Custom JPEG Quantization for Improved Iris Recognition Accuracy

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Outline

- Compression in Biometric Systems
- Iris Image Compression
- Custom JPEG Quantization
- Experimental Study
  - Impact on Image Quality and Hamming Distances
  - Impact on ROC Performance
- Conclusion

Introduction

With the increasing usage of biometric systems the question arises naturally how to store and handle the acquired sensor data. In this context, the compression of these data may become imperative under certain circumstances due to the large amounts of data involved. Two example scenarios for compressing sample data:

1. **Transmission of sample data after sensor data acquisition**: In distributed biometric systems, the data acquisition stage is often dislocated from the feature extraction and matching stage. The sensor data have to be transferred via a network link to the respective location, often over wireless channels with low bandwidth and high latency.

2. **Storage of reference data**: Storing the original sensor data in template databases in addition to the features required for the current matching technique helps to switch to a different feature extraction technique if required for some reason. The amount of data to be stored is obviously high.

Compression of Biometric Data

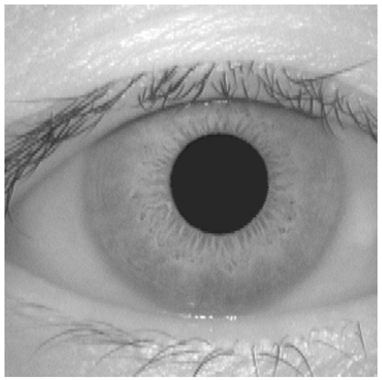
Having found that compression of the raw sensor data can be advantageous in certain applications, we have to identify techniques suited to accomplish this task in an optimal manner. In order to maximize the benefit in terms of data reduction, lossy compression techniques have to be applied. However, the distortions introduced by compression artifacts usually interfere with subsequent feature extraction and may degrade the matching results. In particular, FRR or FNMR will increase (since features of the data of legitimate users are extracted less accurately from compressed data) which in turn affects user convenience and general acceptance of the biometric system. In extreme cases, even FAR or FMR might be affected.

The ISO/IEC 19794 standard defines admissible data formats for a wide range of biometric modalities and image types.

Compression of Iris Imagery

ISO/IEC 19794-6 allows iris image data to be stored in lossy manner in the JPEG and JPEG2000 formats. Two types of iris image data are considered:

- Rectilinear iris images (i.e. images of the entire eye and its "surroundings"), typically with a size of 25-30 kB.
- Polar iris images (which are basically the result of iris detection and segmentation), typically with a size of 2kB.



Related Work

Rectilinear iris images:

- JPEG2000 up to compression ratio 20 applied to CASIA & a proprietary database (Ives et al.)
- JPEG and JPEG2000 applied to NIST ICE database with application of background removal (Daugman & Downing)
- JPEG, JPEG2000, SPIHT, VQ, Fractal applied to CASIA (own previous work)

Polar iris images:

- JPEG2000 up to compression ratio 80 applied to CASIA (Rakshit & Monro)

So far, compression algorithms have been applied to iris imagery with their respective standard settings.

JPEG for Compressing Iris Images

Why are we interested in JPEG, although JPEG2000 delivers significatly better rate-distortion performance ?

- Superior compression performance of JPEG2000 over JPEG is found especially for low bitrates, however, for high and medium quality JPEG is still an option to consider. Typically, a compression scheme employed in a biometric system would operate in that high and medium quality range to limit the effects on recogniiton performance.

- JPEG is significantly faster as compared to JPEG2000 (up to a factor of 10 !) which can be improtant especially when low power eventually mobile sensors are used.

- Despite the availability of a few (2+?: Analog Devices, Ricoh) JPEG2000 chips, hardware availability for JPEG is significantly better.

Custom JPEG Quantization

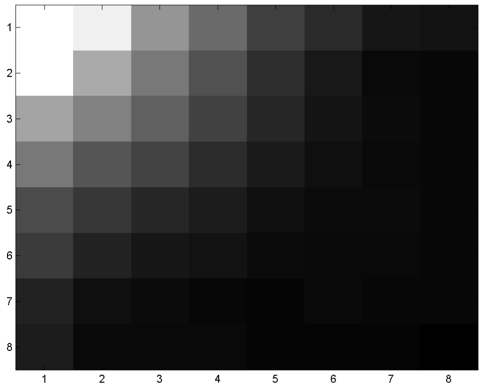
The JPEG still image compression standard allows to use custom quantization tables (Q-tables) in case image material with special properties is subject to compression. These tables are signalled in the header information. The default quantization matrices have been designed with respect to psychovisual optimality employing large scale experimentation involving a high number of test subjects.

