Learning Optimal Gabor Filter Bank Parameters for Iris Recognition

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Abstract

Standard techniques for iris recognition, as popularized by Daugman, use a bank of Gabor filters for feature extraction and encode information about a segmented iris's localized phase information as a quantized bit map, known as an IrisCode. Choosing different parameter values for scaling, rotation, and translation of the wavelet creates a family of filters. In order to compute the similarity metric of two encoded irises the hamming distance between their IrisCodes is computed. We seek to learning the optimal parameters (as defined as those parameters for a family of Gabor filters, which minimize total recognition error) using various optimization techniques. We seek to maximize interclass hamming distance while minimizing intraclass distance.

1 Introduction

1.1 Motivation

Secure identification and authentication will obviously continue to be of vital importance in the future, with biometrics or distinctive physical characteristics of a person that are unique to an individual offering many advantages over traditional means of authentication such as passwords and ID cards--primarily that they remain with the authorized person at all times and are difficult if not impossible to forge. Commonly researched biometrics included facial features, fingerprints, handprints, and hand geometry, amongst others. However, the iris pattern is considered to be amongst the most reliable for high confidence identification due to the enormous variability amongst even genetically identical eyes [1]. Additional advantages of using irises as a biometric include its relative stability over an individual's lifetime, the ease of localization due to its circular form, its unique status as a protected internal organ that is externally visible, and its planar nature.[4]

1.2 How Iris Recognition Works

Much work has been done on developing iris recognition techniques, but the most widely employed procedure for feature extraction, pioneered by Daugman, uses the phase response of 2D Gabor wavelets [2][3][4]. The success of this algorithm has lead to it quickly becoming the gold standard of comparison and its use on all commercially deployed iris recognition systems. An alternative method, based on 1D Log-Gabor filters developed by Libor Masek has also been released publicly [9]. Here we assume that the image containing a properly focused eye has been acquired, and the necessary preprocessing steps of localizing the inner and outer boundaries of the iris, detecting eyelashes and other occlusions, and transforming from the original Cartesian coordinates to normalized polar coordinates has been performed already and focus on the feature encoding and similarity metric steps of Daugman's algorithm. Daugman makes use of 2D Gabor filters, which are of the form:

$$g(x,y) = s(x,y)w_r(x,y)$$

where $s(x,y)$ is a complex sinusoid, known as the carrier, and $w_r(x,y)$ is a 2D Gaussian, known as the envelope.

$$s(x,y) = e^{j(2\pi(u_0x+v_0y)+P)} \quad w_r(x,y) = Ke^{-(\pi(a^2(x-x_0)_r+b^2(y-y_0)_r))}$$

$$(x-x_0)_r = (x-x_0)\cos\theta + (y-y_0)\sin\theta \quad (y-y_0)_r = -(x-x_0)\sin\theta + (y-y_0)\cos\theta$$

