Multi-PIE

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1. Introduction

Facial appearance varies significantly with a number of factors, including identity, illumination, pose, and expression. To support the development and comparative evaluation of face recognition algorithms, the availability of facial image data spanning conditions of interest in a carefully controlled manner is important. Several face databases have been collected over the last decade for this reason, such as the FERET [1], AR [2], XM2VTS [3], Cohn-Kanade [4], and Yale B [5] databases. See [6] for a more comprehensive overview.

To support research for face recognition across pose and illumination the Pose, Illumination, and Expression (PIE) database was collected at CMU in the fall of 2000 [7]. To date more than 450 copies of PIE have been distributed to researchers throughout the world. Despite its success the PIE database has a number of shortcomings; in particular it only contains 68 subjects that were recorded in a single session, displaying only a small range of expressions

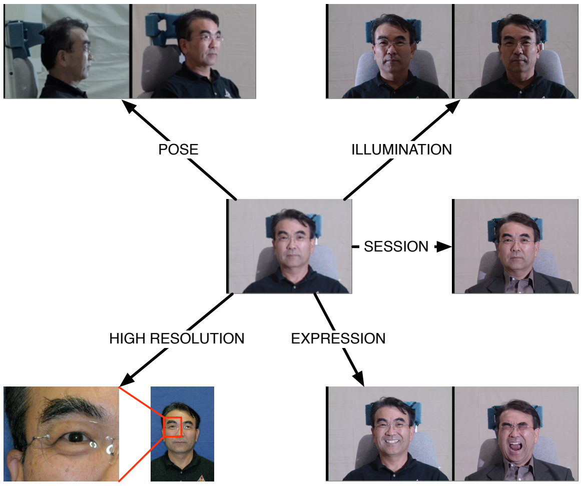


Figure 1: Variation captured in the Multi-PIE face database.

(neutral, smile, blink, and talk).

To address theses issues we collected the Multi-PIE database. The new database improves upon the PIE database in a number of categories as shown in Figure 1 and Table 1. Most notably the number of subjects has been substantially increased to 337 with multiple recording sessions (4 vs. only 1 in PIE). In addition the recording environment of the Multi-PIE database has been improved in comparison to the PIE collection through usage of a uniform, static background and live monitors showing subjects during the recording, allowing for constant control of the head position.

This paper gives an overview of the Multi-PIE database and provides results of baseline face recognition experiments. Section 2 describes the hardware setup used during the collection. Section 3 explains the recording procedure and shows example images. We provide statistics on recording session attendance and the subject population in Section 4. Section 5 shows

	Multi-PIE	PIE
# Subjects	337	68
# Recording Sessions	4	1
High-Resolution Still Images	Yes	No
Calibration Images	Yes	No
# Expressions	6	4
# Cameras	15	13
# Flashes	18	21
Total # Images	750,000+	41,000+
DB Size [GB]	305	40

Table 1: Comparison between the Multi-PIE and PIE databases.

results of evaluations using PCA [8] and LDA [9] in experiments comparing PIE and Multi-PIE as well as in experiments only possible on Multi-PIE.

2. Collection Setup

This section describes the physical setup and the hardware used to record the high resolution still images (Section 2.1), the multi-pose/illumination images (Section 2.2), and the calibration data (Section 2.3).

2.1. High Resolution Images

We recorded frontal images using a Canon EOS 10D (6.3-megapixel CMOS camera) with a Macro Ring Lite MR-14EX ring flash. As shown in Figure 2, subjects were seated in front of a blue background in close proximity to the

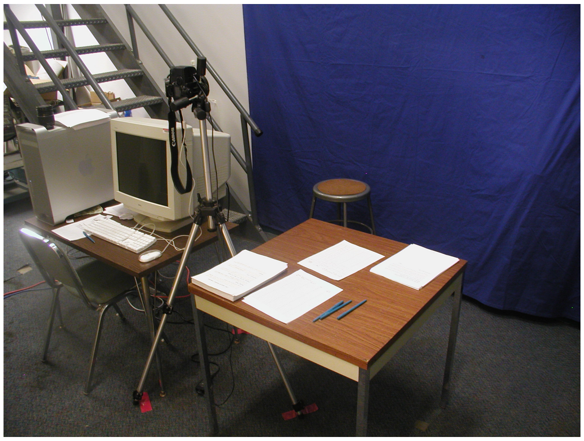


Figure 2: Setup for the high resolution image capture. Subjects were seated in front of a blue background and recorded using a Canon EOS 10D camera with a Macro Ring Lite MR-14EX ring flash.

camera. The resulting images are 3072 × 2048 in size with the inter-pupil distance of the subjects typically exceeding 400 pixels.

