Face Recognition Using Compressive Sensing Ideas

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Abstract

We propose a face recognition paradigm using reweighted ℓ_2 minimization with hashing, whose recognition rates are comparable to the random projection using ℓ_1 minimization. Yet, our method is not only much faster than the standard compressive sensing method of Yang et al [2], but also robust to occlusion. We show that the sparse solution can be recovered with a high probability because hashing preserves the restrictive isometry property [6] and reweighted ℓ_2 mirrors the ℓ_1 (i.e. ℓ_0) solution [1]. Moreover, we present a theoretical analysis on the convergence of the proposed ℓ_2 approach. Experiments show a very promising recognition rate even with occlusion and significant speedup compared with [2].

Introduction

An image is stored as a matrix of pixel intensities. Assuming that a person's image can be represented by a linear combination of his or her own images, we try to ask a computer to perform recognition. Due to the special geometric shape and appearance of the face, this virtual task can be very challenging.

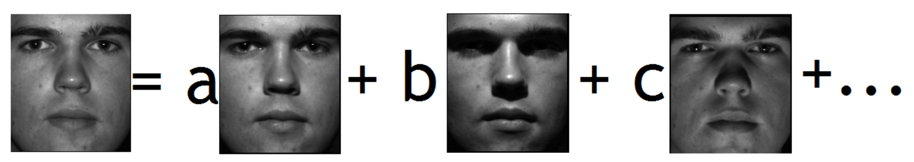

Figure: A Linear Combination of Images in The Same Class

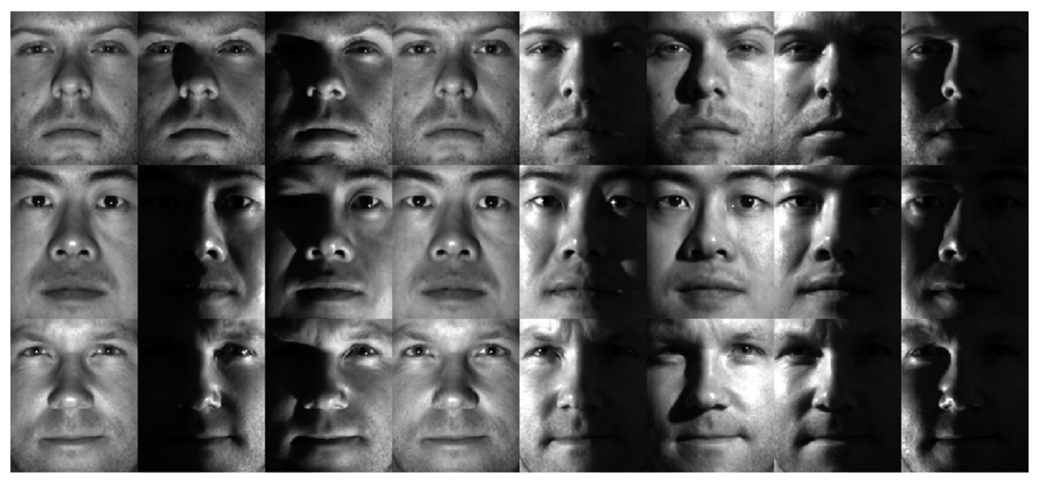

Figure: A sample of Extended Yale B Database. Each row shows the images of one subject under various lighting conditions.

Problem

We desire to experiment with recent advancements in compressive sensing in order to accurately identify images of faces to their respective classes based on a training set of images. Based on the database (Extended Yale B) we are using for testing, we must deal with obstacles such as radical lighting conditions that change brightness levels and result in concealed areas of the face due to shadows. We also would like to examine how the algorithm can handle potential occlusion.

Figure: A sample of Extended Yale B Database with random occlusions over (left eye, right eye, nose, left cheek, right cheek, and mouse).

Method

Algorithm for Face Recognition:

1. Input: A matrix of training images $A \in \mathbb{R}^{m\times n}$ for k subjects, a test image $y \in \mathbb{R}^m$, a linear feature transform[a] $T \in \mathbb{R}^{d\times m}$, and an error tolerance ϵ.
2. Compute features $\tilde{y} = Ty$ and $\tilde{A} = TA$.
3. Solve[b] the convex optimization problem
$$\min_x \|Wx\|_\tau \text{ subject to } \|\tilde{y} - \tilde{A}x\|_{\ell_2} \le \epsilon$$
4. Compute the residuals $r_i(y) = \|\tilde{y} - \tilde{A}\delta_i(x)\|_{\ell_2}$ for $i = 1, 2, \dots, k$
5. Identify$(y)= arg \min_i r_i(y)$

Algorithm of Reweighted ℓ_2 to solve for coefficient x:

1. Set $w^{(0)} = (1, 1, \dots)$ and $\varepsilon_0 = 1$.
2. Compute $x^{(n)} = D^2A^T(AD^2A^T)^{-1}y$.
3. Update $w_j^{(n+1)} = [(x_j^{(n)})^2 + \varepsilon_{(n)}^2]^{-1/2}$ and
$$\varepsilon_{(n+1)} = \min\left(\varepsilon_{(n)}, \frac{r(x^{(n)})_{K+1}}{N}\right) \quad (n = 0, 1, \dots).$$
4. Repeat step 2 to 3. Stop the algorithm if $\varepsilon_{n+1} = 0$ or small enough.

