

Supplementary file

Due to the paper's space limitations, some tables, pictures, and discussions are presented here as the supplementary file.

I. PART 1

This part is complementary to **Experiment 1**. Some hyperparameters need to be set in the comparison methods. In general, we use the defaults provided by the comparison methods. However, some parameters should be reset based on the datasets. Here we set those parameters as feasible solutions when obtaining better results. Table I reports some parameters that need to be reset in comparison methods. Figs. 1-8 shows the results of comparison methods on the eight datasets.

Table I: Some given parameters in comparison methods.

Datasets	ECM	MS-type	BPEC	DPC-DBFN
SD1	$\alpha = 8, \delta = 8$	$r = 0.9$	$K = 250$	$K = 10$
SD2	$\alpha = 8, \delta = 8$	$r = 1.0$	$K = 250$	$K = 10$
SD3	$\alpha = 8, \delta = 8$	$r = 10$	$K = 250$	$K = 10$
SD4	$\alpha = 8, \delta = 8$	$r = 2.0$	$K = 250$	$K = 10$
SD5	$\alpha = 8, \delta = 8$	$r = 0.9$	$K = 250$	$K = 10$
SD6	$\alpha = 8, \delta = 8$	$r = 1.18$	$K = 250$	$K = 30$
SD7	$\alpha = 8, \delta = 8$	$r = 2.0$	$K = 250$	$K = 30$
SD8	$\alpha = 8, \delta = 8$	$r = 1.3$	$K = 250$	$K = 50$

II. PART 2

This part is complementary to **Experiment 2**. Fig. 9 shows the results of different methods on the Olivetti faces dataset. From Fig. 9 we can find that DPC and its improved methods, i.e., CDPC, BPEC, DPC-DBFN, TCASP, fail to select the five real (best) cluster centers because they do not consider the diversity of distribution of different clusters. DPC and DPC-DBFN find only four valid centers, and TCASP finds only three. Moreover, the results of these methods are not reasonable. For example, DPC, CDPC, and DPC-DBFN could not classify the second and third person, while BPEC and TCASP could hardly classify these five people. For MC, ECM and MS-type, they are unable to classify some images in two or more classes, and they even assign images from different classes to one cluster. In contrast, the proposed RUIBC method is able to select the real/reasonable cluster centers and can assign most of the images correctly. For those imprecise images, they are assigned to proper meta-clusters because their neighbors' complementary information is fully considered by the evidential convergence rule. Thus, RUIBC can effectively characterize the uncertainty and imprecision between clusters.

III. PART 3

This part is complementary to **Experiment 3**. Fig. 10 shows the Berkeley Segmentation dataset, the ground truth, and the clustering results by different methods on the given dataset. The discussions have been included in the paper.

IV. PART 4

This part is complementary to **Parametric sensitivity**. Fig. 11 shows the clustering results of RUIBC on the SD1 dataset when we set $\mathcal{K}_1 \in \{200, 250, 300, 350, 400\}$, $\mathcal{K}_2 = 12$, and $\zeta = 0.1$. In contrast, Fig. 12 shows the clustering results when $\mathcal{K}_2 \in \{3, 6, 9, 12, 15\}$ with $\mathcal{K}_2 = 12$ and $\zeta = 0.1$. Fig. 13 is used to show how RUIBC can control the imprecision rate by assigning objects to meta-clusters when setting $\zeta \in \{0, 0.03, 0.06, 0.09, 0.12\}$. We can find that RUIBC has good robustness to these three hyper-parameters, i.e., \mathcal{K}_1 , \mathcal{K}_2 , and ζ . The discussions have been included in the paper.