Related work applies custom Q-tables in pattern recognition with more emphasis on middle and high frequencies and in face recognition using R/D-optimization giving superior recognition performance.

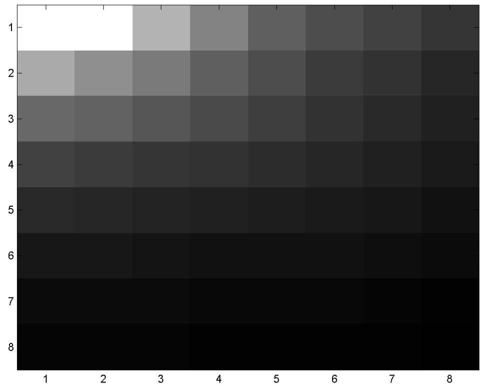
There are two reasons which suggest to use different Q-tables as the default configuration: First, iris imagery might have different properties as compared to common arbitrary images, and second, a pleasant viewing experience as being the aim in designing the default tables, might not deliver optimal matching results in the context of biometric recognition (e.g. sharp edges required for exact matching could appear appealing to human observers).

Properties of Iris Imagery

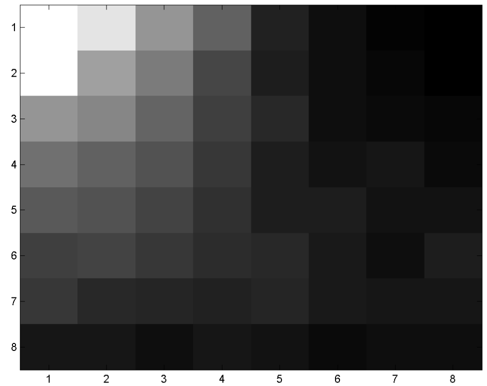
8x8 pixel blocks have been subjected to DCT transform and the resulting coefficients are averaged for a large number of blocks (i.e. 2000, 525, and 44160 blocks for the three types of imagery, respectively). Horizontal blocks are extracted iris texture taken left and right of the pupil.



Common images



Polar iris blocks



Horizontal iris blocks

Polar image blocks exhibit more energy in the higher frequencies in horizontal direction as compared to vertical direction. Vice versa, Horizontal blocks show more energy in the higher frequencies in vertical direction.

Q-Tables used

While the specific directional bias cannot be exploited for rectangular iris images, we conjecture that the highest and medium frequencies might not be required for he matching stage due to the coarse quantization used for template generation.

16	11	10	16	24	40	51	61
12	12	14	19	26	58	60	55
14	13	16	24	40	57	69	56
14	17	22	29	51	87	80	62
18	22	37	56	68	109	103	77
24	35	55	64	81	104	113	92
49	64	78	87	103	121	120	101
72	92	95	98	112	100	103	99

16	11	10	16	24	40	255	255
12	12	14	19	26	255	255	255
14	13	16	24	255	255	255	255
14	17	22	255	255	255	255	255
18	22	255	255	255	255	255	255
24	255	255	255	255	255	255	255
255	255	255	255	255	255	255	255
255	255	255	255	255	255	255	255

16	11	10	16	24	255	255	255
12	12	14	19	255	255	255	255
14	13	16	255	255	255	255	255
14	17	255	255	255	255	255	255
18	255	255	255	255	255	255	255
255	255	255	255	255	255	255	255
255	255	255	255	255	255	255	255
255	255	255	255	255	255	255	255

16	11	10	16	255	255	255	255
12	12	14	255	255	255	255	255
14	13	255	255	255	255	255	255
14	255	255	255	255	255	255	255
255	255	255	255	255	255	255	255
255	255	255	255	255	255	255	255
255	255	255	255	255	255	255	255
255	255	255	255	255	255	255	255

16	11	10	255	255	255	255	255
12	12	255	255	255	255	255	255
14	255	255	255	255	255	255	255
255	255	255	255	255	255	255	255
255	255	255	255	255	255	255	255
255	255	255	255	255	255	255	255
255	255	255	255	255	255	255	255
255	255	255	255	255	255	255	255

Q-tables STQ, 12, 13, 15, 16.

