COMPARISON OF ILLUMINATION NORMALIZATION METHODS FOR FACE RECOGNITION

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Introduction

- Face recognition in a real uncontrolled environment is a great challenge.
- One of the most difficult problems is the large variability of faces due to illumination changes.
- An alternative for illumination invariant face recognition is to process the images prior to the classification stage. This is called *Illumination Normalization*.
- This presentation summarizes the results from our experiments comparing several illumination normalization methods.

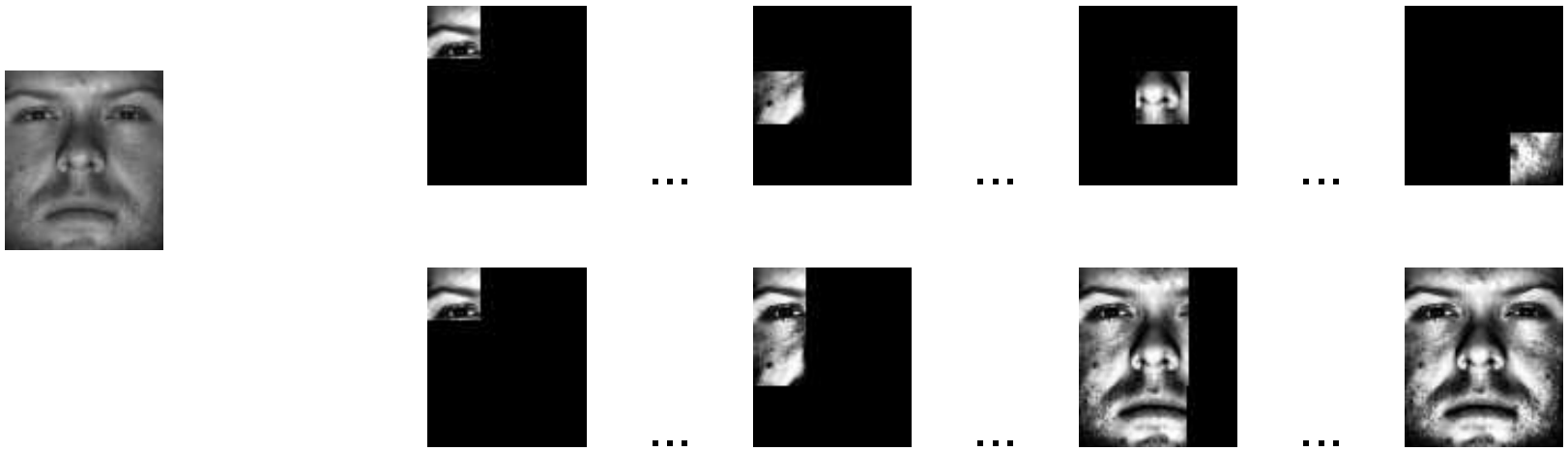
Global Normalization Methods

In these methods the images are processed globally. We chose normalization techniques that can be easily found in the literature.

- Gamma Intensity Correction (GIC): A pixel transform in which the images are related by exponentiation. Needs a model of a well illuminated face.
- Histogram Equalization (HE): The process of making the histogram of an image approximately constant.
- Histogram Matching (HM): The process of making the histogram of an image similar to a specified one. Needs a model of a well illuminated face.
- Normal Distribution (NORM): The process of making the mean and standard deviation of the image to zero and one respectively.

Local Normalization Methods

The local normalization methods used are based on the same functions as the global normalization methods. The difference is that we apply them locally. By applying a normalization function locally we mean the following:



The local normalization methods are: Local Histogram Equalization (LHE), Local Histogram Matching (LHM) and Local Normal Distribution (LNORM).

