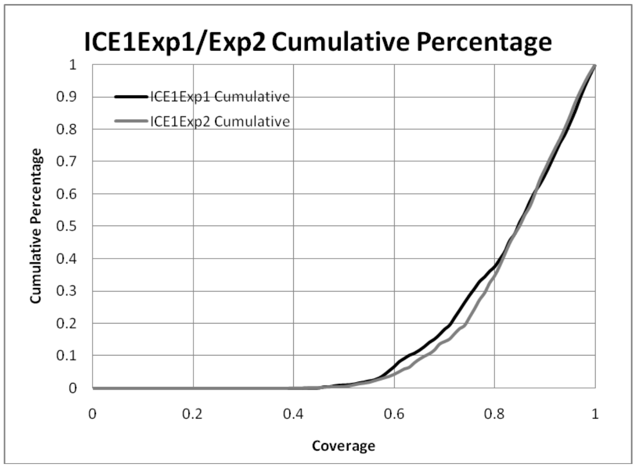
3. The number of images per person is not fixed. Here is the list of images per id:



Therefore the any statistical measurements against ICE1 images are dominated by those who have more images.

4. The iris opening is widely distributed and about 20% of images have less than 70% coverage (ANSI-INCITS specification). This has an important implication for the DOF of the imposter distributions.





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