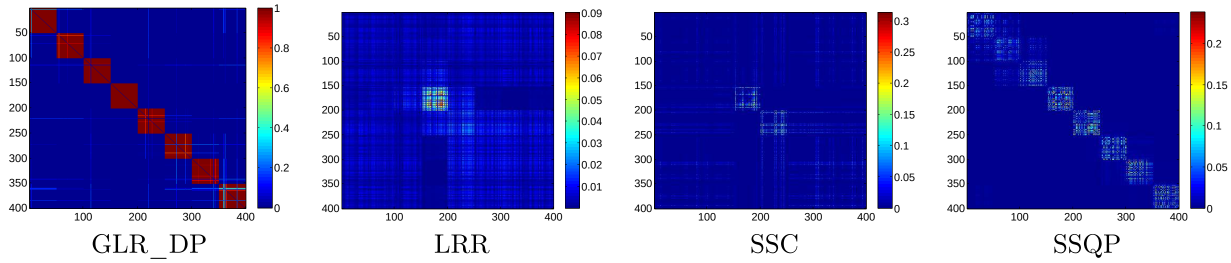

Figure 4. The affinity matrices produced by reconstruction based methods. The samples are ordered so that samples from the same cluster are adjacent.

Table 1. Accuracy on the Hopkins 155 Dataset

Method	Mean	Median	Min
LRR	.9504	.9948	.5820
SSC	.9729	1	.5766
SSQP	.9536	1	.5450
GCR-DP	.9764	1	.5532
GCR	.9608	.9970	.5833

Table 2. Accuracy on the MSRC Dataset with 459 Images

Method	Mean	Median	Min
LRR	.6625	.6500	.3514
SSC	.6548	.6400	.3673
SSQP	.6550	.6374	.3784
GCR-DP	.6651	.6667	.3587
GCR	.7046	.6964	.3838

gion is given a label, and there are totally 23 labels). Following (Cheng et al., 2011), for each image, we group the superpixels, which are small patches in an *over-segmented* result, with subspace clustering methods. The groundtruth (cluster label) for a superpixel is given as the label of region it belongs to.

In our experiment, 100 superpixels are extracted for each image with the method described in (Mori et al., 2004), and each superpixel is represented with the RGB Color Histogram feature of dimensionality 768. We discard all the superpixels with label "background", and then discard the images containing only one label. Finally, we get 459 images. For each image, the average number of superpixels is 91.3, and the number of clusters ranges from 2 to 6. We use PCA to reduce the dimensionality to 20 in order to keep 95% energy. The results are show in Table 2.

Clearly, our methods outperform the other three on this dataset. GCR also performs better than GCR-DP because it utilizes the information about the number of latent subspaces during the reconstruction step.

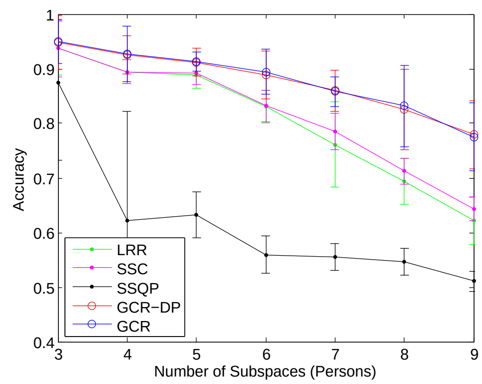

Figure 5. Results On Extended YaleB Dataset with Increasing Number of Subspaces.

4.4. Human Face Dataset

We also evaluate our method on the Extended Yale Database B (Georghiades et al., 2001). This database contains 2414 cropped frontal human face images from 38 subjects under different illuminations, and grouping these images can be treated as a subspace clustering problem, because it is shown in (Ho et al., 2003) that the images for a fixed face under different illuminations can be approximately modeled with low dimensional subspace. To evaluate the performance of all these methods, we form 7 tasks, each of which contains the images from randomly picked $\{3, 4, \cdots, 9\}$ subjects, respectively. We resize the images to 42×48, then use PCA to reduce the dimensionality of the raw features to 30. We repeat the experiment for 5 times and show the results in Figure 5.

The performance of GCR and GCR-DP are better than the other three methods. In particular, with the number of subspaces increasing, the difference between the l.h.s. and r.h.s. of Eq.(1) increases (see Figure 1). Consequently, the performance of LRR, SSC and SSQP, which rely on the subspace independence assumption to build the affinity matrix, degrades quickly. On the contrary, GCR and GCR-DP utilize the information that "the samples can be grouped into subspaces", thus they are less influenced by the violation of subspace independence assumption.