2.2. Pose and Illumination Images

To systematically capture images with varying poses and illuminations we used a system of 15 cameras and 18 flashes connected to a set of Linux PCs. An additional computer was used as master to communicate with the independent recording clients running in parallel on the data capture PCs. This setup is similar to the one used for the CMU PIE database [7]. Figure 3 illustrates the camera positions. [1] Thirteen cameras were located at head height, spaced in 15° intervals, and two additional cameras were located

[1] The camera labels are derived from the names of the computers that they are attached to. We use the format <cc_hh> with the camera number *cc* and the channel number *hh*.

above the subject, simulating a typical surveillance view. The majority of the cameras (11 out of 15) were produced by Sony, model DXC-9000, and the remaining four cameras (positions: `11_0`, `08_1`, `19_1`, and `24_0`) Panasonic AW-E600Ps (see Figure 3). Each camera had one flash (model: Minolta Auto 220X) attached to it; above for the 13 cameras mounted at head height and below for the 2 cameras mounted above the subject. In addition, three more flashes were located above the subject between the surveillance-view cameras `08_1` and `19_1`. See Figure 4 for a panoramic image of the room with the locations of the cameras and flashes marked with red and blue circles, respectively. All components of the system were hardware synchronized, replicating the system in [10]. All flashes were wired directly to a National Instruments digial I/O card (NI PCI-6503) and triggered in sync with the image capture. This setup was inspired by the system used in the Yale dome [5].

The settings for all cameras were manually adjusted so that the pixel value of the brightest pixel in an image recorded without flash illumination is around 128 to minimize the number of saturated pixels in the flash illuminated images. For the same reason we added diffusers in front of each flash. We also attempted to manually color-balance the cameras so that the resulting images look visually similar.

2.3. Calibration Data

Calibration data was recorded after the conclusion of the data collection. During sessions 1 through 3, a number of flashes had to be replaced. As a consequence some camera and flash positions might be slightly different from what was measured during the collection of the calibration data. We

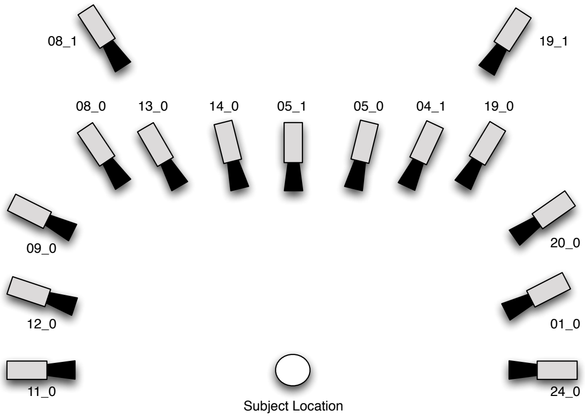


Figure 3: Camera labels and approximate locations inside the collection room. There were 13 cameras located at head height, spaced in 15° intervals. Two additional cameras (08_1 and 19_1) were located above the subject, simulating a typical surveillance camera view. Each camera had one flash attached to it with three additional flashes being placed between cameras 08_1 and 19_1.

recorded camera calibration images as well as color calibration images showing a Gretag Macbeth ColorChecker chart. We furthermore determined the 3D locations of all cameras and flashes and the approximate location of the head of the subject using a theodolite (model: Leica TCA1105, see Figure 5).