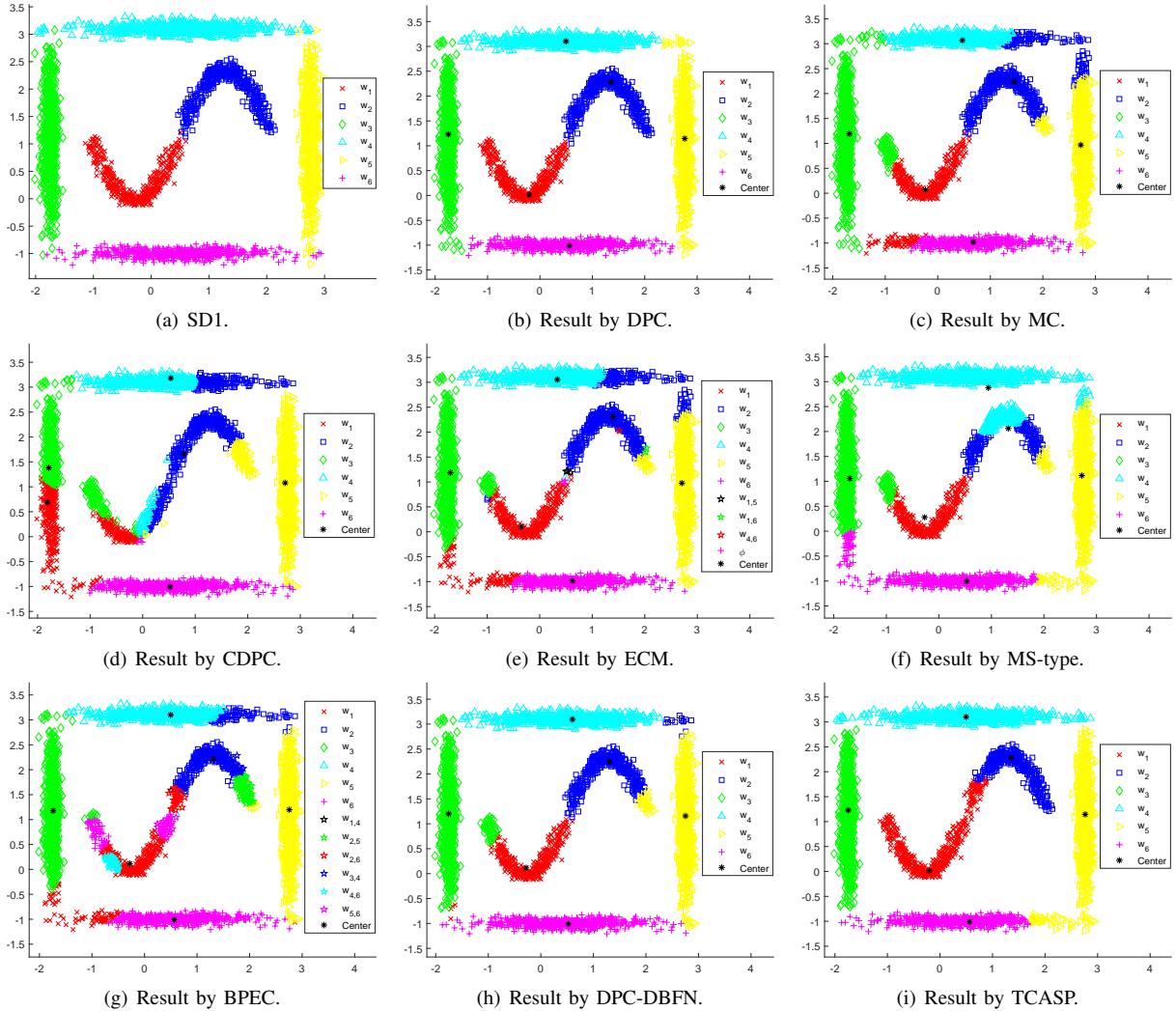


Fig. 1. Clustering results by comparison methods on the SD1 dataset.