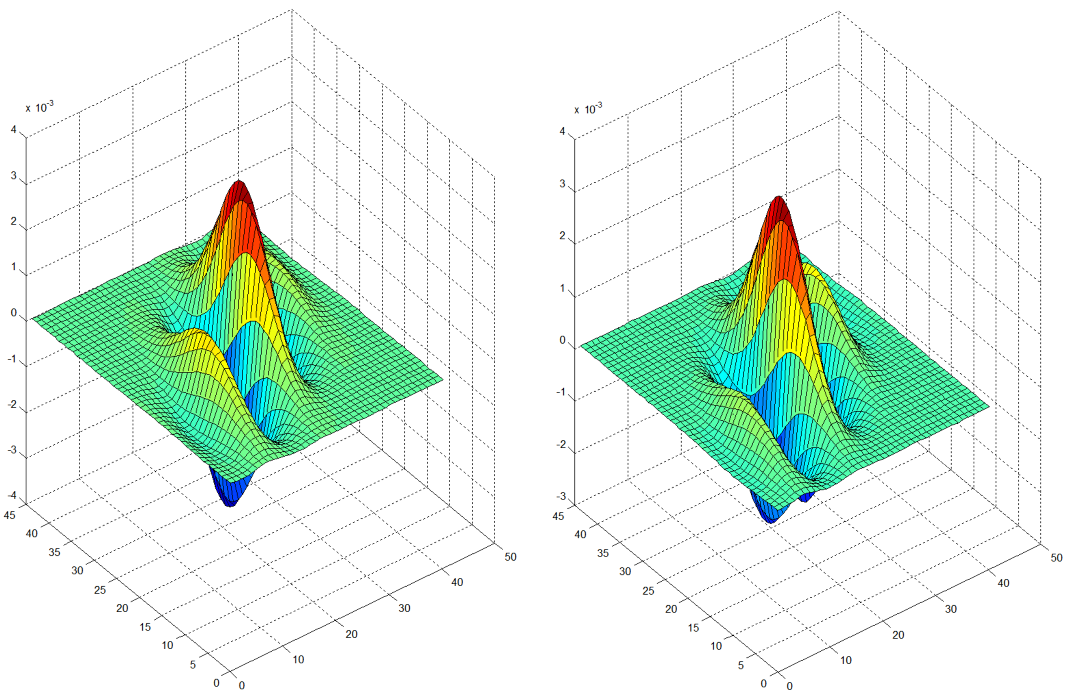


Figure 1: Example real and imaginary components of a Gabor filter

The normalized and transformed polar iris images are convolved with the real and imaginary components of a bank of Gabor filters, whose phase angles are then quantized into one of four quadrants (ie. encoded with 2 bits). Daugman extracts a total of 2048 phase bits per iris but various implementation extract differing numbers of bits. Once an IrisCode template is extracted, two templates can be compared using a fractional Hamming Distance (HD) very rapidly as two 64 bit words can be XOR'd with a single machine instruction.

$$HD = \frac{\|(Code_A \otimes Code_B) \cap Mask_A \cap Mask_B\|}{\|Mask_A \cap Mask_B\|}$$

If two bit patterns are completely independent, as would be the expected case of two templates generated from two distinct irises, the expected value of the fractional HD is 0.5; however, if two templates originate from the same iris, the HD should be close to 0.0 as they are highly correlated. Additionally, two provide a measure of rotational invariance in the plane of the iris, the fractional HD is computed at various bitwise horizontal circular shifts and the lowest HD is taken to be the true distance between two templates [2][3][4].

The decision rule for iris recognition therefore boils down to setting a threshold between the two distributions (intra-class and inter-class HD). If the HD between two iris templates is less than said threshold, then they are taken to have come from the same iris.

2 Problem Definition

2.1 Problem Definition

Determination of optimal parameters for a bank of Gabor filters is of great importance, as these parameters determine which features of the original iris image are captured and emphasized. Ideally we wish to determine parameters that minimize intra-class HD and maximize inter-class HD and therefore minimize our probability of misclassification. We also wish to explore combining linear combinations of Gabor filter-based classifiers using boosting.

2.2 Related Work

The source code of Daugman's implementation has never been released due to its accuracy and inherent profitability, so it is unknown which wavelet parameters he selected. The 1D Log-Gabor filters used by Libor Masek's publicly available iris recognition code are optimized individually using a 'decidability' metric defined as:

$$d' = \frac{|\mu_S - \mu_D|}{\sqrt{\frac{(\sigma_S^2 - \sigma_D^2)}{2}}}$$

Where μ_S and μ_D are the mean of the intra-class HD distribution and inter-class distribution respectively and $\sigma_S$and σ_D are the corresponding standard deviations [9]. However, with 2D Gabor filters we have 5 parameters to tune as compared to only 2 parameters in the 1D Log-Gabor filter and we seek to optimize across all parameters jointly as opposed to independently. Additionally in [7] a boosting algorithm is used to learn a cascade of features based on ordinal measures (OM) filters. We explore a similar optimization but with 2D Gabor filters.

3 Proposed Method

3.1 Intuition

Gabor filter parameter selection can have a large impact on the final accuracy of an iris recognition system, so clearly random selection of parameters is wrong, and designer intuition about which features are optimal in discriminating irises may be totally off base. This is demonstrated by the terrible ROC curve and associated Gabor filers shown below in Figure 2. Additionally, there is interplay between the various parameters of a Gabor filter, so to obtain optimal performance, all 5 parameters ought to be learned simultaneously.