3. Data Collection Procedure

We recorded data during four sessions over the course of six months. During each session we recorded a single neutral high resolution frontal image. In addition, during the first session an additional image showing the subjects smiling was recorded. Figure 6 shows all high resolution images from one

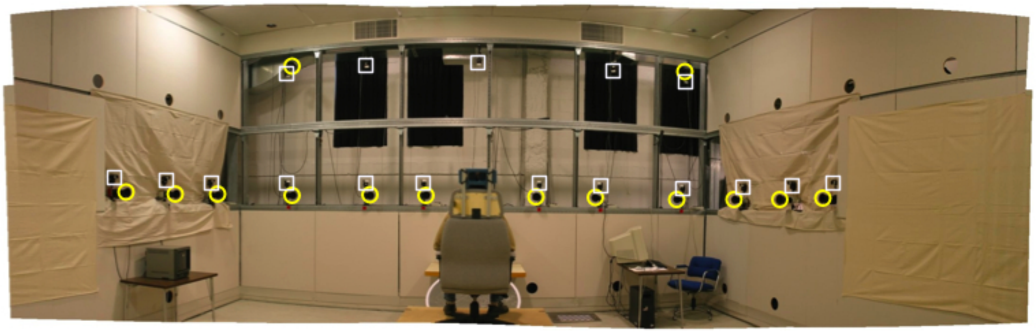


Figure 4: Panoramic image of the collection room. 14 of the 15 cameras used are highlighted with yellow circles, 17 of the 18 flashes are highlighted with white boxes with the occluded camera/flash pair being located right in front of the subject in the chair. The monitor visible to the left was used to ensure accurate positioning of the subject throughout the recording session.

subject for sessions 1 through 4.

After the recording of the high resolution images, subjects were taken inside the collection room and seated in a chair. The height of the chair was adjusted so that the head of the subject was between camera `11_0` and camera `24_0`. We used two live monitors attached to cameras `11_0` and `05_1` to ensure correct head location of the subjects throughout the recording procedure. In each session, multiple image sequences were recorded, for which subjects were instructed to display different facial expressions. Subjects were shown example images of the various expressions from the Cohn-Kanade database [4] immediately prior to the recording. Table 2 lists the expressions captured in each session. Figure 7 shows example images for all facial expressions contained in the database.

For each camera 20 images were captured within 0.7 seconds: one image

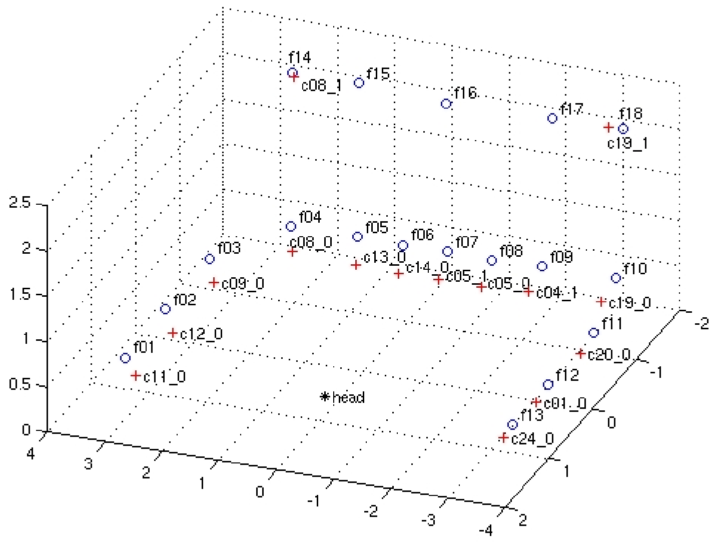
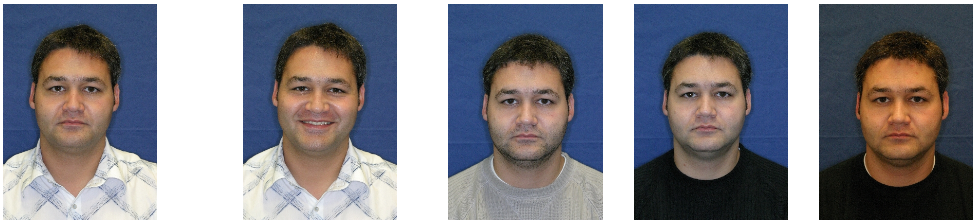


Figure 5: Plot of the camera and flash locations along with the approximate head location. The position information is based on theodolite measurements with distances specified in meter.

without any flash illumination, 18 images with each flash firing individually, and then another image without any flash illumination. Taken across all cameras a total of 300 images were recorded for each sequence. See Figure 8 for a montage of all 15 camera views shown with frontal flash illumination. Unlike in the previous PIE database [7] the room lights were left on for all recordings. Flash-only images can be obtained through simple image differencing of flash and non-flash images as shown in Figure 9. Due to the rapid acquisition of the flash images subject movement between images is neglectible.