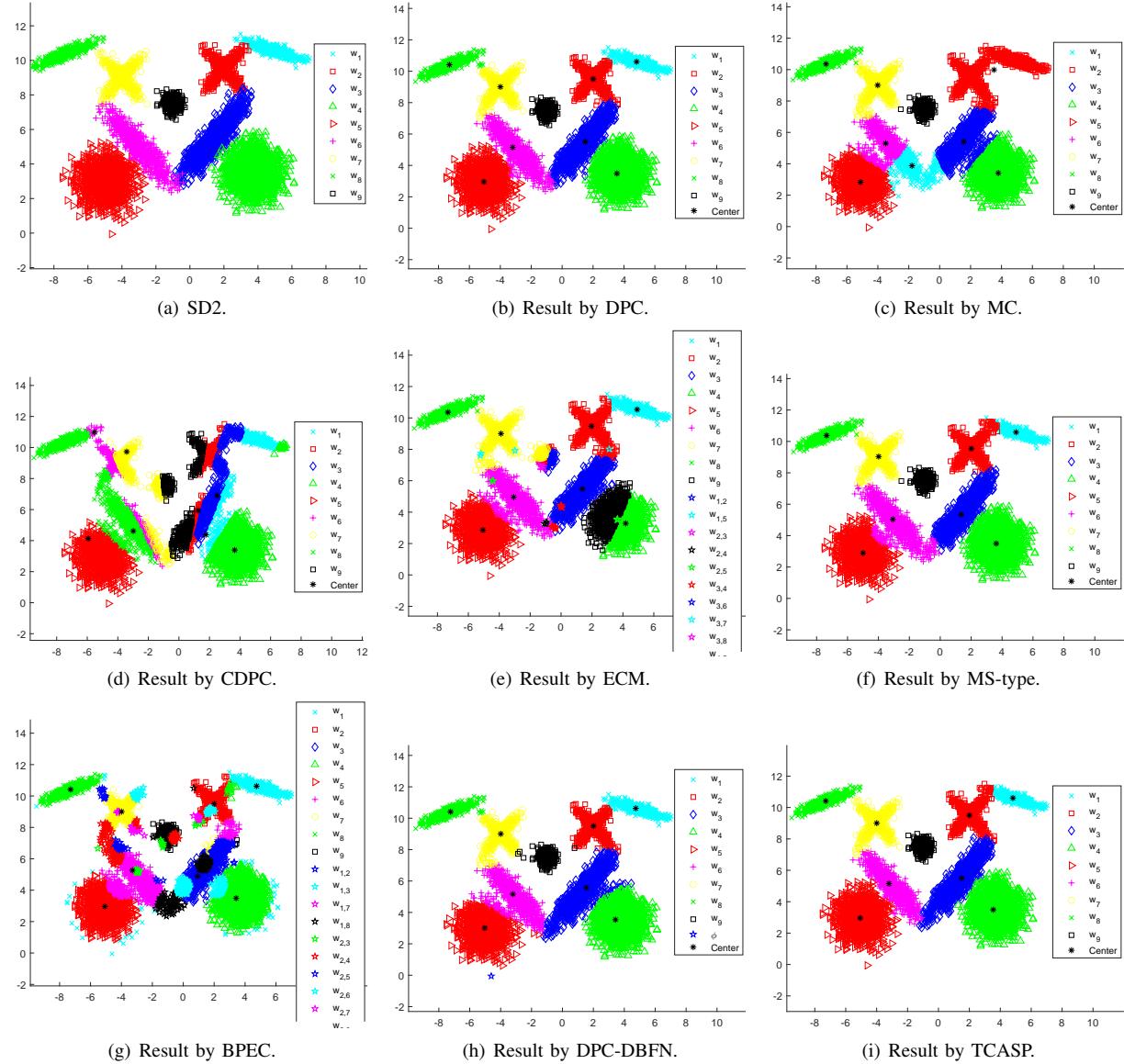


Fig. 2. Clustering results by comparison methods on the SD2 dataset.