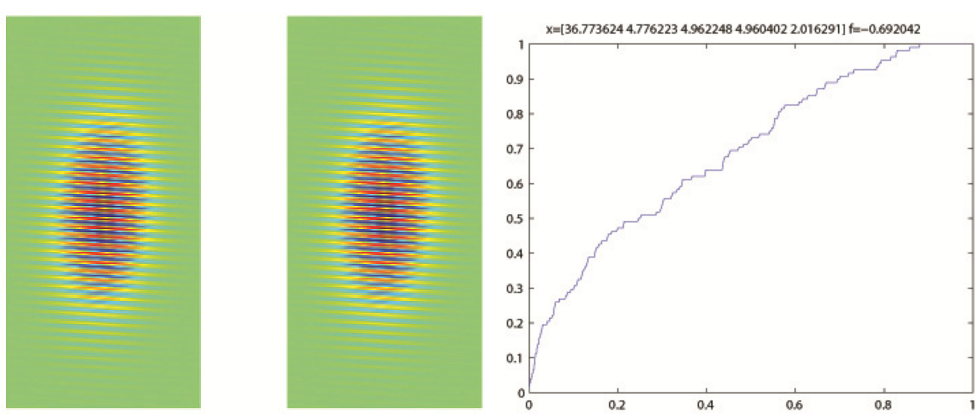


Figure 2: Real and imaginary components of a Gabor filter with associated terrible ROC curve

3.2 Proposed Method

There are two primary components to our proposed method: optimization of a single complex Gabor filter using iterative optimization and using boosting to select an ensemble of Hamming Distance-2D Gabor based classifiers. We seek to minimize a cost function defined in terms of the ROC curve. For most biometrics applications, the cost of a False Accept is much greater than the cost of a False Reject, for example allowing an imposter access to a secure facility has a much greater cost than rejecting someone who actually in a database of authorized personnel. Therefore we fix our FAR (False Accept Rate) at a certain maximal level that we are willing to accept, and seek the maximum VR (Verification Rate) achievable.

We are using a preprocessed database of segmented and normalized irises from the ICE database as shown below, this allows us to focus on the much more limited task of learning optimal filters without having to implement an entire working iris recognition system.

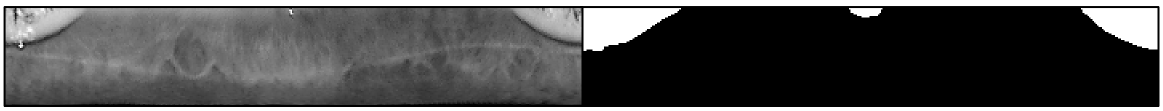


Figure 3: Preprocessed iris image and mask from ICE database

From this database we compute the filter response of each iris image given a set of 5 Gabor filter parameters, and then we quantize the phase response of each pixel as described above in Daugman's algorithm. We then compute a pair-wise fractional hamming distance between all templates in our training set, over a shift of -7 pixels to +7 pixels, in order to create a similarity matrix. From this similarity matrix we compute a ROC curve by scanning our threshold across its full range, select the threshold that maximizes the VR s.t. FAR $\leq \zeta$ and return 1-VR (or the False Reject Rate) as the cost function to minimize. Simulated annealing (SA) followed by a simplex search for local optimization was selected as our minimization technique, as both of these methods are derivative free. This entire process is repeated for random start values (of valid Gabor filter parameters), and the best result is deemed our global maximum. The SA algorithm is a probabilistic method for finding the global minimum of a function, and is so named because it mimics the physical process of annealing where a hot solid is slowly cooled. It can be viewed as a local search algorithm which has occasional local moves "upwards", hopefully to avoid getting stuck in local minima. The probability of these non-descending moves is governed by a temperature parameter T, which decreases over iterations according to a cooling schedule; when T is high, non-locally optimal moves are very common and movements are essentially random, but as T decreases the probably of strictly descending becomes much higher, and moves are essentially deterministic.

