Double low-rank representation with projection distance penalty for clustering
(Supplementary Material)

Zhiqiang Fu[1,2], Yao Zhao[1,2]*, Dongxia Chang[1,2], Xingxing Zhang[3], Yiming Wang[1,2]

[1]Institute of Information Science, Beijing Jiaotong University

[2]Beijing Key Laboratory of Advanced Information Science and Network Technology

[3]Department of Computer Science and Technology, Tsinghua University

{zhiqiangfu, yzhao, dxchang}@bjtu.edu.cn, xxzhang2020@mail.tsinghua.edu.cn, wangym@bjtu.edu.cn

In this supplementary material, some additional experimental results are shown to evaluate our method. In section 1, the comparision of computational time is are given. The ablation experiments, comparision with deep method and addtional result on the noisy data are shown in section 2, 3 and 4 respectively.

1. Computational time

The computational time of our method is shorter than most improved LRR methods. Here, the Control database is used as an example, and the time cost is shown in Fig. 1. We can find that the time cost of our method is less than the other improved LRR methods.

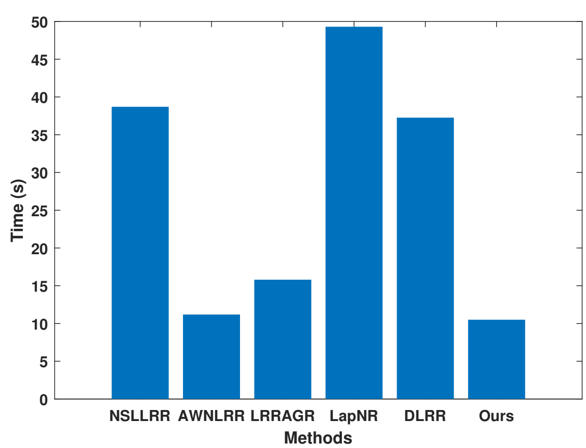

Figure 1. The time cost of improved LRR methods on Control

2. Ablation experiments

We have conducted more ablation experiments. The results are shown in Table 1 , where I_1, I_2 and I_3 denote our three improvements: projection distance penalty, rank constraint and Frobenius norm. It can be found from the Table 1 that the each term is important and can improve the clustering results. In addtion, $z\mathbf{1} = 1$ is used to avoid the trivial solution, and the ablation experiments are shown in Table 2.

Table 1. Effectiveness of each improvement measured by ACC

Dataset	$I_2 + I_3$	$I_1 + I_3$	$(I_1 + I_2)^a$	$I_1 + I_2 + I_3$
Cars	63.32	67.86	67.86	68.37
Control	70.50	67.67	71.00	76.33
Glass	51.40	52.80	55.61	58.48

^{a} This denotes using nuclear norm instead of Frobenius norm.

Table 2. Ablation experiments of $z\mathbf{1} = 1$.

Condition	Cars	Control	Glass	Auto
with $z\mathbf{1} = 1$	68.37	76.33	58.48	46.83
without $z\mathbf{1} = 1$	67.85	74.86	56.86	43.41

3. Comparision with JULE

JULE[1] and our method are compared on seven image databases. Our method outperforms JULE on six databases. Some results are shown in Table 3.

4. Additional results on noisy data

Fig.2 shows the recovered faces that are recovered from Umist database with salt & pepper noise. We can find that the proposed method can effectively learn the principal features from the noised data. In addition, the robustness of our method can also be shown by handling the data with Gaussian noise. In this experiment, random Gaussian noise with the fixed variance is added to the Umist and MSRA. And then, the clustering results of noisy data are shown in Fig.4, where the variance is set to $[0, 300, 600, 900, 1200, 1500]$ and some noisy images are also shown. We can find that: 1) compared with salt & pepper noise, all methods are less sensitive to Gaussian noise; 2) our DLRRPD can obtain competitive accuracies under different noise levels. Hence, our method is also robust for handling the data with Gaussian

Table 3. Clustering ACC of JULE and DLRRPD

Database	Umist	MSRA	Jaffe	Dig	USPS	Binalpha	COIL20
JULE	62.74	51.14	96.73	88.12	59.70	44.32	87.50
DLRRPD	80.17	72.98	100	88.81	59.90	49.20	86.30

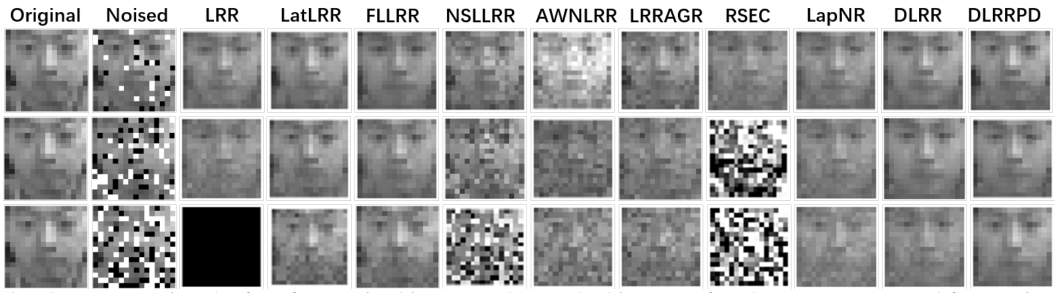

Figure 2. Results about recovering the face from noised images. The resulted images of each row are recovered from noised images with 10%, 30% and 50% salt & pepper noise, respective.

noise. Furthermore, Fig.5 and 6 show some recovering results. As shown, the proposed method can recover more details when the faces recovered by the other methods are over-smoothing.

References

[1] J. Yang, D. Parikh, and D. Batra. Joint unsupervised learning of deep representations and image clusters. In *IEEE Conf. Comput. Vis. Pattern Recog.*, pages 5147–5156, 2016. 1