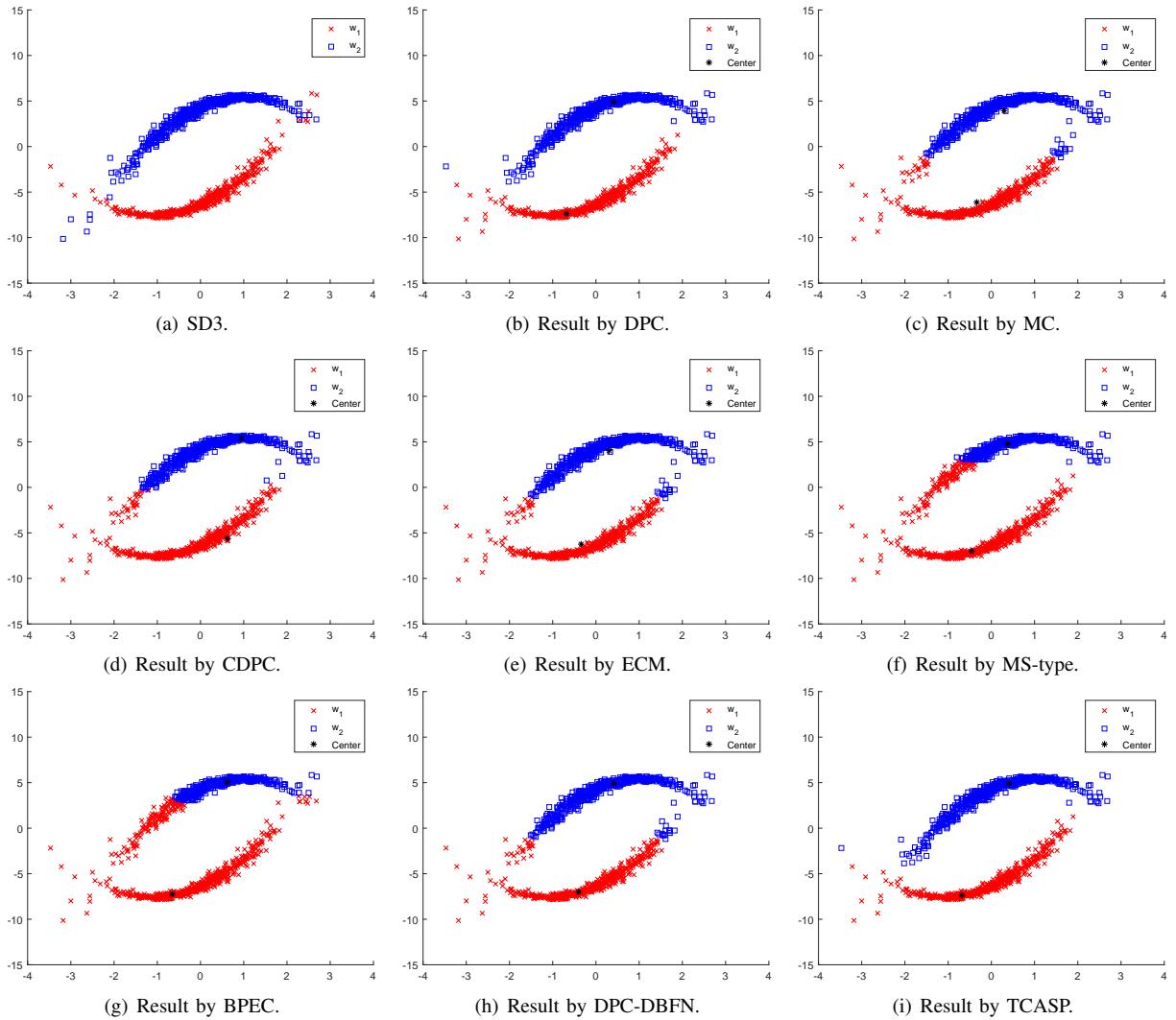


Fig. 3. Clustering results by comparison methods on the SD3 dataset.

