Deep Iris Compression

Ehsaneddin Jalilian, Heinz Hofbauer, Andreas Uhl

Department of Computer Sciences
University of Salzburg

Outlines

1. Introduction
2. Generative Adversarial Networks
3. Deep Compression Framework
4. Encoding and Decoding
5. Experimental Framework
6. Compression Evaluation Experiments
7. Recognition Evaluation Experiments
8. Analysis and Conclusion
9. References

Introduction

- Lossy image compression can reduce the space and bandwidth required for image storage and transmission, which is increasingly in demand by the iris recognition systems developers.
- Currently wide variety of compression techniques are used for imagery (iris) data compression (i.e. JPEG, JPEG2000, WEBP, BPG, ..).
- Deep learning techniques (i.e. CNN, and GAN networks) are quickly becoming a tool of choice for general image compression tasks.
- We investigate and evaluate the expediency of a GAN-based deep compression model for iris compression in terms of compression and recognition performance on different iris databases.
- The obtained results then are compared (against the classical methods) and analyzed to show the actual competence of the model for iris compression.

Generative Adversarial Networks

- Networks architecture:

  Generator G: $x \Rightarrow x'$: translates images from x to x'

  Generator F: $x' \Rightarrow x$: translates images from x' to x

  Discriminator Dx : scores how real an image of x looks

  Discriminator Dx' : scores how real an image of x' looks

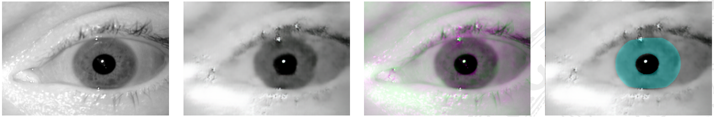

Figure: **Sample iris image reconstructed using a GAN network**

- The major drawback of applying the GAN networks is their lack of spatial precision, which results in structural distortions in the reconstructed images.

DSSLIC

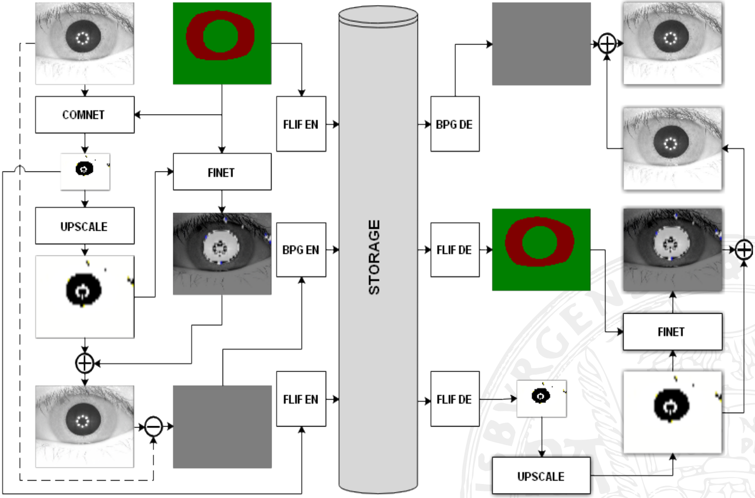

Figure: DSSLIC model

Encoding and Decoding

- The encoding module takes the iris image and its corresponding segmentation mask as the input.
- The compact representation $c \in \mathbb{R}^{(\frac{h}{a} \times \frac{w}{a} \times k)}$, of the input (x) is generated using CompactNet respectively.
- Conditioned on the input segmentation $s \in \mathbb{Z}^{(h \times w)}$ and up-scaled c, a generative adversarial network (GAN) 'FineNet' reconstructs the input (x').
- The reconstructed image (conditioned on the up-scaled c and the input (x)) along with the segmentation (s) and input (x) are encoded into the channel.
- The encoding process is repeated reversely to decode the data from channel and regenerate the iris images

Experimental Framework

- Databases: Casia4i (2640 images of 249 subjects), IITD (2240 images of 224 subjects), Casia5a (1880 images of 47 subjects) and Notredam (835 images of 30 subjects).
- Compression algorithms: JPEG, JPEG2000 (J2K), WEBP, BPG, CPDIC [1].
- Compression metrics: Peak signal-to-noise ratio (PSNR), Multi-scale structural similarity index (MS-SSIM) [2].
- Other segmentation algorithms: Osiris [3], Caht (contrast-adjusted hough transform) [4].
- Recognition pipeline: We used 1-D local Gabor filters for feature extraction, and the Hamming distance with rotation correction for matching.
- Recognition metrics: Genuine and impostor scores are calculated (considering all possible comparisons) and EER scores are generated as the measure of recognition accuracy.