Session 1 Neutral Session 1 Smile Session 2 Session 3 Session 4

Figure 6: Example high resolution images of one subject across all four recording session. For session 1 we recorded a smile image in addition to the neutral image.

4. Database Statistics

In total, the Multi-PIE database contains 755,370 images from 337 different subjects. Individual session attendance varied between a minimum of 203 and a maximum of 249 subjects. Of the 337 subjects 264 were recorded at least twice and 129 appeared in all four sessions. See Table 3 for details.

The subjects were predominantly men (235 or 69.7% vs. 102 or 30.3% females). 60% of subjects were European-Americans, 35% Asian, 3% African-American and 2% others. The average age of the subjects was 27.9 years. As part of the distribution we make the following demographic information available: gender, year of birth, race and whether the subject wears glasses.

5. Baseline Recognition Results

To illustrate the similarities and differences between the PIE and Multi-PIE databases we report results of baseline experiments with PCA [8] and

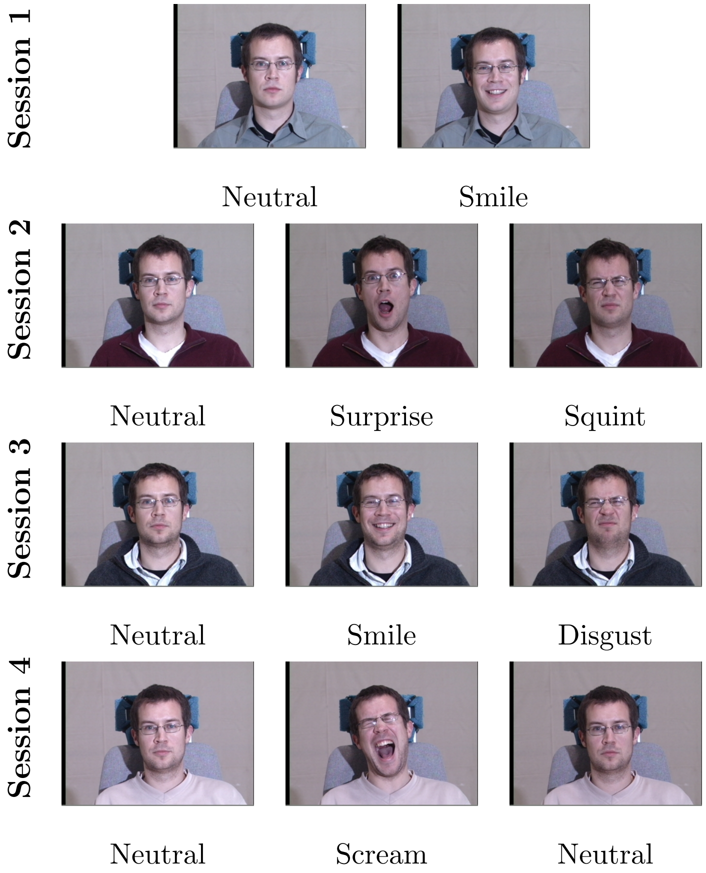


Figure 7: Example images of the facial expressions recorded in the four different sessions.

LDA [9] classifiers, both using a cosine distance measure.[2] We describe the evaluation procedure in Section 5.1 and show results of comparative experiments on PIE and Multi-PIE in Section 5.2. Section 5.3 presents results of

[2] For face PCA spaces, the whitened cosine distance measure used here has been shown to perform well [11]. For LDA, the optimal distance measure appears to depend on the specific dataset [12].