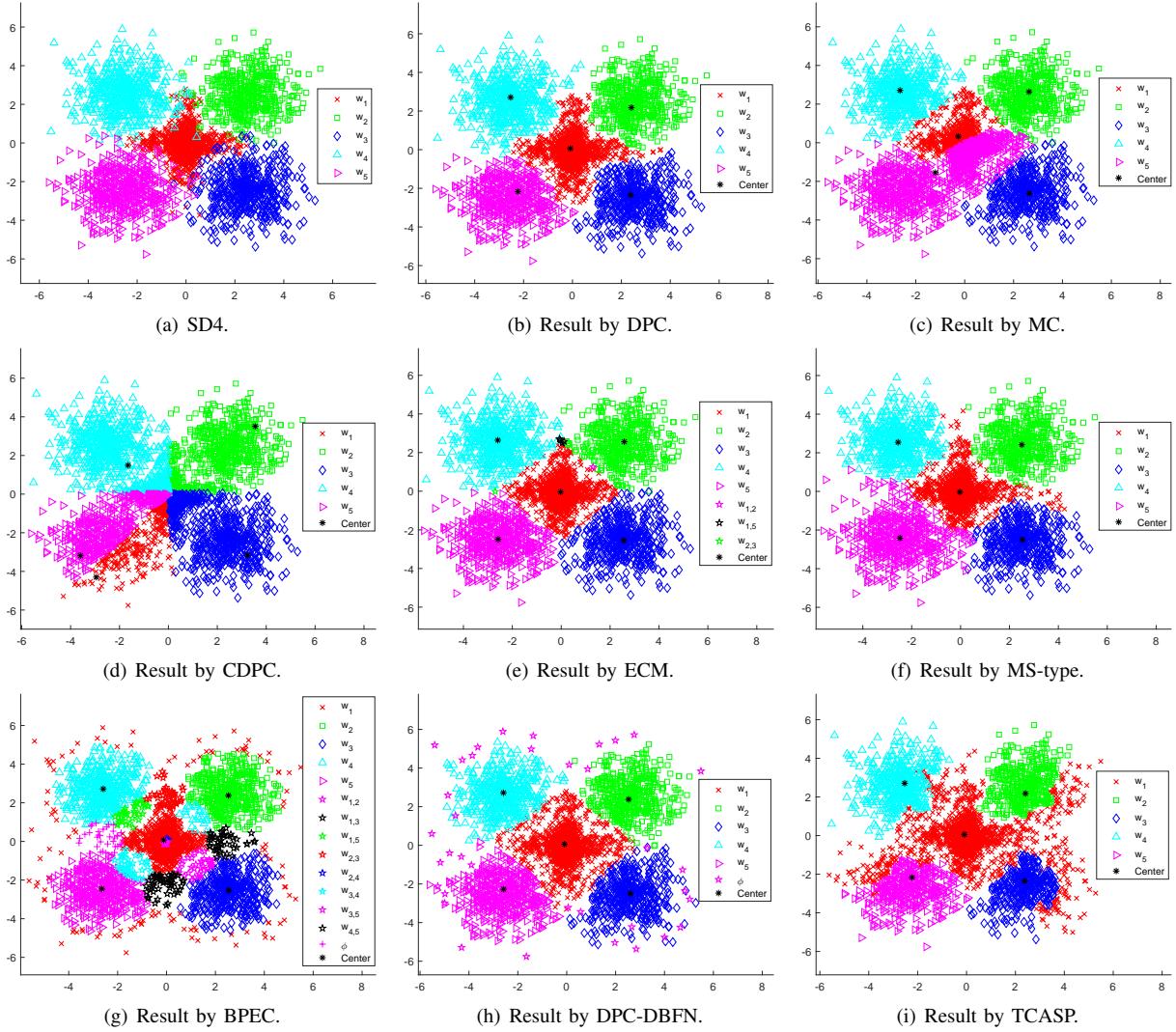


Fig. 4. Clustering results by comparison methods on the SD4 dataset.