Compression Evaluation Experiments

- To address the fixed bandwidth/storage compression limit requirement we set two bandwidth limits of 0.30 (A) and 0.60 (B), corresponding to the higher and the lower compression levels respectively.

Dataset	Casia4i				Casia5a				IITD				Notredame			
Method	par	bpp	par	bpp	par	bpp	par	bpp	par	bpp	par	bpp	par	bpp	par	bpp
DSSLIC	23	0.20	16	0.44	23	0.16	14	0.45	27	0.30	19	0.53	23	0.16	14	0.51
BPG	37	0.21	30	0.54	30	0.19	24	0.42	33	0.29	26	0.60	33	0.18	24	0.55
J2K	35	0.23	21	0.55	45	0.18	14	0.55	28	0.27	14	0.55	45	0.18	14	0.55
JPEG	23	0.20	57	0.50	12	0.19	57	0.51	17	0.30	57	0.53	09	0.18	57	0.58
WEBP	1	0.21	82	0.44	45	0.20	82	0.44	1	0.29	45	0.57	25	0.19	82	0.57
CPDIC	11	0.29	22	0.60	11	0.27	22	0.57	11	0.29	22	0.60	11	0.27	22	0.57
bpp	A (0.30)		B (0.60)		A (0.30)		B (0.60)		A (0.30)		B (0.60)		A (0.30)		B (0.60)	

Compression Evaluation Experiments

- Algorithms compression performance in terms of MS-SSIM and PSNR.

Dataset	Casia4i		Casia5a		IITD		Notredame	
Compress	B	A	B	A	B	A	B	A
DSSLIC	0.998	0.994	0.995	0.989	0.998	0.994	0.997	0.990
BPG	0.996	0.988	0.994	0.985	0.997	0.992	0.996	0.988
J2K	0.991	0.966	0.992	0.970	0.987	0.945	0.988	0.964
JPEG	0.993	0.950	0.988	0.931	0.994	0.957	0.991	0.949
WEBP	0.993	0.982	0.991	0.965	0.995	0.987	0.992	0.981
CPDIC	0.897	0.889	0.844	0.852	0.881	0.875	0.909	0.902

Dataset	Casia4i		Casia5a		IITD		Notredame	
Compress	B	A	B	A	B	A	B	A
DSSLIC	49.1	44.0	45.2	41.6	45.5	41.3	45.7	40.3
BPG	44.5	39.8	44.0	40.9	44.7	40.5	43.5	40.0
J2K	41.8	35.5	43.1	37.9	40.5	34.4	41.1	35.5
JPEG	39.7	33.0	39.6	32.4	39.6	32.5	39.1	32.5
WEBP	41.0	37.0	41.8	37.5	41.5	37.6	41.0	37.2
CPDIC	16.1	16.0	18.7	18.7	17.8	17.8	16.8	16.4

Compression Evaluation Experiments

- DSSLIC model shows superior performance over all other codecs for both compression levels considered in terms of PSNR and MS-SSIM.
- This is a quite remarkable result given that the files produced by DSSLIC are smaller in size than files produced by the competing methods.
- Visual inspection of the corresponding output iris images shows that the model is able to preserve spatial precision and the uniqueness of the iris features very well.
- BPG algorithm ranks the second-best and CPDIC algorithm ranks the worst in terms of PSNR and MS-SSIM. Considering the average performance, the ranking for other algorithms is: WEBP, J2K, and JPEG respectively.

Recognition Evaluation Experiments

- Recognition performance using CAHT and Manual masks (the perfect case).