[a] Pixel Selection, Random Gaussian, or Hashing Matrix.

[b] W is identity or a diagonal weight matrix, τ is ℓ_1 or ℓ_2

Experiment and Results

The Yale B data consists of 2,414 frontal face images from 38 individuals captured under various lighting conditions. To fairly compare the performance, we randomly select about half of the images from each person for training, and the other half for testing. Below is a chart of Recognition Rate and Speed per testing image in seconds.

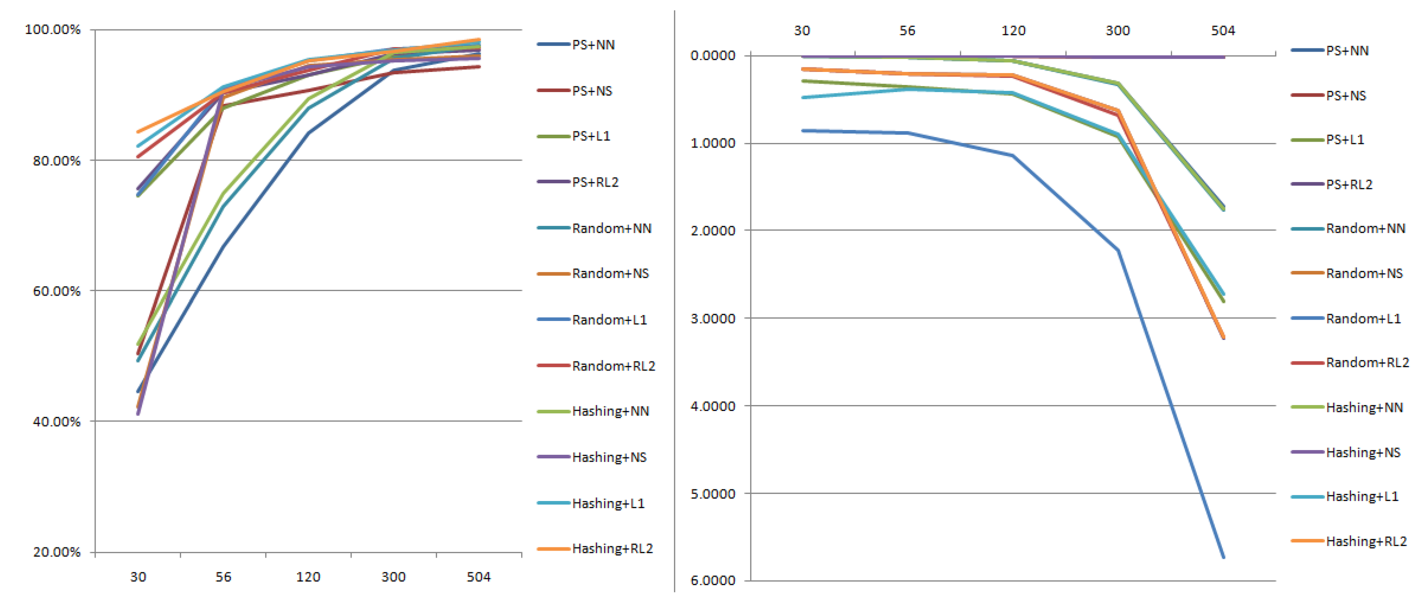

Figure: Face Recognition on Yale B database

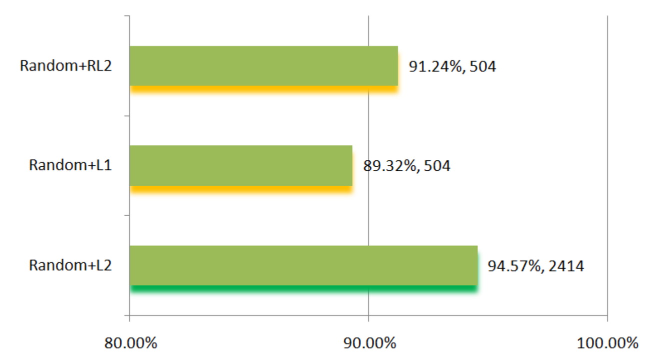

Figure: Recognition Rate with Occlusion

Experiment and Results (continued)

Observations:

- Run-time depends exponentially in the dimension of the face space.
- The highest recognition rate that we can achieve with Yale B database is 98.5% with hashing and reweighted ℓ_2.
- Run-time of Nearest Subspace with dimension reduction ranges from 3ms to 21.8ms, which is 130 times faster than Random projection using ℓ_1 minimization.
- As long as sufficient measurements are extracted (3%) and the sparse representation is correctly found, high recognition rates can be achieved.
- Reweighted ℓ_2 algorithm is very comparable to traditional ℓ_1 algorithm.
- Even if there are random occlusions in the testing images, high recognition rates can be achieved as long as sufficient measurements are extracted and the sparse representation is correctly found.

Conclusion

Using hashing and reweighted least squares, we have proposed an alternative face recognition methodology, which speeds up the state-of-the-art in [5] with comparable recognition rates and more stable under possible occlusion. We conclude experimentally that exploiting sparsity is critical for high-performance face recognition. Iteratively reweighted least squares minimization can mirror ℓ_1 minimization with significantly faster speed. ℓ_1 minimization may not have absolute advantage in face recognition on Extended Yale B database.

References

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