Supplementary Material for "Self-Supervised Convolutional Subspace Clustering Network"

Anonymous CVPR submission

Paper ID 3260

1. Ablation Study

To gain further understanding of the proposed dual self-supervision, we conduct ablation studies for both of S^{2}ConvSCN-ℓ_1 and S^{2}ConvSCN-ℓ_2 on all the four datasets—ORL, COIL20, COIL100 and Extended Yale B. The experimental results are shown in Table 1, 2, 3, and 4.

Loss	ORL	COIL20	COIL100
$\mathcal{L}_0$	15.25	7.92	34.94
$\mathcal{L}_0 + \mathcal{L}_1 + \mathcal{L}_2$(DSC)	14.25	5.65	33.62
$\mathcal{L}_0 + \mathcal{L}_1 + \mathcal{L}_2 + \mathcal{L}_3$	12.75	3.42	31.14
$\mathcal{L}_0 + \mathcal{L}_1 + \mathcal{L}_2 + \mathcal{L}_4$	12.25	3.27	28.53
$\mathcal{L}_0 + \mathcal{L}_1 + \mathcal{L}_2 + \mathcal{L}_3 + L_4$	**10.50**	**2.14**	**26.67**

Table 1. Ablation Study of S^{2}ConvSCN-ℓ_1.

Loss	ORL	COIL20	COIL100
$\mathcal{L}_0$	15.40	7.92	32.63
$\mathcal{L}_0 + \mathcal{L}_1 + \mathcal{L}_2$(DSC)	14.25	5.65	30.96
$\mathcal{L}_0 + \mathcal{L}_1 + \mathcal{L}_2 + \mathcal{L}_3$	12.25	3.15	31.79
$\mathcal{L}_0 + \mathcal{L}_1 + \mathcal{L}_2 + \mathcal{L}_4$	12.00	2.75	28.17
$\mathcal{L}_0 + \mathcal{L}_1 + \mathcal{L}_2 + \mathcal{L}_3 + L_4$	**11.25**	**2.33**	**27.83**

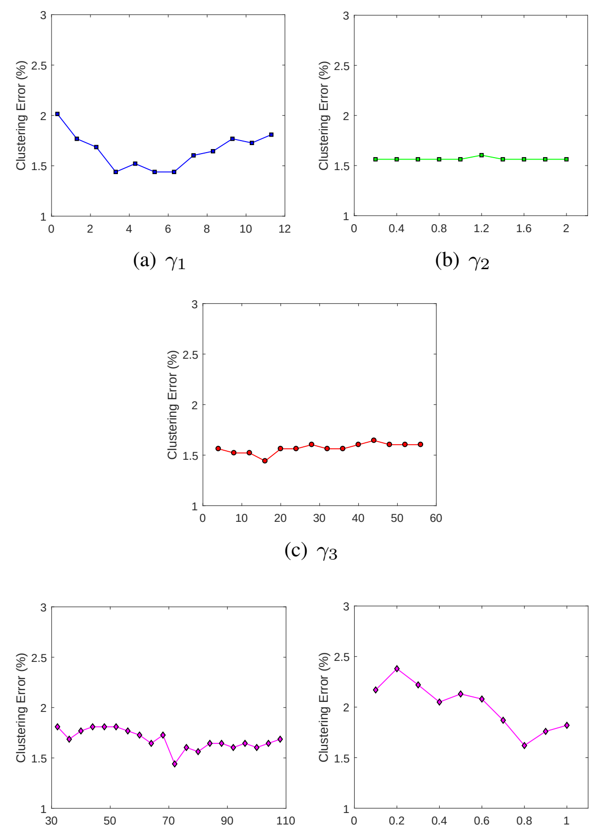
Table 2. Ablation Study of S^{2}ConvSCN-ℓ_2.

In DSC [1], the combination of the loss $\mathcal{L}_0 + \mathcal{L}_1 + \mathcal{L}_2$ is used. As a baseline, we also add the experimental results of using only $\mathcal{L}_0$ to train the convolutional feature extraction module.

As could be read, the dual self-supervision does yield the best performance on all the four datasets. These results confirm the effectiveness of using the labeling information from spectral clustering to supervise both the feature extraction module and the self-expression model.

2. Evaluation on Tradeoff Parameters

To evaluate the performance of using different parameters, we use S^{2}ConvSCN-ℓ_1 as an example and conduct experiments with varying one parameter while keeping other parameters fixed on dataset Extended YaleB ($n = 38$). Experimental results are listed in Fig. 1.



(a) γ_1 (b) γ_2 (c) γ_3 (d) γ_4 (e) τ

Figure 1. Performance Evaluation of S^{2}ConvSCN-ℓ_1 under Varying Each Parameter $\gamma_1, \gamma_2, \gamma_3$, γ_4, and τ on Extended Yale B ($n = 38$).

3. Curves of Loss Functions during Iteration Period Compared to DSCNet [1]

To compare our proposed S^{2}ConvSCN-ℓ_1 and DSCNet-ℓ_1, we conduct experiments on Extended Yale B and record each loss as a curve of the iteration index. Experimental results are displayed in Fig. 2.