Although performance of a single Gabor classifier is not such that is would be considered a weak classifier, we also propose using AdaBoost [10][11] and Asymmetric Adaboost [12], which accounts for different weights given to False Positives and False Negatives, to develop an

$Given: (x_1, y_1), \ldots, (x_1, y_1);\ x_i \in X, y_i \in \{-1, +1\}$

$Initialize: D_{1(i)} = \frac{1}{m}, i = 1, \ldots, m$

$For\ t = 1, ..T$

$$h_t = \underset{h_j \in H}{\operatorname{argmin}} \epsilon_j, where\ \ \epsilon_j = \sum_{i=1}^{m} D_t(i)[y_i \neq h_j(x_i)]$$

$$if\ \epsilon_t \geq 0.5\ then\ stop$$

$$\alpha_t = \frac{1}{2} \ln\left(\frac{1 - \epsilon_t}{\epsilon_t}\right)$$

$$D_{t+1}(i) = \frac{D_t(i) \exp(-\alpha\, y_i\, h_t(x_i))}{Z_t}$$

$$H(x) = sign(\sum_{i=1}^{m} \alpha_t h_t(x_i))$$

$Given: (x_1, y_1), \ldots, (x_1, y_1);\ x_i \in X, y_i \in \{-1, +1\}, C_1, C_2$

$Define: I_+ = \{i | y_i = +1\}\quad I_- = \{i | y_i = -1\}$

$$T_+ = \sum_{i \in I_+} D_{t+1}(i)\ \ T_- = \sum_{i \in I_-} D_{t+1}(i)$$

$$b = \sum_{i \in I_+} D_{t+1}(i) I(y_i \neq h(x_i))\, d = \sum_{i \in I_-} D_{t+1}(i) I(y_i \neq h(x_i))$$

$$Initialize: \quad D_{1(i)} = \frac{1}{2|I_+|}, \forall i \in I_+, \qquad D_{1(i)} = \frac{1}{2|I_-|}, \forall i \in I_-$$

$For\ t = 1, ..T$

$$Solve\ for\ \alpha_t: 2C_1\, b \cosh(C_1 \alpha_t) + 2C_2 d \cosh(C_2 \alpha_t) = C_1 T_+ \exp(-C_1 \alpha_t) + C_2 T_- \exp(-C_2 \alpha_t)$$

$$h_t = \underset{h_j \in H}{\operatorname{argmin}} \epsilon_j, where\ \ \epsilon_j = (\exp(C_1 \alpha_t) - \exp(-C_1 \alpha_t)) b + \exp(-C_1 \alpha_t T_+) + (\exp(C_2 \alpha_t) - \exp(-C_2 \alpha_t))\, d + \exp(-C_2 \alpha_t) T_-$$

$$D_{t+1}(i) = \begin{cases} D_t(i) \exp(-\alpha_t C_1\, y_i\, h_t(x_i)), i \in I_+ \\ D_t(i) \exp(\alpha_t C_2\, y_i\, h_t(x_i)), i \in I_- \end{cases}$$

$$H(x) = sign\left(\sum_{i=1}^{m} \alpha_t h_t(x_i)\right)$$

Figure 4: Psuedocode for Adaboost and Asymmetric Adaboost

ensemble of Daugman type classifiers to potentially get superior accuracy to a single classifier. In this boosting setting, we will consider there to be two labels "Matches" and "Nonmatches" that correspond to if two iris images belong to the same eye, and our data is the fractional HD between iris pairs. We are seeking a classifier that minimizes misclassification error between these two labels.

We use the same objective function as we used to optimize a single Gabor filter to evaluate the fitness of each constituent Gabor-based weak classifier and propose investigating several variants which differ in how the weak classifier in each boosting round is selected: random selection from the entire world of Gabor filters, random selection from a bank of high performance (evaluated with the original uniform weighting) Gabors, selection of best Gabor from bank after revaluating performance of each filter with new weighting, and finally performing the full optimization routine detailed above for a single filter at each boosting iteration.