Experimental Settings - Iris Recognition System

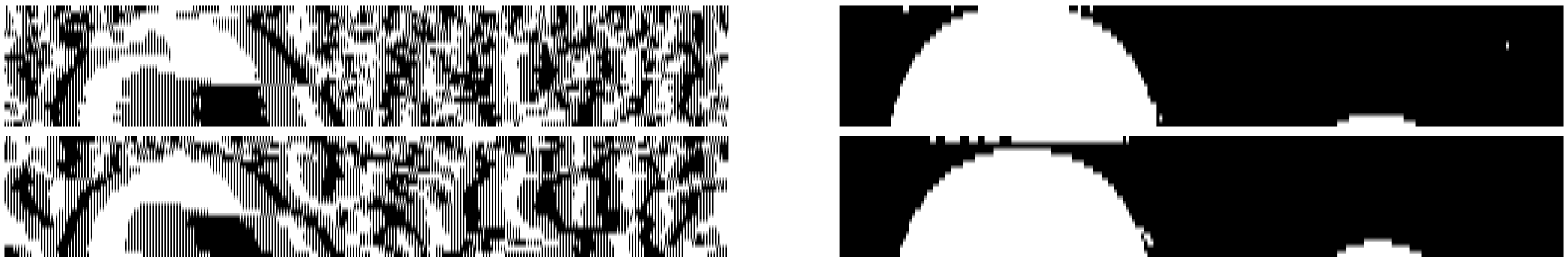
We use Libor Masek's Matlab implementation of a 1-D version of the Daugman iris recognition algorithm.

First, this algorithm segments the eye image into the iris and the remainder of the image. Iris image texture is mapped to polar coordinates resulting in a rectangular patch which is denoted "polar image". After extracting the features if the iris (which are strongly quantized phase responses of complex 1-D Gabor filters in this case), considering translation, rotations and disturbed regions in the iris (a noise mask is generated), the algorithm outputs the similarity score by giving the hamming distance between two extracted templates. The range of the hamming distance reaches from zero (ideal matching of two iris images of the same person) to 0.5 (ideal mismatch between two iris images of different persons).

Experimental Settings - Sample Data

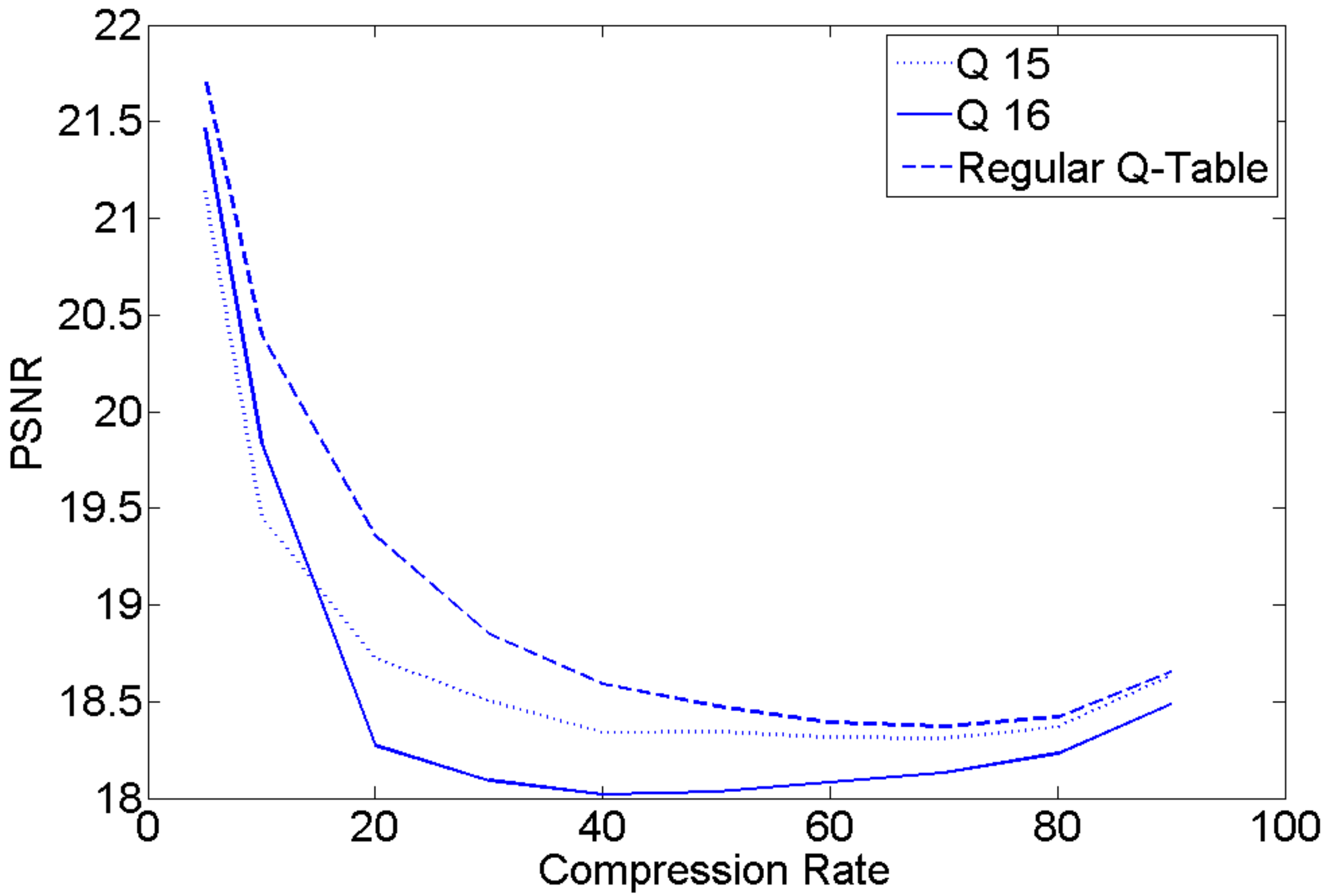
320x280 pixel images with 8-bit grayscale information (CASIA 1.0 iris image database), we applied the experimental calculations on the images of 100 persons using 3 images for each eye (i.e. 600 images).