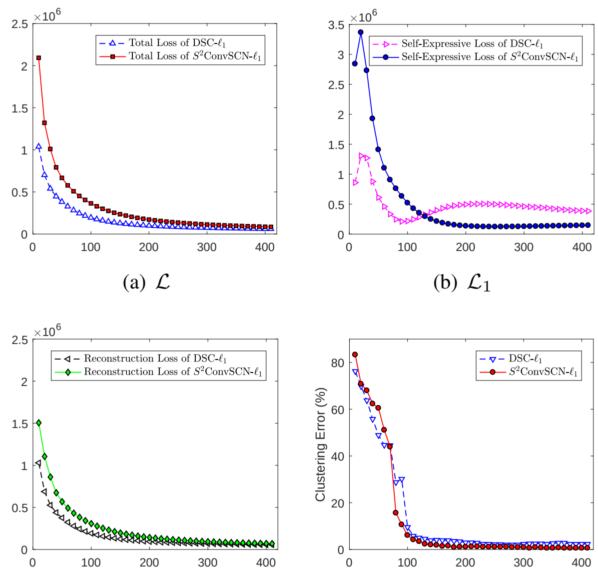
Compared to DSCNet [1], the curves of each loss func-

Losses \ No. Subjects	10 subjects		15 subjects		20 subjects		25 subjects		30 subjects		35 subjects		38 subjects	
	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median
$\mathcal{L}_0$	2.20	1.88	2.41	2.29	2.38	2.34	2.58	2.75	2.89	2.92	3.30	3.28	3.21	3.21
$\mathcal{L}_0+\mathcal{L}_1+\mathcal{L}_2$(DSC)	2.23	2.03	2.17	2.03	2.17	2.11	2.53	2.19	2.63	2.81	3.09	3.10	3.33	3.33
$\mathcal{L}_0+\mathcal{L}_1+\mathcal{L}_2+\mathcal{L}_3$	1.58	1.25	1.63	1.55	1.67	1.57	1.61	1.63	2.74	1.82	2.64	2.65	2.75	2.75
$\mathcal{L}_0+\mathcal{L}_1+\mathcal{L}_2+\mathcal{L}_4$	1.32	1.09	1.31	1.30	1.54	1.48	1.48	1.98	1.87	**1.61**	1.82	1.84	1.92	1.92
$\mathcal{L}_0+\mathcal{L}_1+\mathcal{L}_2+\mathcal{L}_3+\mathcal{L}_4$	**1.18**	**1.09**	**1.12**	**1.14**	**1.30**	**1.25**	**1.29**	**1.28**	**1.67**	1.72	**1.62**	**1.60**	**1.52**	**1.52**

Table 3. Ablation Study of S^{2}ConvSCN-ℓ_1 on Extended Yale B.

Losses \ No. Subjects	10 subjects		15 subjects		20 subjects		25 subjects		30 subjects		35 subjects		38 subjects	
	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median
$\mathcal{L}_0$	2.22	2.03	2.44	2.29	2.38	2.34	2.58	2.75	2.89	2.92	3.34	3.35	3.17	3.17
$\mathcal{L}_0+\mathcal{L}_1+\mathcal{L}_2$(DSC)	1.59	1.25	1.69	1.72	1.73	1.80	1.75	1.81	2.07	2.19	2.65	2.64	2.67	2.67
$\mathcal{L}_0+\mathcal{L}_1+\mathcal{L}_2+\mathcal{L}_3$	1.48	1.25	1.42	1.36	1.66	1.65	1.58	1.60	2.68	1.71	2.15	2.16	2.54	2.54
$\mathcal{L}_0+\mathcal{L}_1+\mathcal{L}_2+\mathcal{L}_4$	1.18	1.09	1.15	1.14	1.37	1.34	1.43	1.98	1.99	2.18	2.22	1.74	1.85	1.85
$\mathcal{L}_0+\mathcal{L}_1+\mathcal{L}_2+\mathcal{L}_3+\mathcal{L}_4$	**1.18**	**1.09**	**1.14**	**1.14**	**1.31**	**1.32**	**1.32**	**1.43**	**1.71**	**1.77**	**1.67**	**1.69**	**1.56**	**1.56**

Table 4. Ablation Study of S^{2}ConvSCN-ℓ_2 on Extended Yale B.



(a) $\mathcal{L}$ (b) $\mathcal{L}_1$

(c) $\mathcal{L}_0$ (d) Clustering Error (%)

Figure 2. Comparison between DSC-ℓ_1 and our S^{2}ConvSCN-ℓ_1 on Extended Yale B (n=10).

tion of our proposed S^{2}ConvSCN-ℓ_1 are smoother. The smoother curves of the loss function during training iterations indicate an improved convergence property, which is coming from the dual self-supervision. Thus, exploiting the labeling information from spectral clustering to supervise not only the feature extraction module but also the self-expression model is beneficial to produce better performance and also make the training easier.

References

[1] P. Ji, T. Zhang, H. Li, M. Salzmann, and I. Reid. Deep subspace clustering networks. In *Neural Information Processing Systems (NIPS)*, 2017. 1