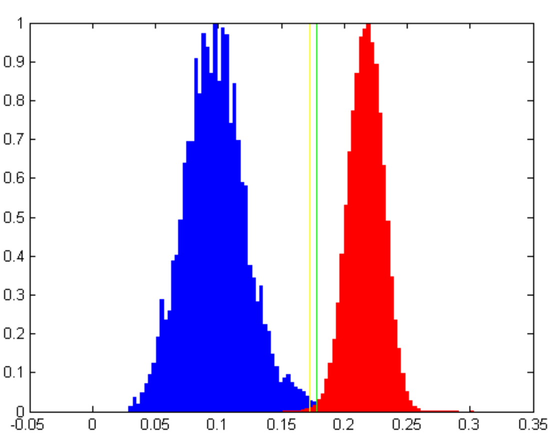
4 Experiments

4.1 Experimental Testbed

We are primarily developed code in MATLAB due to its rapid prototyping ability and numerous built-in optimization functions; however, as our objective function that we seek to maximize is based on the pairwise computation of hamming distances of the filter outputs of some 1000+ iris images in the ICE database (currently only using left eyes), we have made extensive use of Nvidia's CUDA to implement pdist and conv2 on the GPU. This has led to dramatic speedups in our calculations and allows for direct optimization on the verification error. For the entire database of 1528 iris images we compute, using FFTs on a Nvidia Tesla GPU, the filter response and IrisCodes in approximately 3.5 seconds versus 50+ seconds running the MATLAB implementation of conv2(). The pairwise HD computation on the GPU takes 12 seconds versus more than 4 minutes in MATLAB. Both conv2CUDA() and pdistCUDA() are implemented in .mex files. This use of GPU computation allows the evaluation of a trial classifier in less than 15 seconds for each set of Gabor filter parameters and greatly facilitates rapid convergence of iterative optimization routines.

4.2 Experimental Results/Observations

Initially, we set out to learn parameters for the single maximally discriminative Gabor filter that was achievable over the entire dataset of 1528 iris images and ignore any problems of overfitting. The ROC curves achieved for 3 separate optimization cycles are shown in Figure 6, and served as an upper limit to what should be achievable in testing when working just with a training subset. A standard FAR threshold at which many iris recognition systems are compared is 0.001, and we were able to achieve a verification rate of 0.9698. We then selected a random training subset of 500 iris images and reserved the remaining 1028 as our testing data set.



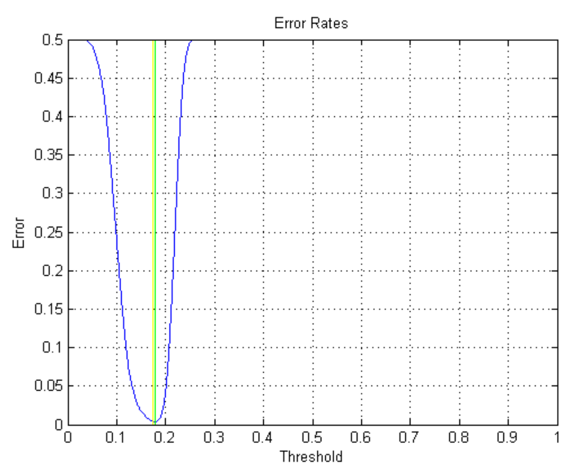


Figure 5a: Fractional HD distributions for true matches and true imposters of training dataset
Figure 5b: Threshold selection at both Minimal Error Rate (green) and FAR at 0.001 (yellow)