Compression can be used in various stages of the matching process. Either the stored reference data may be in compressed form, or the sample data acquired for verification may be compressed, or both. Therefore, we use two settings in our experiments: either both images are compressed and matched against each other or only one image is compressed in the matching stage.



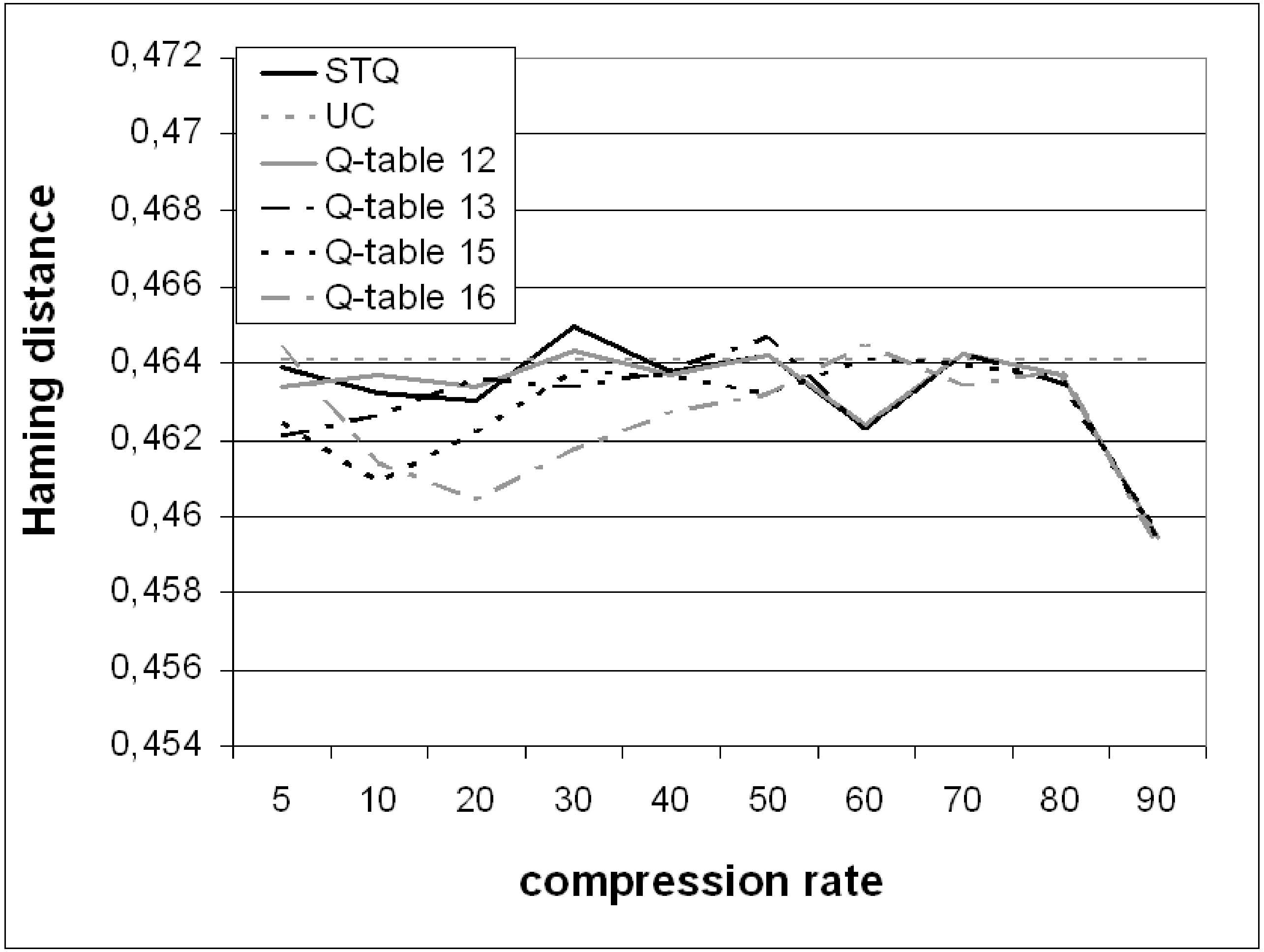
Example templates and noise masks extracted from uncompressed data (first line) and compressed data (second line: JPEG2000 with ratio 96).