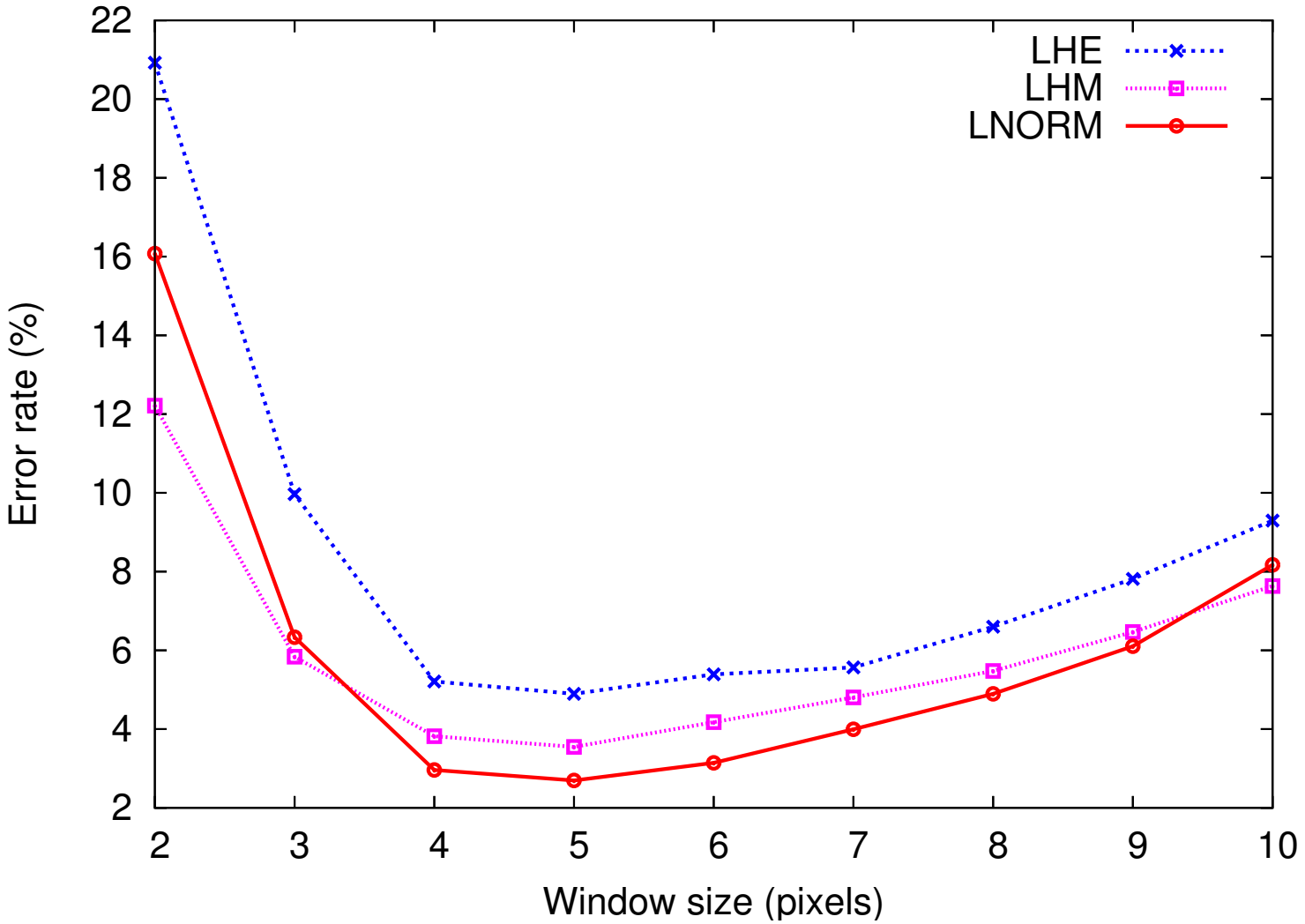
Corpus Used in the Experiments

- The corpus used was the Yale Face Database B (10 subjects) and the extended Yale Face Database B (28 subjects).
- Both databases have images for each subject in 64 different illumination conditions (single point sources at different angles) at 9 different poses. In the experiments only the frontal pose was used.
- It is custom to divide these databases in subsets that group images depending on the angle of the light source with respect to the camera axis.
  - S1: angles lower than 12° (7 images)
  - S2: 12°-25° (12 images)
  - S3: 25°-50° (12 images)
  - S4: 50°-77° (14 images)
  - S5: above 77° (19 images)