Expression	S1	S2	S3	S4
Neutral	x	x	x	xx
Smile	x		x	
Surprise		x		
Squint		x		
Disgust			x	
Scream				x

Table 2: Overview of the facial expressions recorded in the different sessions. Note that we recorded two neutral expressions during session four, one before and one after the scream expression.

new experiments on Multi-PIE that could not be conducted using PIE data.

5.1. Evaluation Procedure

For all experiments, frontal faces were normalized using the location of 68 manually established facial feature points. These points are triangulated and the image warped with a piecewise affine warp onto a coordinate frame in which the canonical points are in fixed locations. This process is similar to the preprocessing used prior to the computation of Active Appearance Models (AAMs) [13, 14]. The resulting images are approximately 90×93 in size (with slight variations for the different data subsets). Throughout we use the data of 14 subjects (20% of the 68 subjects available in PIE) to compute the PCA or LDA subspaces and evaluate performance on the remaining subjects. In all cases we report rank-1 accuracy rates.

We report rank-1 accuracies computed as averages over 20 independent

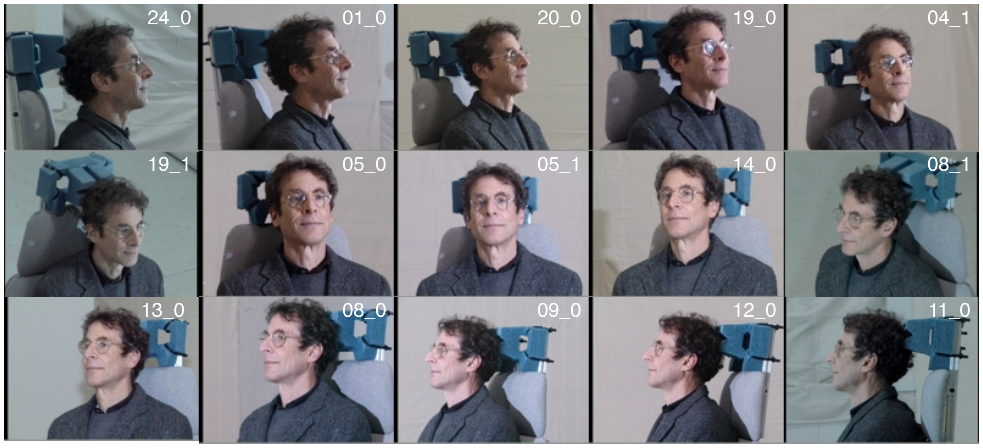


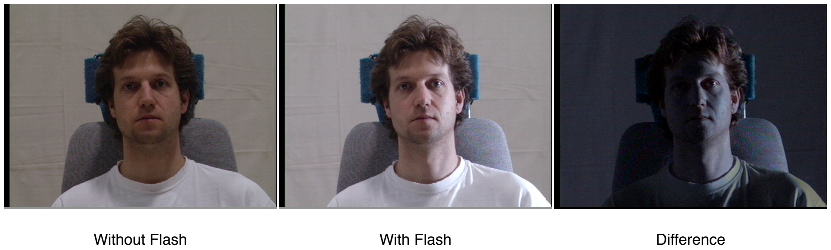
Figure 8: Montage of all 15 cameras views in the CMU Multi-PIE database, shown with frontal flash illumination. 13 of the 15 cameras were located at head height with two additional cameras mounted higher up to obtain views typically encountered in surveillance applications. The camera labels are shown in each image (see Figure 3).

random assignments of subjects to training and testing sets. In the experiments comparing performance on PIE and Multi-PIE we show results for matched conditions using 68 subjects from each database (labeled as “PIE 68” and “M-PIE 68”) as well as results using the full set of subjects available in Multi-PIE (labeled as “M-PIE Full”).

5.2. Comparing PIE and Multi-PIE

5.2.1. Recognition across Sessions

The Multi-PIE database contains up to four sessions per subject recorded over a span of six months (see Table 3) whereas subjects were seen only once in the PIE database. As a consequence we can report recognition accuracies



Without Flash

With Flash

Difference

Figure 9: Computation of flash-only images as difference between flash and non-flash images.