Experimental Results: R/D-Performance



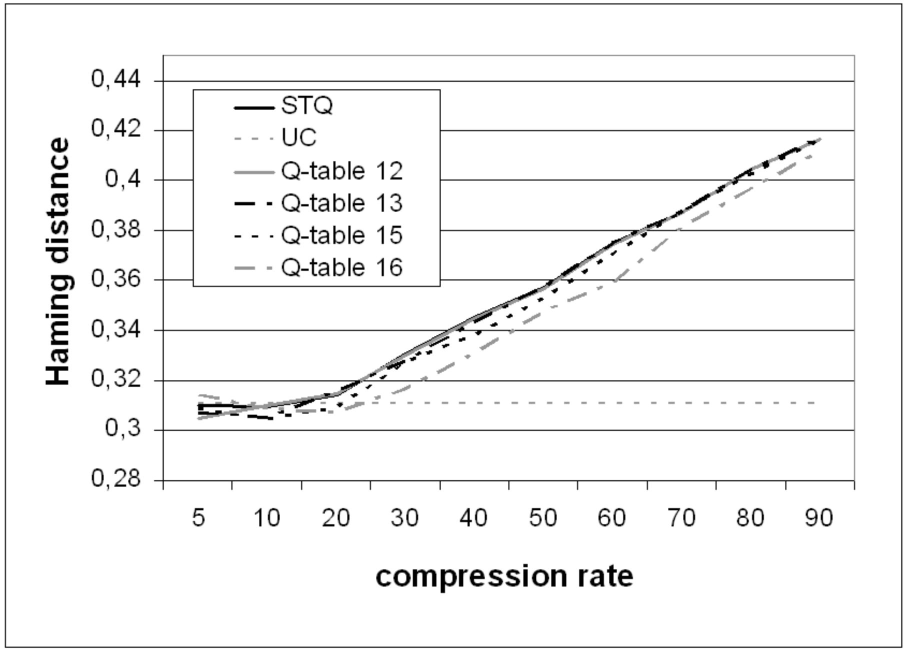
PSNR vs. Compression Rate: STQ has highest PSNR across the entire range of compression ratios.