The First Experiment

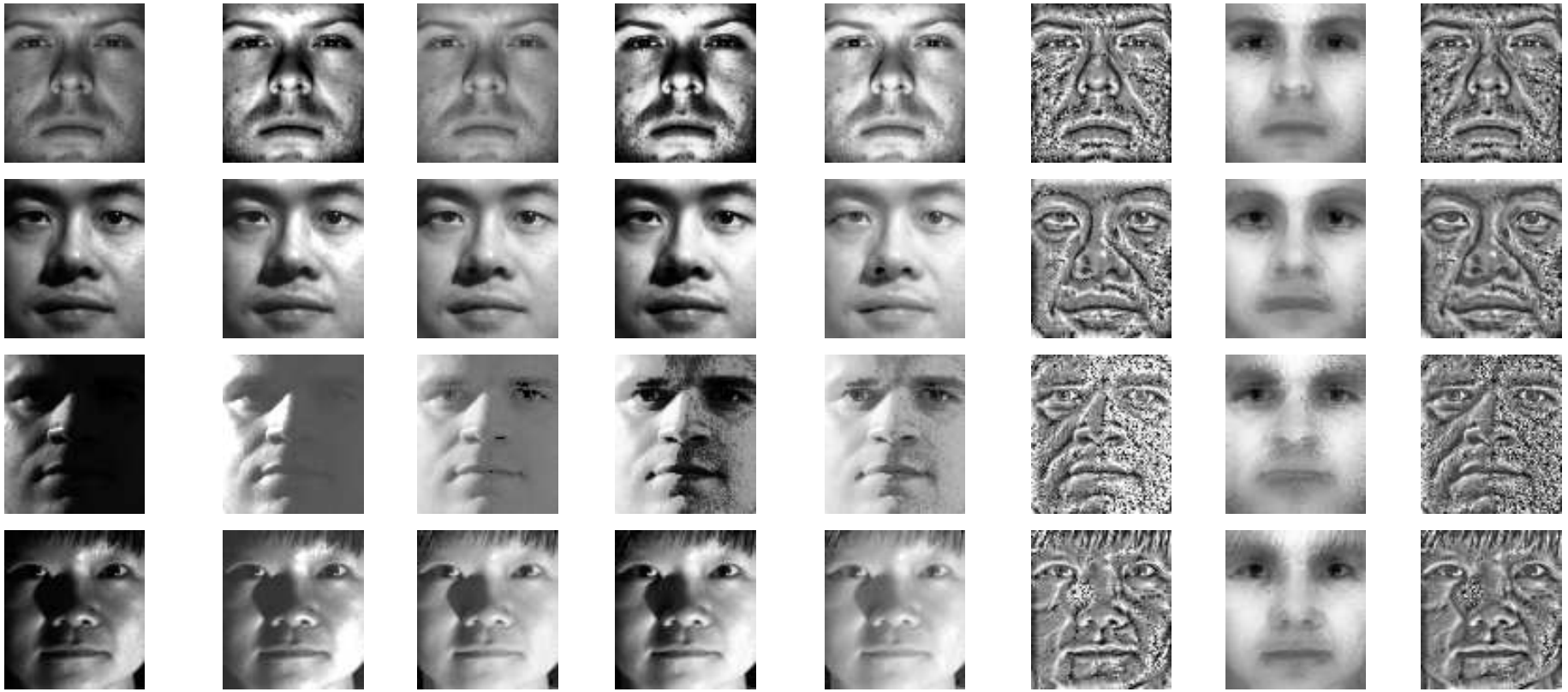
- Objective:
  - Calculate the optimal window size for the local normalization methods.
  - Estimate and compare the classification errors for all the methods.
- Corpus: Extended Yale Face Database B (38 subjects).
- Training set: 5 images per subject form S1.
- Test set: The remaining 59 images.
- Classification method: Nearest neighbor using Euclidean distance.