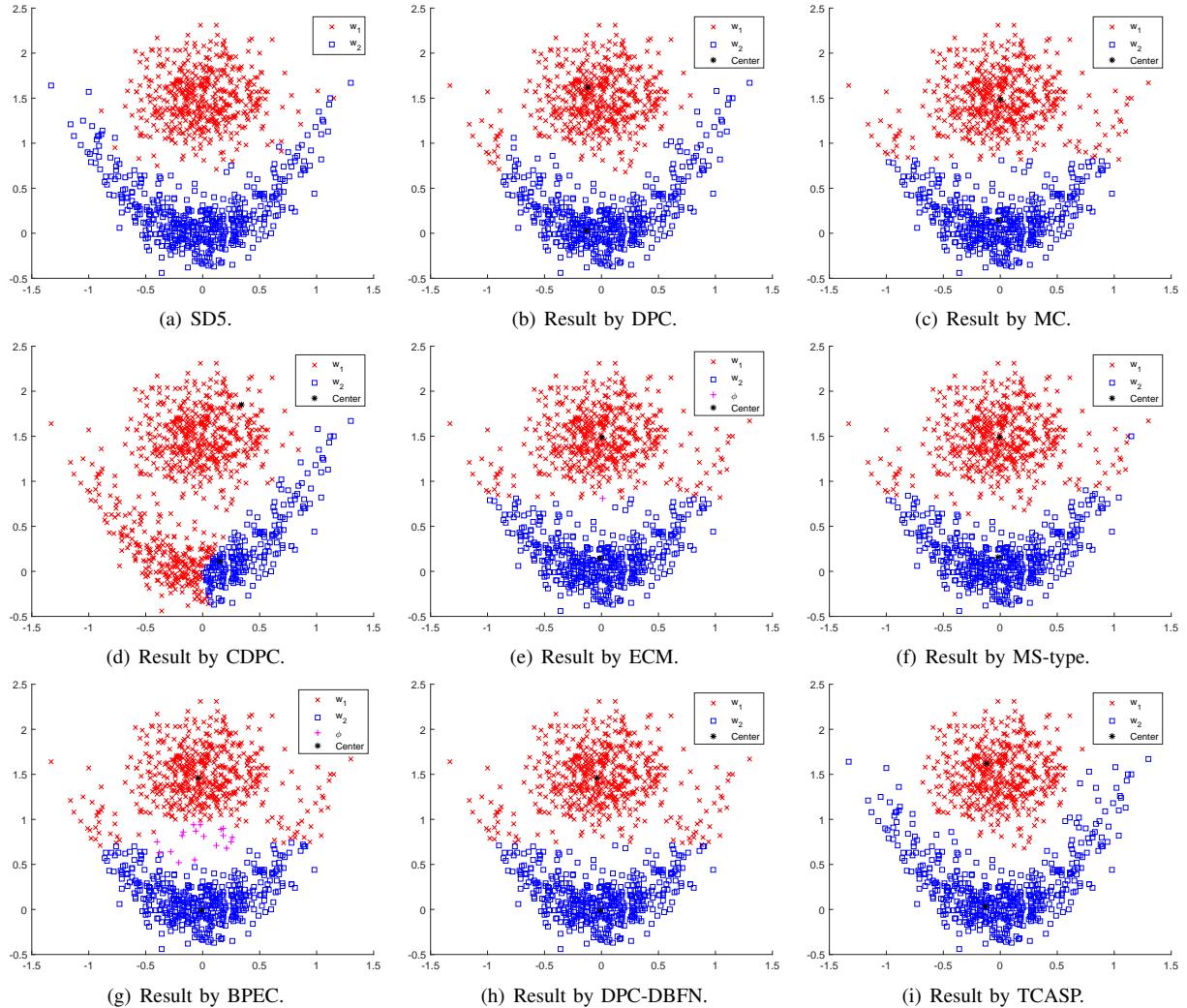


Fig. 5. Clustering results by comparison methods on the SD5 dataset.