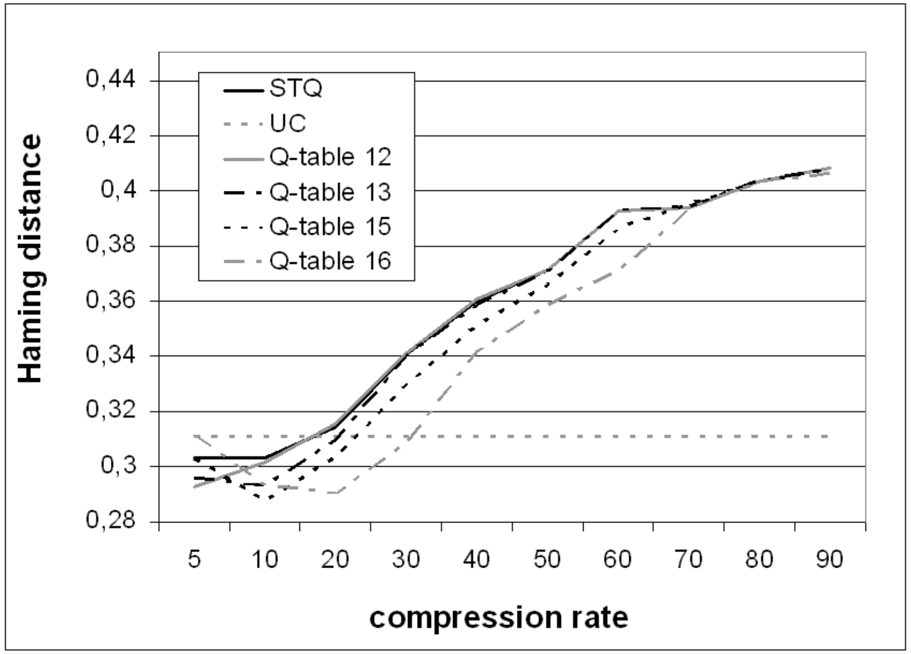
Experimental Results: Hamming Distance (Imposters)



HD vs. Compression Rate: no significant impact.

Experimental Results: Hamming Distance (Genuine Users)



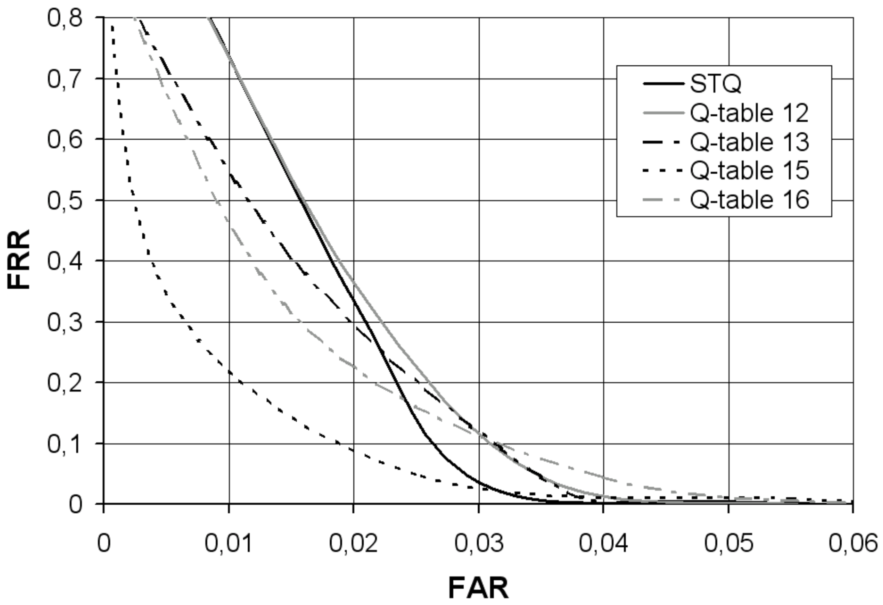


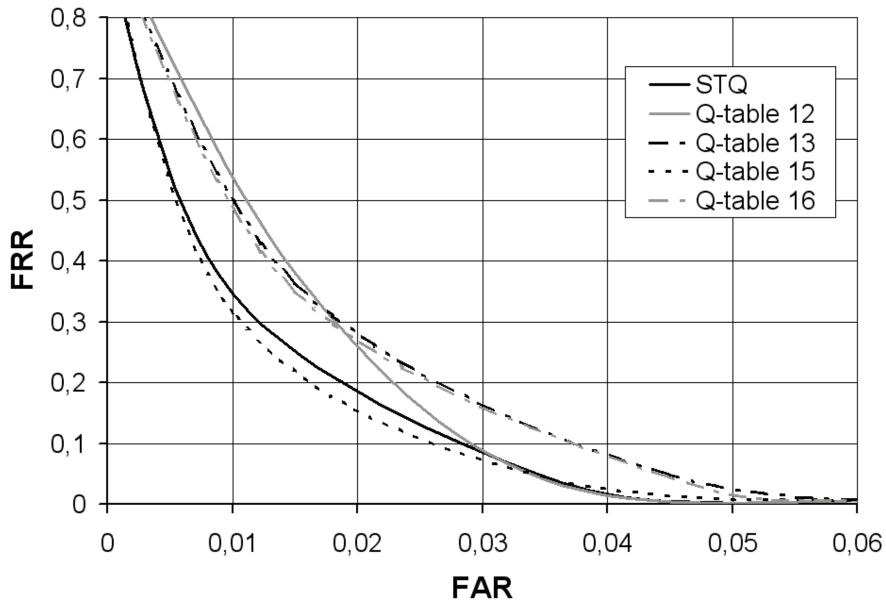
One image compressed vs. two images compressed .