Individual Session Attendance			
Session 1	Session 2	Session 3	Session 4
249	203	230	239

Repeat Recordings			
4 Sessions	$\geq$ 3 Sessions	$\geq$ 2 Sessions	1 Session
129	191	264	73

Table 3: Attendance statistics for the different recording sessions of the Multi-PIE database. 264 of the 337 subjects were recorded at least twice.

as function of time between the acquisition of gallery and probe images (here for neutral expression faces without flash illumination). Figure 10 shows the recognition rates for both PIE and Multi-PIE using a PCA recognizer. For PIE, the probe and gallery images are identical, resulting in perfect recognition. For Multi-PIE, we recorded two neutral expression images in session 4, enabling a within-session test (for time difference 0). Performance decreases noticeably when comparing images recorded during the same session (time difference 0) versus comparing images recorded during different sessions (time

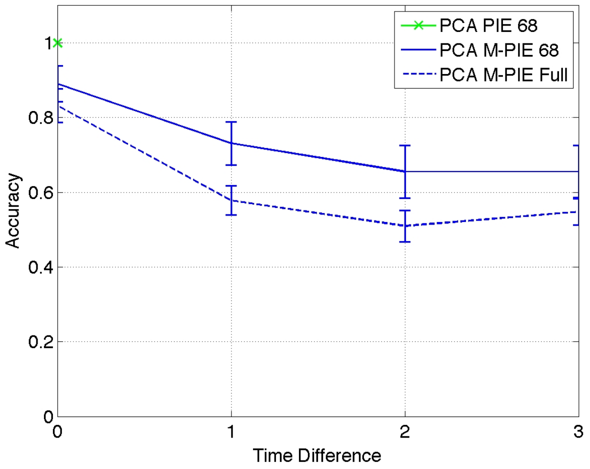


Figure 10: PCA performance for PIE and Multi-PIE across recording sessions. Since PIE only contains images from one session, gallery and probe images are identical, resulting in perfect recognition (PIE 68). For Multi-PIE, accuracies decrease with increasing time difference between the acquistition of gallery and probe images. We show results for a 68 subject subset of Multi-PIE (M-PIE 68) as well as for the full set of available subjects (M-PIE Full).

difference 1, 2, and 3). As expected, an increase in testing set size also results in lower recognition rates (M-PIE 68 vs. M-PIE full).

5.2.2. Recognition across Illumination

In the illumination experiments we use images recorded without flashes as gallery (in the case of PIE from the recording with room lights on) and all flash images in turn as probe. Figure 11 shows recognition accuracies for both PCA and LDA on PIE and Multi-PIE across all illuminations. The physical setup of light sources used in PIE and Multi-PIE is comparable, resulting in both comparable illumination conditions as well as matching relative changes (see Figure 5 and Figure 1(b) in [7]). As a consequence, for corresponding experimental conditions (PCA PIE 68 in Figure 11(a) and PCA M-PIE 68 in Figure 11(b)), accuracies are nearly identical (36.6% vs. 35.4%). Furthermore, matching performance curves have similar shapes.

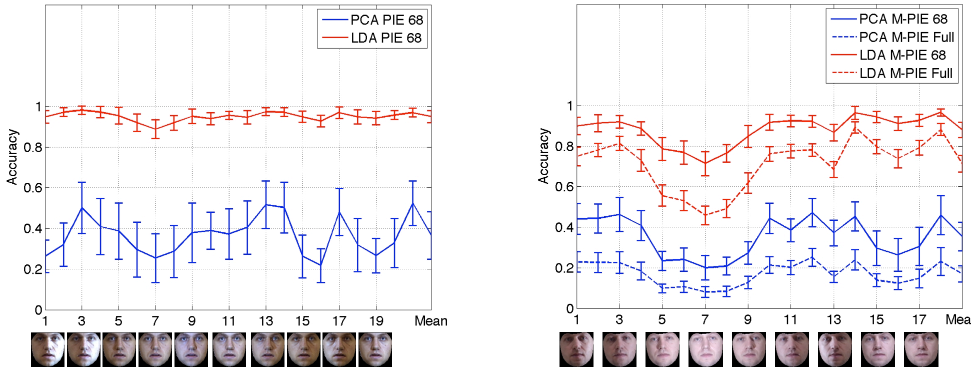
LDA performance saturates over PIE (95%, LDA PIE 68), whereas accuracies on Multi-PIE with the much larger test set of subjects still leaves room for improvement (71.3%, LDA M-PIE Full). Note that in order to enable comparability of conditions between the two databases only 14 subjects (20% of the number of subjects of PIE) were used during training (see Section 5.1). A larger number of training subjects would likely improve the performance of LDA [15].

