Dataset

There are 40 subjects and each subject has 10 different face pictures.

The training dataset is made of 5 pictures of each subject and the test dataset is the other 5 pictures of each subject. Training dataset has 200 faces and test dataset has 200 faces. Two-fold cross validation is used for this project.

The original face pictures have dimension of 112*92 with 10304 number of pixels.

SRC algorithm with down-sampled faces as feature vector

All faces in the training and test datasets are down-sampled and then they are reshaped into column vectors. Each down-sampled vector is normalized to have norm-2 equal to 1. The vectors from the training set are used as the columns of the dictionary.

Feature size	2-dim Size	Recognition Rate (round-1)	Recognition Rate (round-2)	Average Recognition Rate
12	4*3	0.74	0.745	0.74
30	6*5	0.93	0.935	0.93
72	9*8	0.88	0.97	0.93
120	12*10	0.84	0.905	0.87
168	14*12	0.73	0.79	0.76

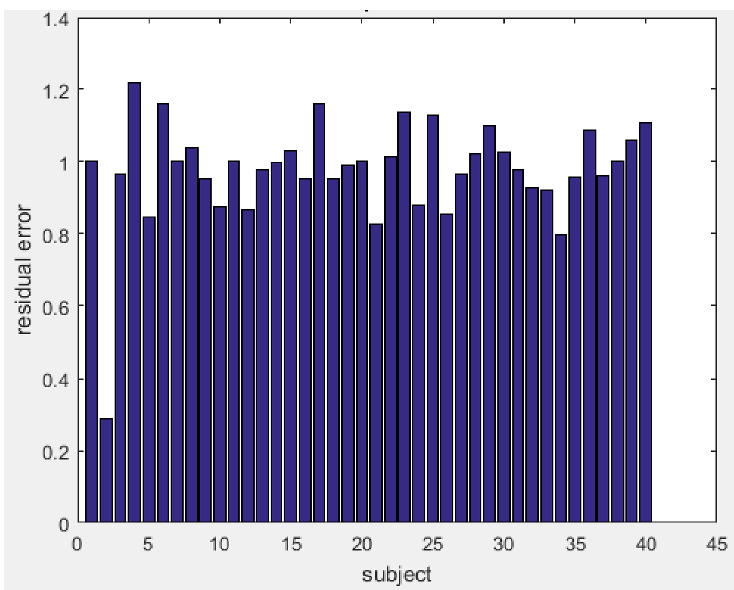

Figure 1-Subject 2 has lowest error by SRC algorithm

SRC algorithm with DCT as feature vector

Two-dimensional DCT transform of all faces are calculated and the DCT coefficient in the top-left block are reshaped into a feature vector.

Feature size	Recognition Rate (round-1)	Recognition Rate (round-2)	Average Recognition Rate
4	0.365	0.345	0.36
9	0.75	0.71	0.73
25	0.90	0.945	0.92
64	0.895	0.945	0.92
100	0.86	0.905	0.88
144	0.80	0.84	0.82
196	0.41	0.375	0.39

SRC algorithm with PCA as feature vector

The Eigen-faces of the training faces are calculated. The Eigen-faces with the highest Eigen-values are selected to make a face-space. Then the projection of each training and test image into the Eigen-face space is calculated. This projection vector is considered as the feature vector for each image.

Feature size	Recognition Rate (round-1)	Recognition Rate (round-2)	Average Recognition Rate	Average Recognition Rate
2	0.175	0.165	0.17	0.17
5	0.59	0.68	0.64	0.66
10	0.86	0.835	0.85	0.84
15	0.86	0.87	0.87	0.87
25	0.88	0.895	0.89	0.89
45	0.89	0.875	0.88	0.88
60	0.875	0.87	0.87	0.87
100	0.84	0.79	0.82	0.81
120	0.83	0.695	0.76	0.73

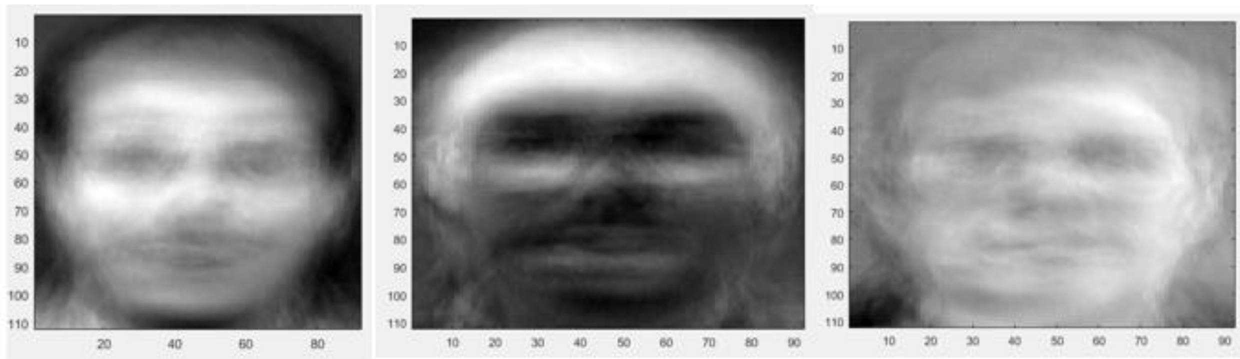

Figure 2- First 3 Eigen-faces (in order from left to right)

SRC algorithm with random feature as feature vector

Random face feature descriptors code was used to extract random features from each face.

Feature size	Recognition Rate (round-1)	Recognition Rate (round-2)	Average Recognition Rate
10	0.31	0.38	0.35
20	0.64	0.645	0.64
40	0.63	0.645	0.64
80	0.585	0.615	0.60
100	0.535	0.59	0.56
120	0.54	0.57	0.56

Reduce the columns of A to 120

Down-sampled faces as features

Feature size	Recognition Rate
12	0.65
30	0.78
72	0.755
120	0.585
168	0.7

DCT

Feature size	Recognition Rate
4	0.24
9	0.61
25	0.8
64	0.74
100	0.655
144	0.66
196	0.765

PCA

Feature size	Average Recognition Rate
10	0.515
15	0.63
25	0.56
45	0.52
60	0.465
120	0.39

Random Features

Feature size	Average Recognition Rate
20	0.465
80	0.42
120	0.095

LC-KSVD Algorithm

Here are the results using Label Consistent K-SVD algorithm. This method is very parameter dependent and needs to be tuned carefully. The results of this method using a smaller dictionary is better compared to the same results from SRC.

sparsitythres	sqrt_alpha	sqrt_beta	iterations	iterations4ini	dictsize	Feature	Feat-size	LC-KSVD1	LC-KSVD2
10	2	3	60	50	200	Downsampled	120	0.240	0.910
					120	Downsampled		0.245	0.590
					200	PCA		0.825	0.815
					120	PCA		0.795	0.800
					200	Random		0.815	0.815
					120	Random		0.725	0.790

Summary

The face recognition was done using SRC (sparse representation-based classification) algorithm. Four different types of features were used along with this algorithm. Then the dictionary size was reduced to almost half, by choosing 3 out of 5 pictures for each person, so the total number of columns was reduced to 120 instead of 200. This reduction made the recognition rate to decrease. Using the smaller dictionary in LC-KSVD algorithm had slightly better recognition rates.