⟶ PSNR is not a good predictor for HD !!

But what does this mean for recognition performance ?

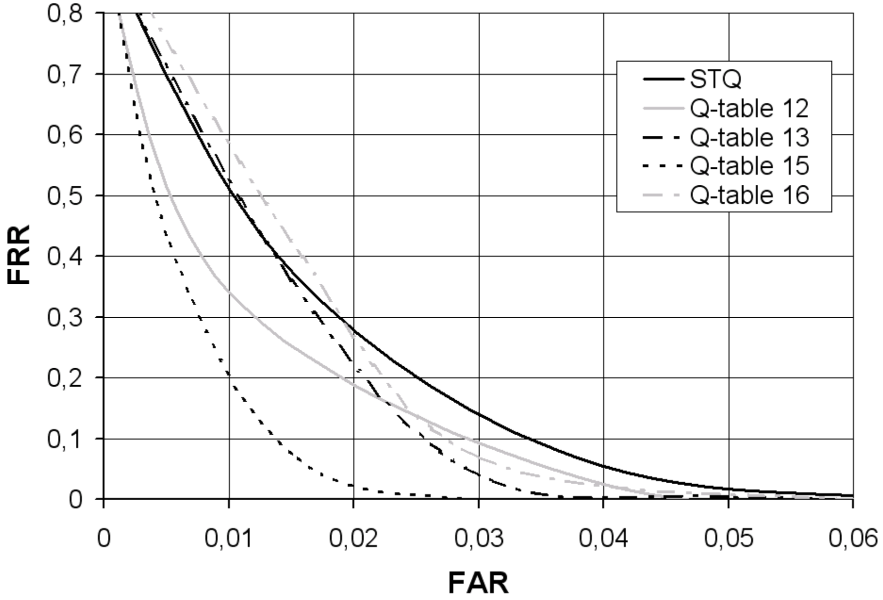
Experimental Results: Recognition Performance (ROC) @ Compression Rate 5

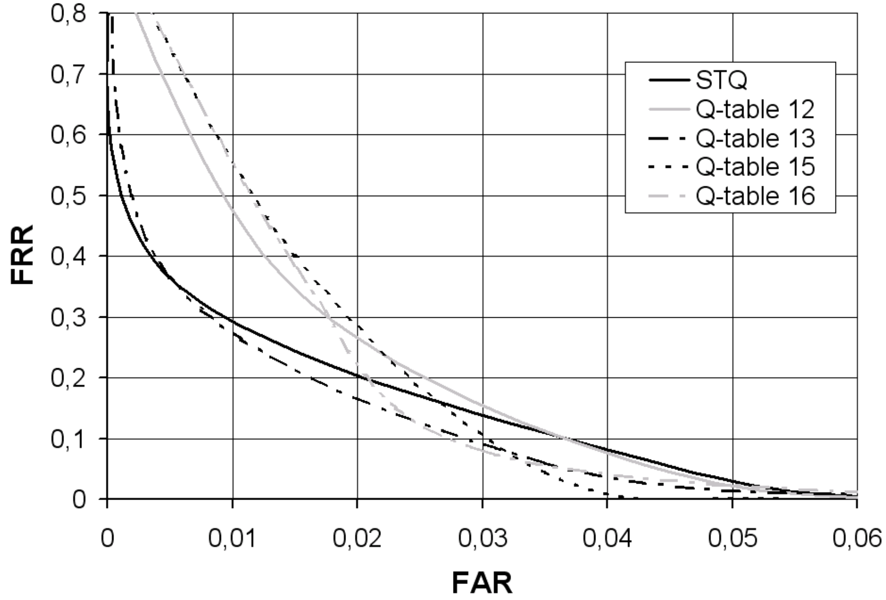




2 compressed images: improvements for lower FAR (Q-15)
1 compressed image: hardly improvements (Q-15)