5.3. Beyond PIE

For the most part, PIE supports single factor experiments (e.g. recognition across pose or recognition across illumination). The data in Multi-PIE enables a range of new experiments examining cumulative effects of multiple recording conditions which can not be conducted using PIE data. As examples we show results for recognition across both illumination and sessions in Section 5.3.1, across expressions and illumination in Section 5.3.2, and across expressions and sessions in Section 5.3.3.

5.3.1. Recognition across Illumination and Sessions

The availability of illumination data from multiple sessions enables us to evaluate recognition performance across illumination *and* sessions. Figure 12 shows the performance of PCA and LDA classifiers on the task. Similar to the



(a) PIE

(b) Multi-PIE

Figure 11: Comparison of PCA and LDA recognition across illumination conditions in PIE and Multi-PIE. For matched experimental conditions (PCA PIE 68 in (a) and PCA M-PIE 68 in (b)), performance is comparable, experimentally veryifying the similarity in the physical setup of the two collections. Whereas LDA performance over PIE nearly saturates at 95%, the average accuracy over Multi-PIE using the largest test set (LDA M-PIE Full) indicates further room for improvement.

results in Section 5.2.1 there is a noticeable drop in performance between time difference 0 and time differences 1, 2, and 3. However, overall performance levels are much lower than in Figure 10 due to the influence of the illumination differences.

5.3.2. Recognition across Expression and Illumination

The range of facial expressions captured in Multi-PIE (*neutral*, *smile*, *surprise*, *squint*, *disgust*, and *scream*) is much larger than the subtle expressions contained in PIE (*neutral*, *smile*, *blink*, and *talk*). Furthermore, Multi-PIE

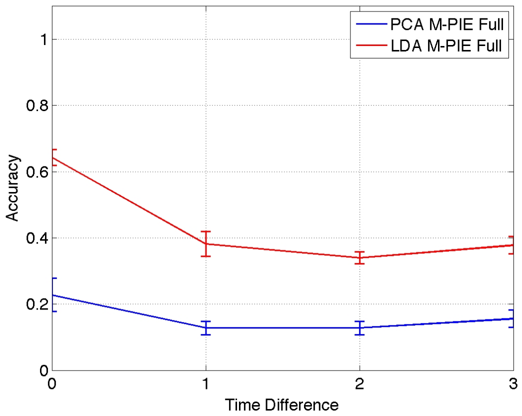


Figure 12: PCA and LDA performance on Multi-PIE across illumination and sessions. Results shown are averages over all illumination conditions. Performance decreases with increasing time difference between the recording of gallery and probe images. Performance overall is lower than in Figure 10 due to the influence of the illumination differences.

contains images from all illuminations conditions for all facial expressions. We are therefore able to evaluate the cumulative effect of changes in illumination *and* expression on recognition accuracies. Figure 13 shows PCA and LDA accuracies for different probe expressions, averaged over all illumination conditions. In all cases, a neutral expression image recorded in the same session without flash illumination was used as gallery image. As comparison we also show results of PCA recognition with identical illumination conditions for gallery and probe (PCA M-PIE). The combined influence of illumination and expression reduces accuracies drastically, with PCA rates varying between 13.7% (for *scream*) and 21.1% (for *squint*). LDA accuracies are higher on average (41.4% vs. 18.5%), peaking at 50.1% (again for *squint*).