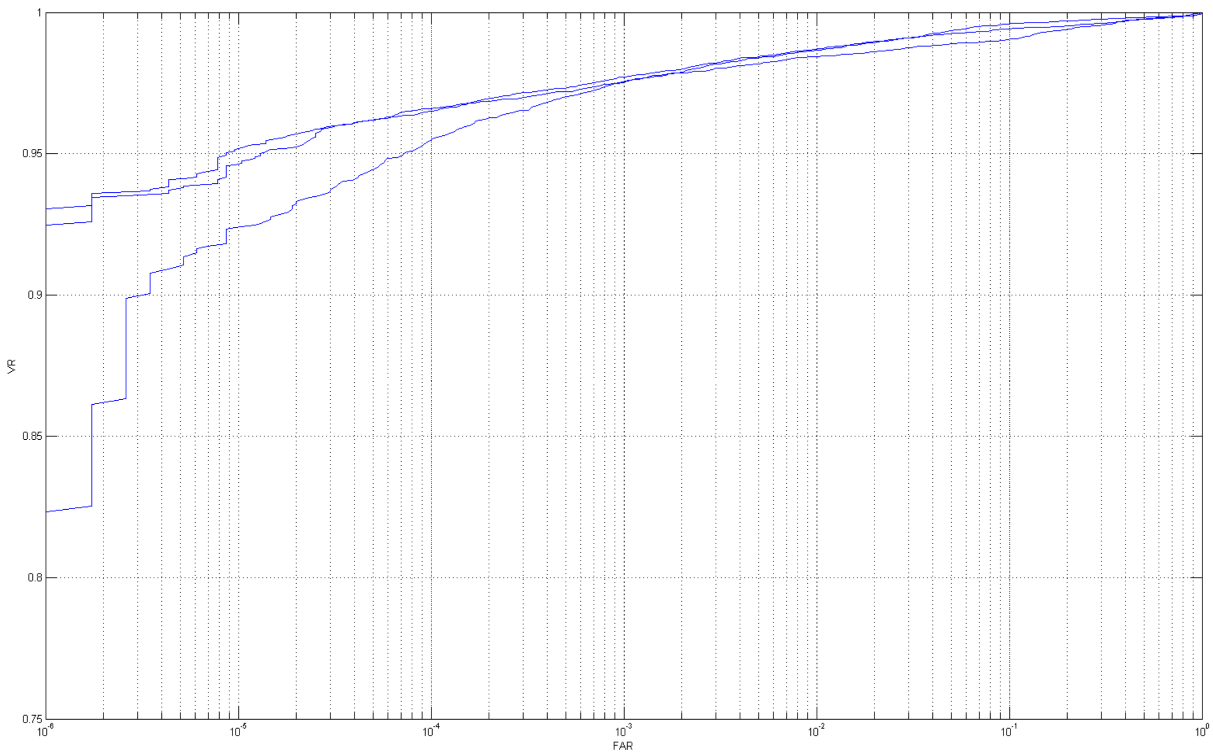


Figure 6: ROC curves for Gabor Classifiers optimized over entire database

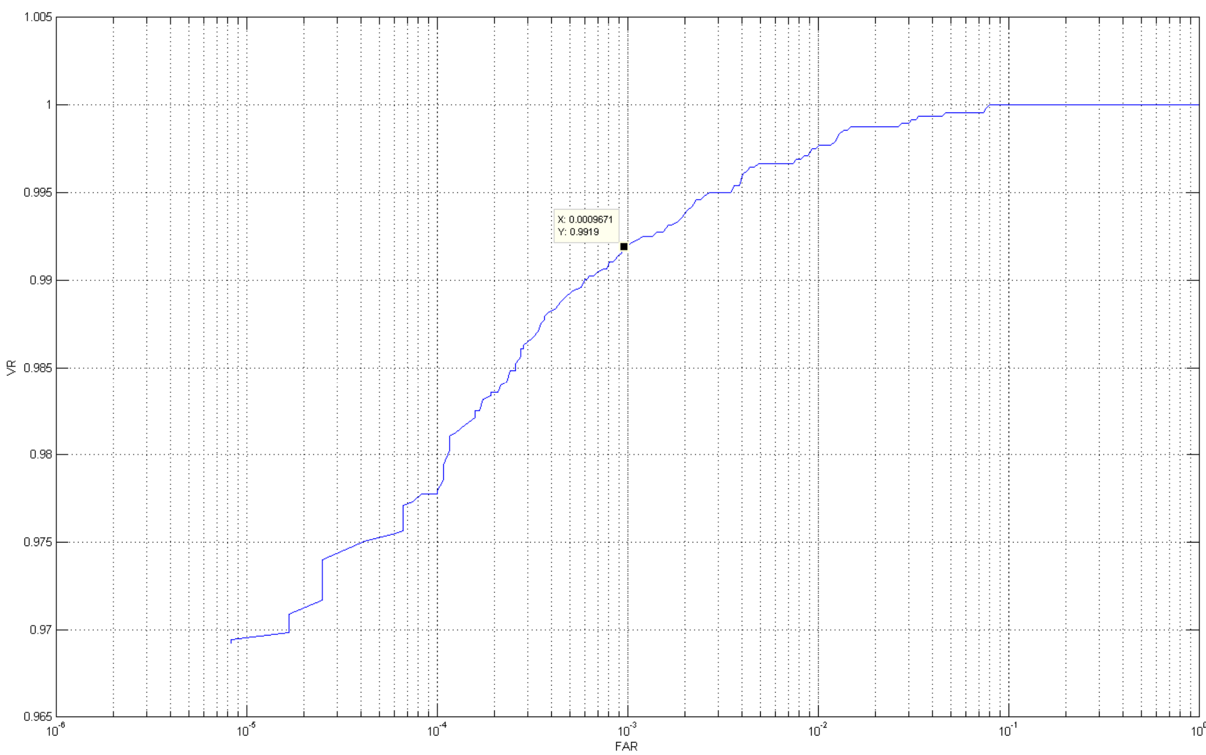


Figure 7: Training ROC curve for Gabor classifier optimized 500 iris training dataset

As can be seen in Figure 7 and Figure 8, we were able to achieve a training VR of 0.9919 at a FAR of 0.001 and a test VR of 0.964777. It can also be seen from Figure 8, that our best classifier trained on only 500 irises, performed almost as well as the purposefully over-fit classifier trained on the entire database. This seems to indicate that our Gabor filter should generalize well to additional iris images. Overall this is an excellent ROC curve, especially given the simple nature