Results for the First Experiment



Results for the First Experiment

ORIGINAL	NORM	GIC	HISTEQ	HMATCH	LHE	LHM	LNORM
70.86%	53.71%	48.90%	48.00%	43.02%	4.89%	3.54%	2.69%



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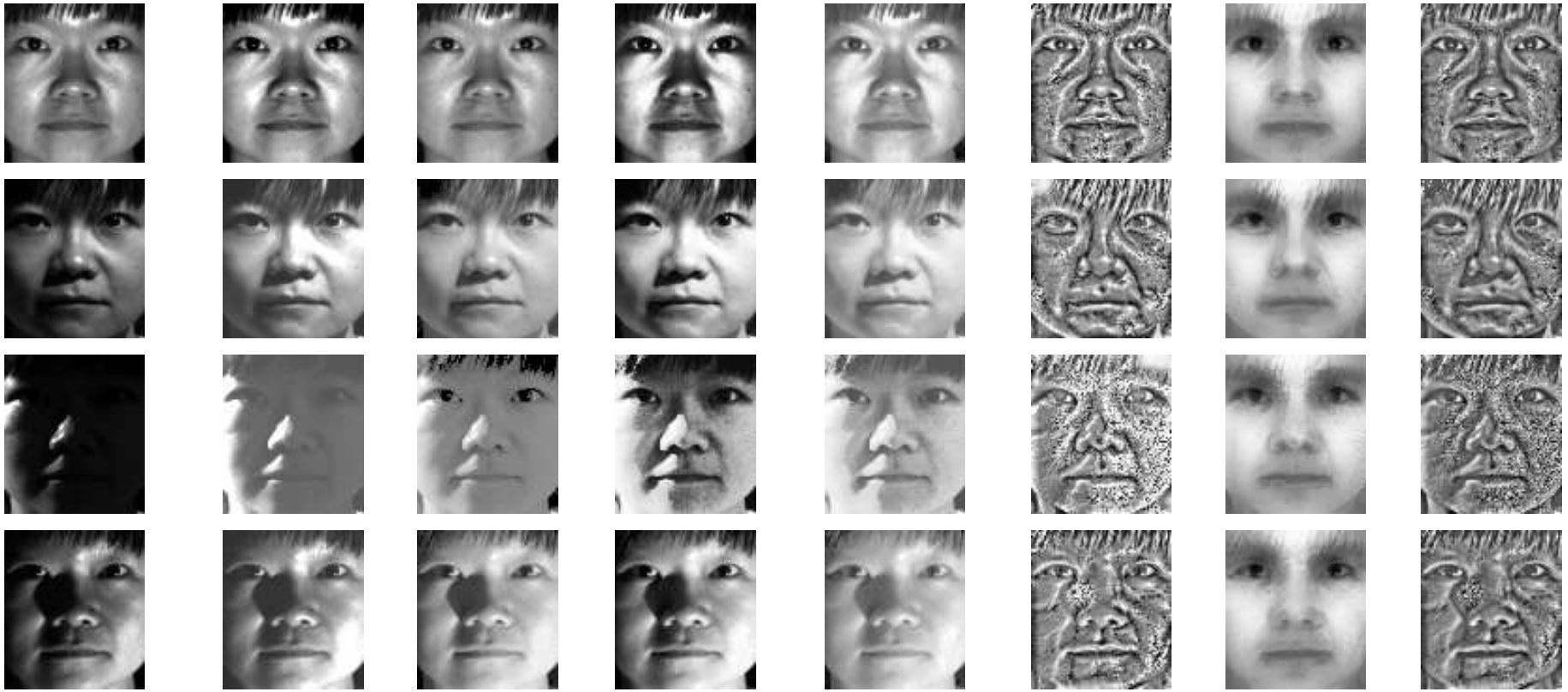

The Second Experiment

- Objective:
  - Estimate the classification error for the best normalization method.
  - Compare with the results found in the literature.
- Corpus: Yale Face Database B (10 subjects).
- Training set: 5 images per subject from S#.
- Test set: The remaining 59 images.
- Classification method: Nearest neighbor using Euclidean distance.

Results for the Second Experiment

	S1	S2	S3	S4	S5	ALL
Tr S1	0.00	0.00	0.00	1.36	1.68	0.86
Tr S2	0.00	0.00	0.58	1.00	4.26	1.72
Tr S3	0.00	0.83	0.86	1.21	0.05	0.57
Tr S4	5.57	1.92	1.92	3.33	0.32	2.05
Tr S5	10.14	8.67	4.67	1.57	0.00	4.29

Comparison with Results Found in the Literature

Method	Training set	S1	S2	S3	S4	S5
LNORM Tr S1	S1 (5 images)	0	0	0	1.4	1.7
QIR	S1 (7 images)	0	0	0	9.4	17.5
9PL	S4 (7 images)	0	0	0	2.8	-
Harmonic Exemplars	S1,S2,S3 (8 images)	0	0	0.3	3.1	-
Cones-cast	S1,S2 (19 images)	0	0	0	0	-

Conclusions

- Illumination normalization methods are a good and simple alternative for illumination invariant face recognition.
- Applying locally well known normalization techniques achieves comparable or even better results with the ones found in the literature.
- Although the LNORM method presented produces non realistic face images, it is demonstrated that it is a good illumination invariant representation suitable for face recognition.

Questions ?

Thank You !