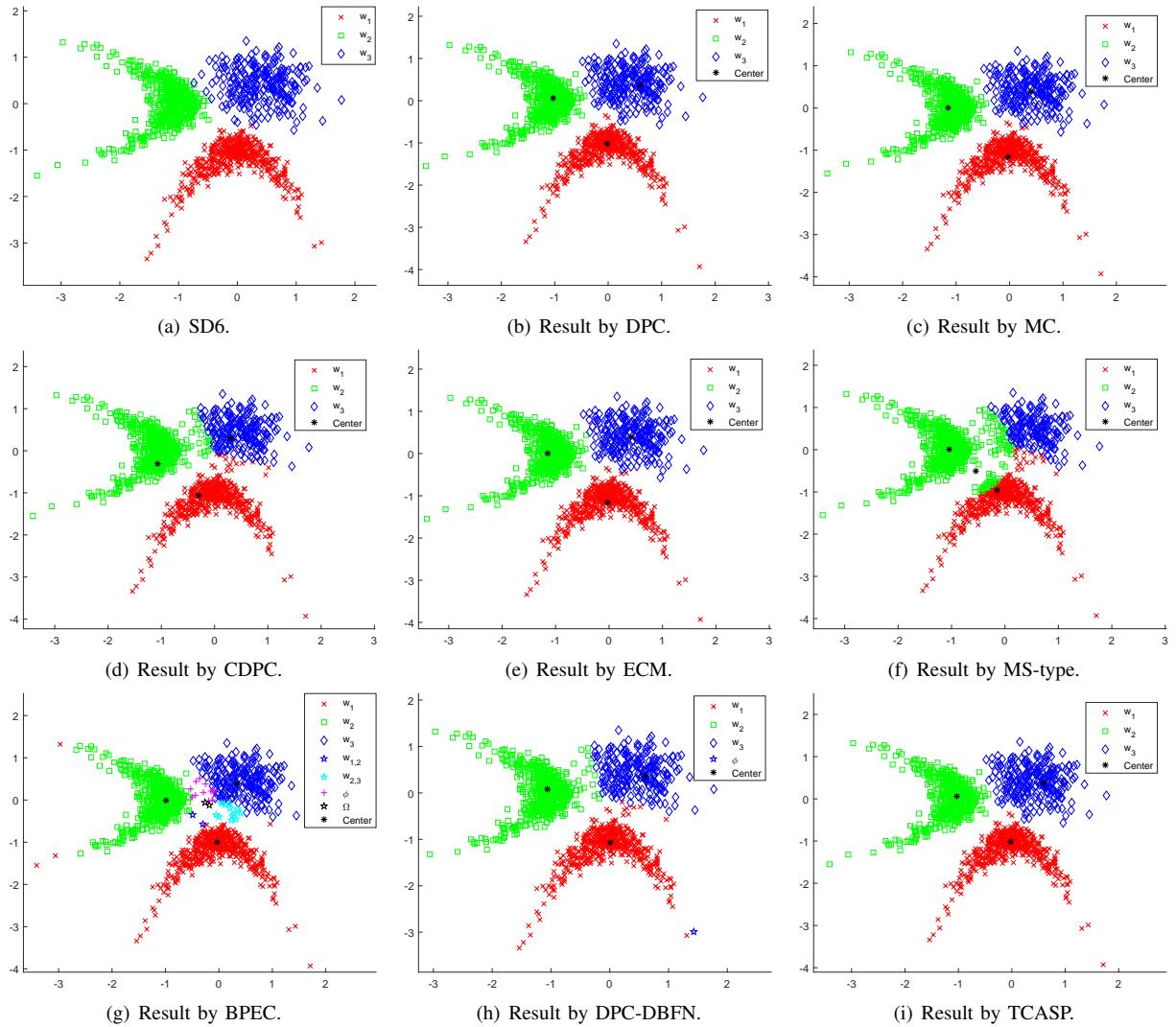


Fig. 6. Clustering results by comparison methods on the SD6 dataset.

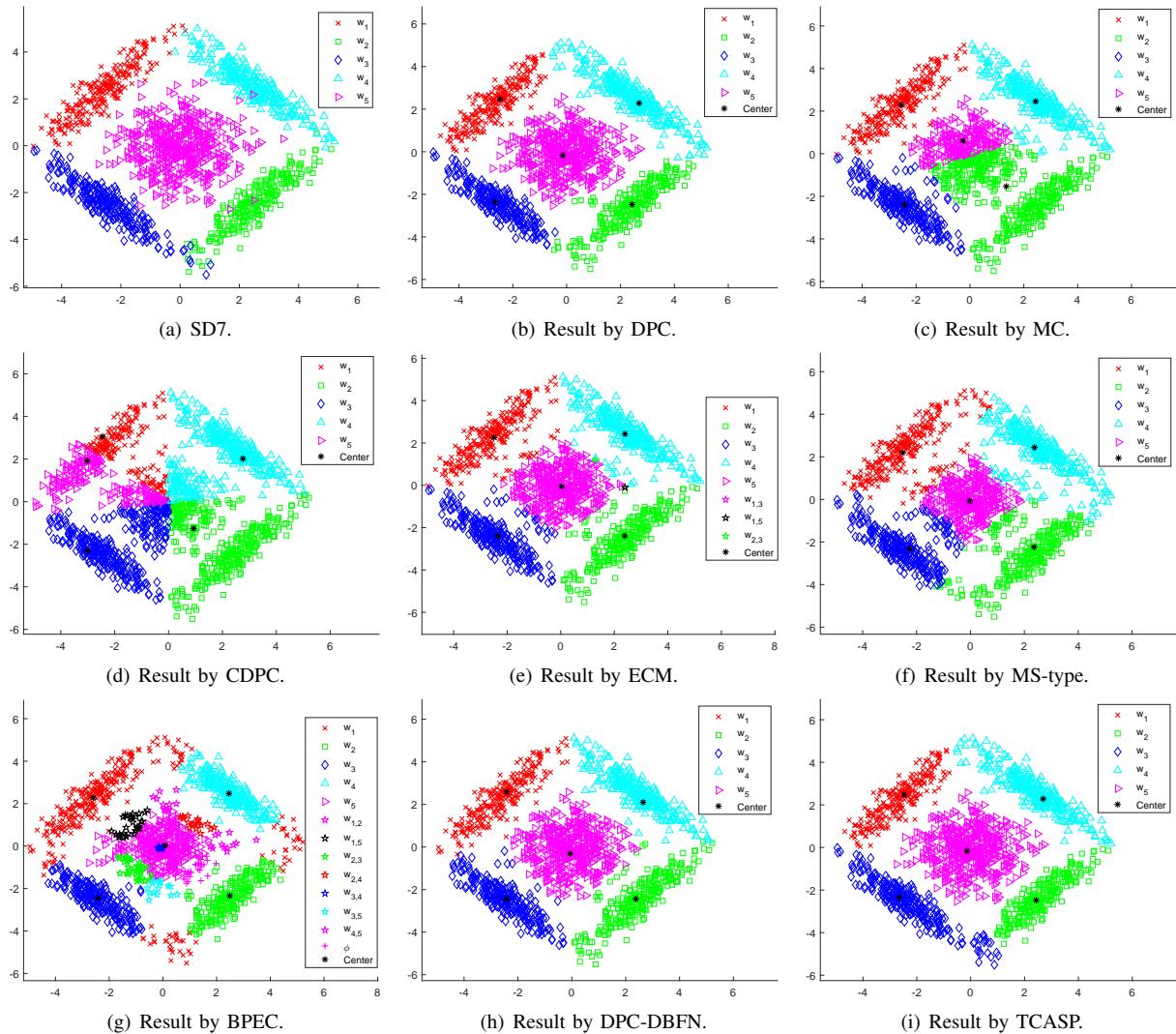


Fig. 7. Clustering results by comparison methods on the SD7 dataset.