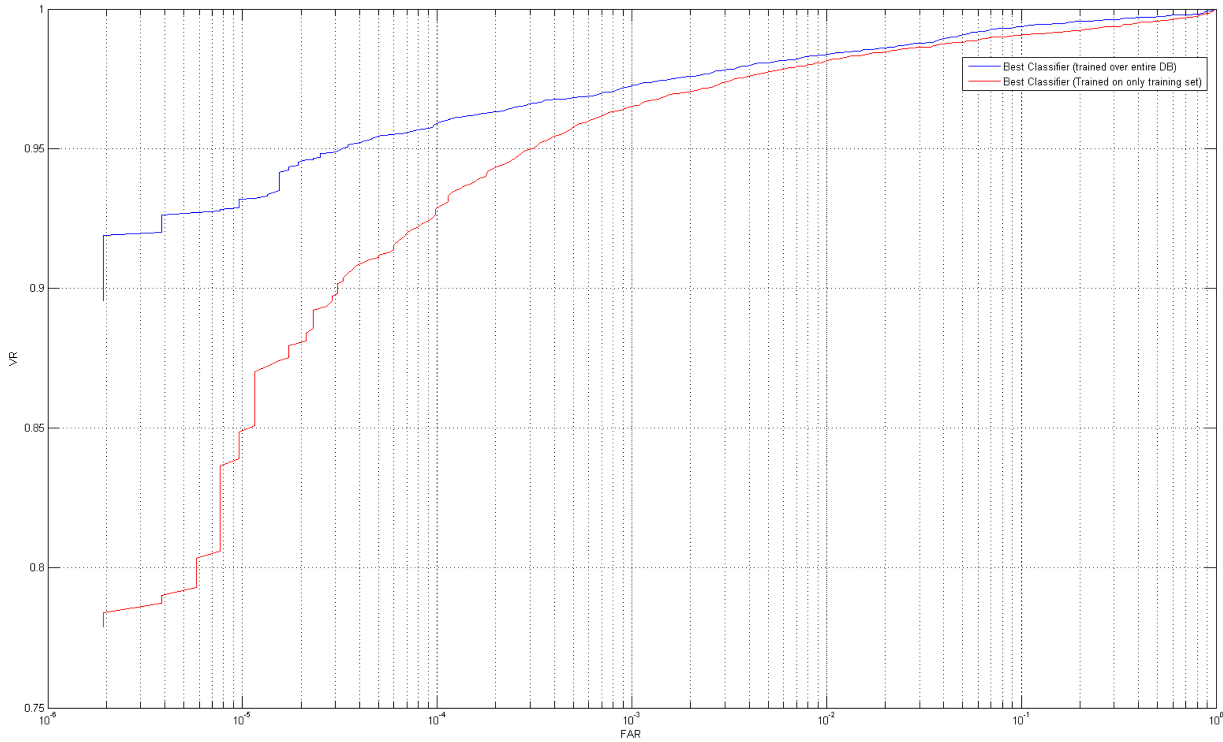


Figure 8: Test ROC curve for Gabor Classifier optimized over training set

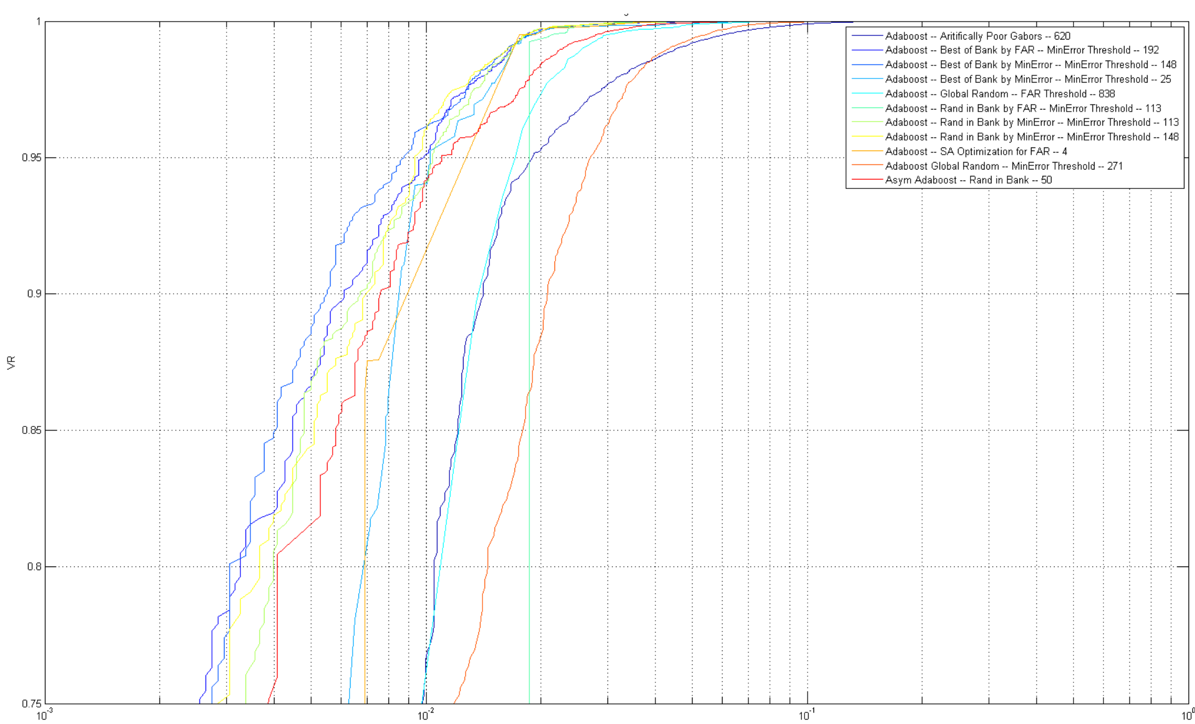


Figure 9: Test ROC curves for boosted Gabor classifiers

of the classifier but we hoped to achieve even better performance by creating an ensemble of Gabor based classifiers. Figure 9 shows the testing results of our best Adaboost and Asymmetric Adaboost trained classifiers. The legend in the graph indicates the boosting algorithm used, how each Gabor filter was selected, how the threshold for the decision boundary in each weak classifier was selected, and the number of boosting iterations included. During training, we boosted for a fixed number of iterations and then selected the number of boost iterations that yielded the best accuracy with validation dataset. Although with enough boosting iterations, the final classifier was able to beat the test error of all of its constituent weak classifiers, unfortunately none of the boosted classifiers were able to beat the performance of our SA derived, single optimal filter when run on test data.

4 Conclusions

Ultimately, optimizing for a single Gabor filter based classifier directly on its training error was successful and made feasible in a realistic time frame by GPU computation. Not achieving improved performance with Adaboost or Asymmetric Adaboost was disappointing, but we still believe that the general idea of boosting Gabors has merit; it resembles a Viola-Jones type face detector, but there is a much larger parameter space to search. Improved performance may require a different objective function or perhaps a different boosting algorithm. Overall, even a single Gabor, properly optimized provides a great deal of discrimination for a cheap computational cost.

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