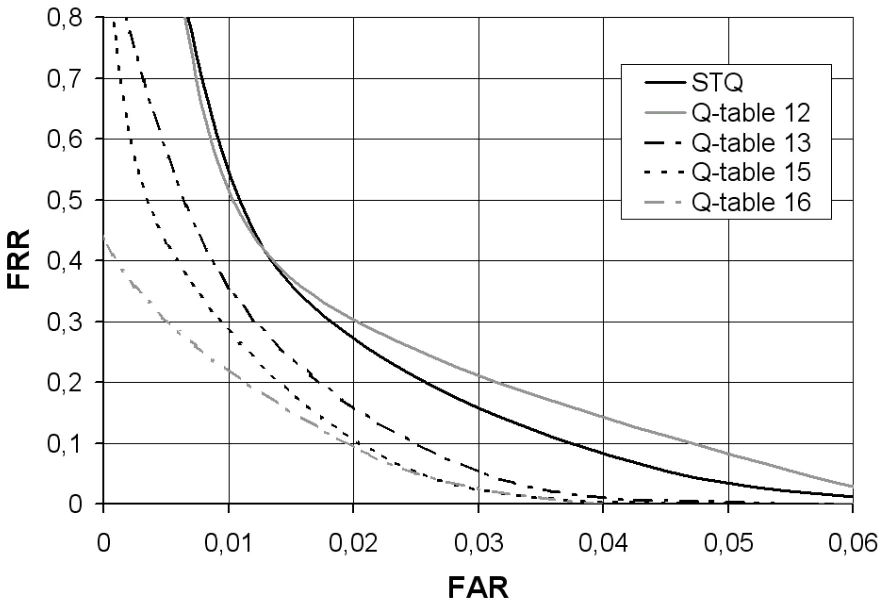
Experimental Results: Recognition Performance (ROC) @ Compression Rate 10

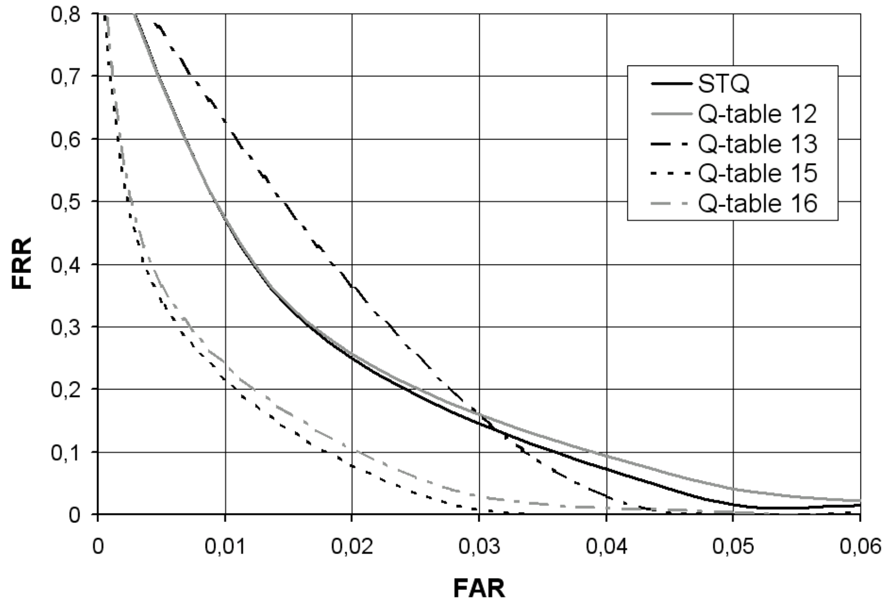




2 compressed images: significant improvements (Q-15)
1 compressed image: minor improvements (Q-13)

Experimental Results: Recognition Performance (ROC) @ Compression Rate 20





2 compressed images: significant improvements (Q-13, Q-15, Q-16)
1 compressed image: significant improvements (Q-15, Q-16)

Conclusion

We have found that custom designed quantization tables in JPEG can improve matching results in terms of average HD and ROC behaviour. This is especially true for compression rates of 10 and higher where improvements are seen especially for low FAR. In this case, FRR can be limited much more effective as compared to the default quantization table.

We have found PSNR to be not at all suited to predict the recognition performance in iris recognition systems.

The advantage of compressing both images involved in the matching process cannot be confirmed, in contrary, evidence for the opposite is found for higher compression rates.

Future Work

- How can we design even better Q-tables in a systematic manner ? Optimization techniques like GA's can help here.
- Application to polar images: paper @ ICB 2009 involving GA optimization.
- Optimization of JPEG2000 in the context of Part 2.
- Extension to other modalities.

Thank you for your attention !

Questions ?