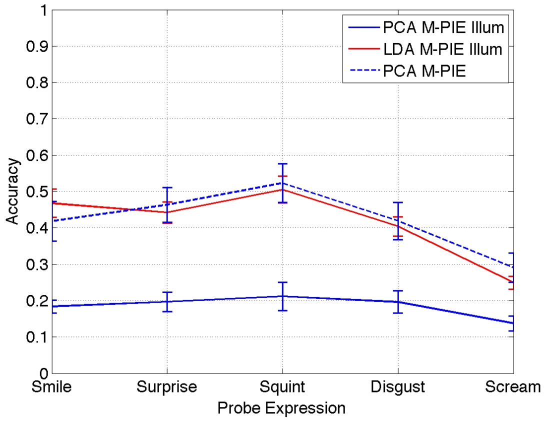
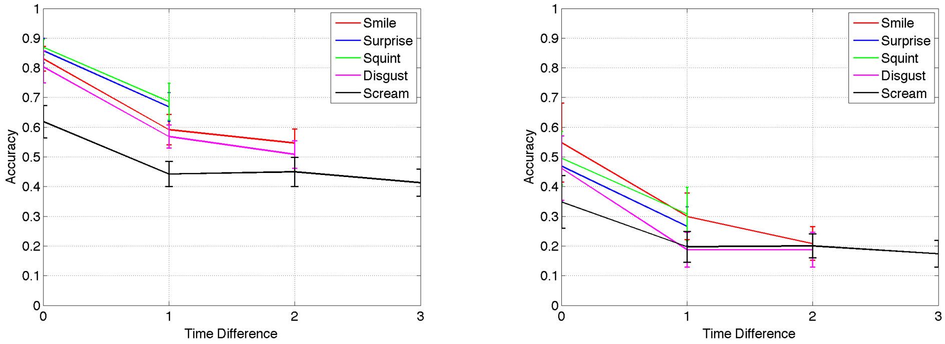


Figure 13: PCA and LDA performance on Multi-PIE across expressions and illuminations. We use the neutral images (without flash illumination) recorded in the same session as gallery and the expression images under all illumination conditions as probe. The combined influence of illumination and expression reduces accuracies drastically, with PCA rates varying between 13.7% (for *scream*) and 21.1% (for *squint*). LDA accuracies are higher on average (41.4% vs. 18.5%), peaking at 50.1% (again for *squint*). As comparison we also show PCA recognition rates for identical gallery and probe illumination conditions (labeled "PCA M-PIE").

5.3.3. Recognition across Expression and Sessions

While different expressions were captured in the four recordings of Multi-PIE (see Table 2), the availability of neutral images in all sessions enables evaluation of performance across expressions *and* sessions. We use each expression as probe and compare it to neutral images from the same session as well as earlier sessions whenever available. Figure 14 shows PCA and LDA accuracies for the different expressions across different numbers of sessions. As expected performance drops when going from same session comparisons



(a) PCA

(b) LDA

Figure 14: PCA and LDA performance for recognition across expression and sessions. Recognition performance drops with increased time between acquisition of gallery and probe images. On average PCA performs better across expressions and illuminations than LDA (63.3% versus 31.1%).

(time difference 0) to across session comparisons (time difference 1, 2, and 3). The biggest reduction in accuracy occurs when comparing same session results (average 79.6% for PCA and 46.5% for LDA) with results for a one session difference (59.1% for PCA and 25.2% for LDA). Overall PCA performs noticeably better than LDA (63.3% versus 31.1%), potentially due to the comparatively small size ($14trainingsetsubjects$) of the dataset used here [15]. Note that to exclude additional variation due to differences in subjects we only use images of the 129 subjects which were imaged in all four sessions. As a consequence, results can not be directly compared to those reported in Section 5.3.2.

6. Availability

Multi-PIE is available to all interested researchers for the cost of media (a 400GB hard drive) and shipping. Details of the distribution procedure are published at `http://multipie.org`. On the web page, we will also make the experimental protocols used in this paper, normalized images, and 3-point feature data available.

7. Conclusion

In this paper we introduced the CMU Multi-PIE face database. Multi-PIE improves upon the highly successful PIE database in a number of aspects: a larger set of subjects, more recording sessions, more facial expressions, and the inclusion of high resolution images. We reported results of baseline experiments using PCA and LDA classifiers discussing both the similarities and as well as the differences between the two databases. All experiments shown here only used frontal face images. In future work we plan on expanding the evaluations across pose as well.

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