Dataset	Casia4i		Casia5a		IITD		Notredame	
Compress	B	A	B	A	B	A	B	A
DSSLIC	1.2	1.0	21.1	21.2	1.4	1.8	29.9	29.9
BPG	1.0	1.2	21.6	21.3	1.6	2.4	29.6	30.3
J2K	1.1	1.3	20.6	22.3	2.0	2.6	30.0	30.1
JPEG	1.2	2.8	20.6	26.1	1.9	2.5	29.9	32.4
WEBP	1.2	1.7	21.5	23.0	2.0	2.6	30.3	31.5
CPDIC	3.4	4.0	28.8	29.4	2.3	2.8	32.5	34.1

Dataset	Casia4i		Casia5a		IITD		Notredame	
Compress	B	A	B	A	B	A	A	B
DSSLIC	0.4	0.4	2.5	2.9	0.4	0.5	23.8	23.9
BPG	0.4	0.6	2.9	3.9	0.4	0.5	23.8	23.9
J2K	0.4	0.6	2.7	5.1	0.4	0.5	23.8	24.0
JPEG	0.5	1.7	3.0	14.0	0.4	0.5	23.8	25.7
WEBP	0.5	0.7	3.4	5.4	0.4	0.5	24.0	24.6
CPDIC	1.6	2.0	15.1	18.2	0.5	0.6	26.6	29.3

Recognition Evaluation Experiments

- For IITD and Casia4i data DSSLIC compression frequently shows the best performance, especially for the high compression level.
- When using the manual masks, recognition does not work for Notredame data (as the CAHT), while for the remaining datasets, DSSLIC results are never surpassed by any other compression scheme.
- Given the fact that DSSLIC also produces the smallest actual files, these results imply that DSSLIC compression is able to preserve iris texture very well.
- Certainly better than the other algorithms under test, as the segmentation effects are ruled out due to using the manual segmentation.

Recognition Evaluation Experiments

- Recognition performance using Osiris algorithm.

Dataset	Casia4i		Casia5a		IITD		Notredame	
Compress	B	A	B	A	B	A	A	B
DSSLIC	1.1	1.0	2.0	2.2	0.7	0.8	25.2	25.5
BPG	0.9	1.0	2.0	2.5	0.3	0.3	26.9	26.4
J2K	0.8	0.9	2.0	3.1	0.4	0.7	25.7	25.1
JPEG	0.8	1.8	2.4	9.7	0.5	0.6	24.7	24.7
WEBP	0.8	0.9	2.9	4.0	0.4	0.4	25.1	25.0
CPDIC	2.2	2.6	15.9	19.2	0.6	0.6	26.1	27.8

- Using Osiris algorithm, recognition on Notredame data does not work either, but otherwise the ranking of the algorithms is fairly different. DSSLIC is the best performer only for Casia5a, while it is actually the worst performing algorithm on IITD dataset.

Analysis and conclusion

- DSSLIC showed superior compression performance over all other algorithms using different datasets and compression rates.
- The model was able to cope with iris images with complex feature characteristic, and preserved spatial precision and the uniqueness of the iris features very well.
- The higher compression performance of DSSLIC algorithm was directly translated into better recognition rates in majority of the cases.
- However, the segmentation techniques used in the recognition pipeline reacted quiet differently to the compressed iris features, and thus altered the corresponding recognition performance by far.
- The experiments also showed that an increase in compression rate results in reduction of recognition performance in majority of cases.

Thank you, Remarks?

References

Eirikur Agustsson, Fabian Mentzer, Michael Tschannen, Lukas Cavigelli, Radu Timofte, Luca Benini, and Luc Van-Gool.
Soft-to-hard vector quantization for end-to-end learned compression of images and neural networks.
CoRR, abs/1704.00648, 2017.

Zhou Wang, Eero P Simoncelli, and Alan C Bovik.
Multiscale structural similarity for image quality assessment.
In *The Thrity-Seventh Asilomar Conference on Signals, Systems & Computers, 2003*, volume 2, pages 1398–1402. Ieee, 2003.

D Petrovska and A Mayoue.
Description and documentation of the biosecure software library.
Project No IST-2002-507634-BioSecure, Deliverable, 2007.

Christian Rathgeb, Andreas Uhl, and Peter Wild.
Iris Recognition: From Segmentation to Template Security, volume 59 of *Advances in Information Security*.
Springer Verlag, 2013.