Report on PCA-based Face Reconstruction and Video Calling Performance

Name: Mudit Gupta **Roll Number: 2024201058**

Note : Videos were recorded before code change on Tuesday. So in server.py reconstruction cost and compression ratio values are not visible.

1. Introduction

Principal Component Analysis (PCA) is widely used for facial recognition and compression by identifying key eigenfaces. This report presents our approach, experimental results, and failure cases across different training and testing conditions in video calling using eigenfaces.

2. Key Concepts

2.1. Compression Ratio

Compression Ratio defines how much data is reduced when using PCA. It is given by:

$$CompressionRatio = \frac{N-k}{N} \times 100\%$$

where N is the total number of features, and k is the selected number of eigenfaces.

2.2. Reconstruction Cost

Reconstruction Cost measures the error in reconstructing faces from compressed data. Lower cost means better reconstruction.

2.3. Loss

Loss quantifies how much facial identity is lost after reconstruction. It increases when fewer eigenfaces are used.

3. Test Conditions & Results

3.1. Task 1: Normal Setup (All Faces Used in Training)

Setup: PCA trained on the full dataset, tested under real-time video calling.

Observations:

k Value	Compression Ratio	Reconstruction Cost	Loss
700	80.56%	35–40%	30%
1200	66.66%	11–15%	8–10%
2000	44.44%	6–8%	5–6%
13500	1–3%	-275%	0–1%

Table 1: Task 1: Observations for Normal Setup

Analysis: As k increases, compression ratio decreases (from 80.56% to 1–3%), reflecting less data reduction. Reconstruction cost drops significantly (from 35–40% to 6–8%) up to k = 2000, then becomes negative at $k = 13500$, suggesting overfitting or an anomaly.

- **Face Angle Variation:** Reconstruction cost fluctuated depending on the face angle. Some angles resulted in lower cost, while others increased the error significantly.

Recommendation:

- If compression is your priority, use 2000–2500 eigenfaces (good balance and 5% loss).

- If maximum storage savings are needed, use 1000–1500 eigenfaces (8–10% loss).
- For feature extraction, 400–800 eigenfaces might be enough.

Ideal k Value: For feature extraction, k = 700 performs best. However, since this assignment prioritizes video calling, **k = 1200** is the ideal value due to better video quality and a good balance between compression and reconstruction cost.

3.2. Task 2: Cross-Gender Testing (Trained on Women, Tested on Men)

Setup: PCA trained only on women's faces, tested on men.

Observations:

k Value	Compression Ratio	Reconstruction Cost	Loss
700	80.56%	60–70%	25–28%
1200	66.66%	30–35%	18–22%
2000	44.44%	17%	10–16%
13500	1–3%	70–99%	—

Table 2: Task 2: Observations for Cross-Gender Testing

Analysis: Compression ratio decreases with higher k (80.56% to 1–3%). Reconstruction cost improves from 60–70% at $k = 700$ to 17% at $k = 2000$, but rises sharply to 70–99% at $k = 13500$, indicating poor generalization at extreme k.

- **Face Angle Variation:** Face angles significantly affected loss. Some facial orientations resulted in higher reconstruction costs.

Ideal k Value: For feature extraction, k = 700 performs best. However, since this assignment prioritizes video calling, **k = 1200** is the ideal value due to better video quality and a good balance between compression and reconstruction cost.

3.3. Task 3: Training on 500 Images Only

Setup: PCA trained on 500 random images.

Observations: Reconstruction cost is highly variable.

k Value	Compression Ratio	Reconstruction Cost	Loss
700	80.56%	90–120%	65%
1200	66.66%	80–100%	—
2000	44.44%	80–105%	—
13500	1–3%	90–110%	—

Table 3: Task 3: Observations for Training on 500 Images

Analysis: Compression ratio decreases as k rises (80.56% to 1–3%). Reconstruction cost remains high (80–120%) across all k, showing PCA struggles with limited data, with little improvement as k increases.

- **Face Angle Variation:** Loss fluctuated significantly at different angles.

Ideal k Value: PCA fails; augmentation or deep learning is required.

3.4. Task 4: Training on Two Persons' Faces Only

Setup: PCA trained on 100 images each of two individuals (200 total).

Without Data Augmentation:

Analysis (Without Augmentation): Compression ratio drops from 80.56% to 1–3% as k increases. Reconstruction cost is extremely high (690–850%) across all k, worse for different persons, indicating severe overfitting to the small dataset.

With Data Augmentation (3000 images):

Scenario	k Value	Compression Ratio	Reconstruction Cost	Loss
Same Person	700	80.56%	720–780%	90–96%
Same Person	1200	66.66%	740–760%	—
Same Person	2000	44.44%	720–740%	—
Same Person	13500	1–3%	690–700%	—
Different Person	700	80.56%	800–850%	95–98%
Different Person	1200	66.66%	780–820%	—
Different Person	2000	44.44%	750–800%	—
Different Person	13500	1–3%	710–750%	—

Table 4: Task 4: Observations Without Data Augmentation

Scenario	k Value	Compression Ratio	Reconstruction Cost	Loss
Same Person	2000	44.44%	50–55%	35–40%
Different Person	2000	44.44%	55–60%	40–50%

Table 5: Task 4: Observations With Data Augmentation

Analysis (With Augmentation): At $k = 2000$, compression ratio is 44.44%, and reconstruction cost drops to 50–60%, a significant improvement over no augmentation, though still higher for different persons.

- **Face Angle Variation:** Significant cost fluctuations based on face orientation.

Ideal k Value: PCA fails; but with data augmentation video quality is improved by some significant margin and k value can be taken in range of 1000–2000 with data augmentation.

Note: When tested on a different/third person, reconstruction cost slightly increased by 5–10%.

4. Conclusion & Recommendations

Best k-Values for Different Applications:

Application	Priority	Best k Range
Video Calls	Real-time performance & low cost	1000–2000
Face Recognition	Feature extraction efficiency	400–800
Compression	Maximum storage savings	1000–1500
Generalization	Low reconstruction cost	1800–2500

Table 6: Best k-Values for Different Applications

Key Takeaways:

- Since in this assignment our primary focus is video calling, value of k in range [1000–2000] gives good quality, real-time performance, low cost, and good balance between compression ratio and reconstruction cost.
- PCA needs a diverse dataset to generalize well.
- Augmentation significantly improves reconstruction quality.
- Data efficiency is lower when trained on fewer individuals.
- Small datasets (200–500 images) lead to high reconstruction cost across all k values.