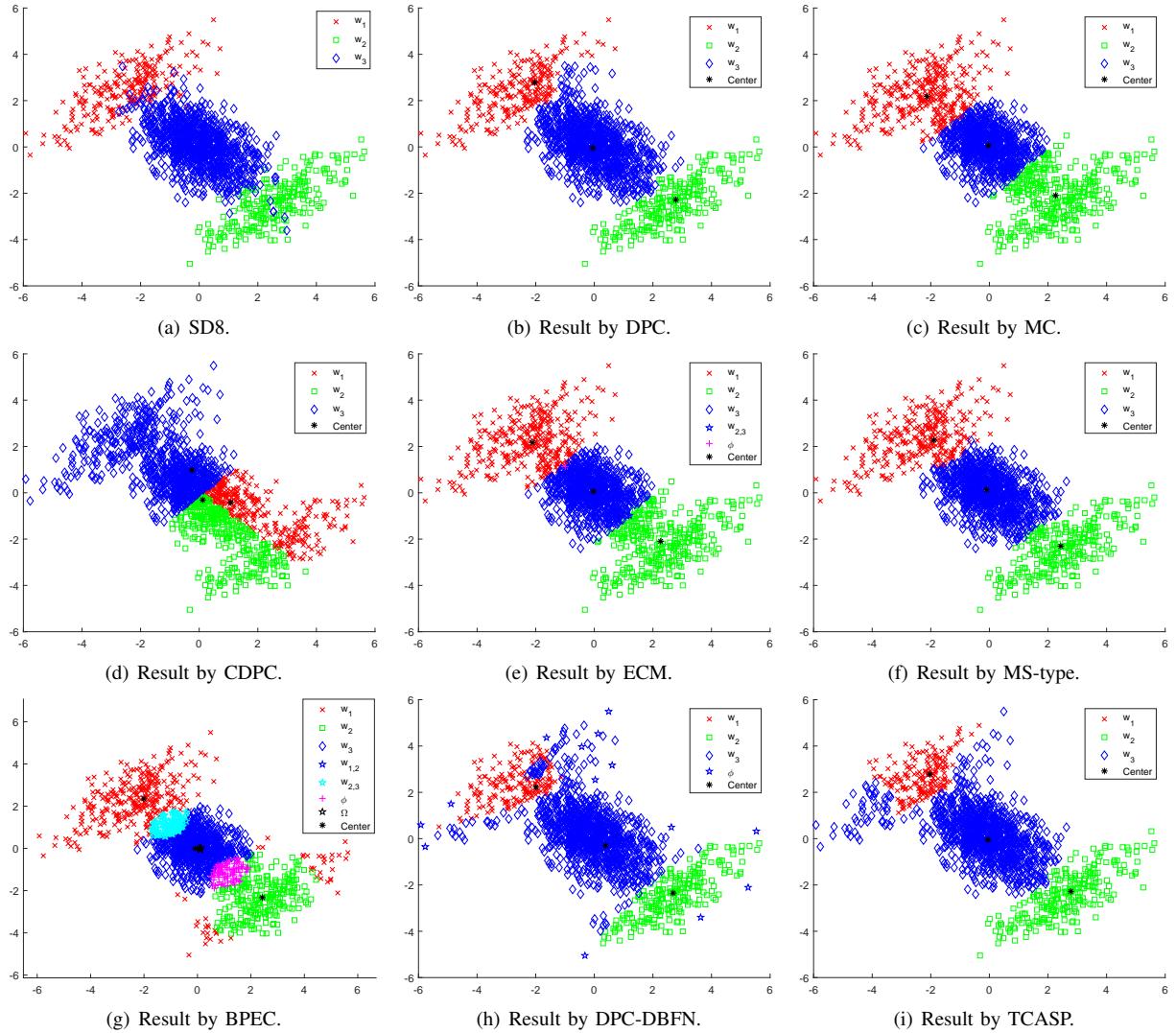


Fig. 8. Clustering results by comparison methods on the SD8 dataset.

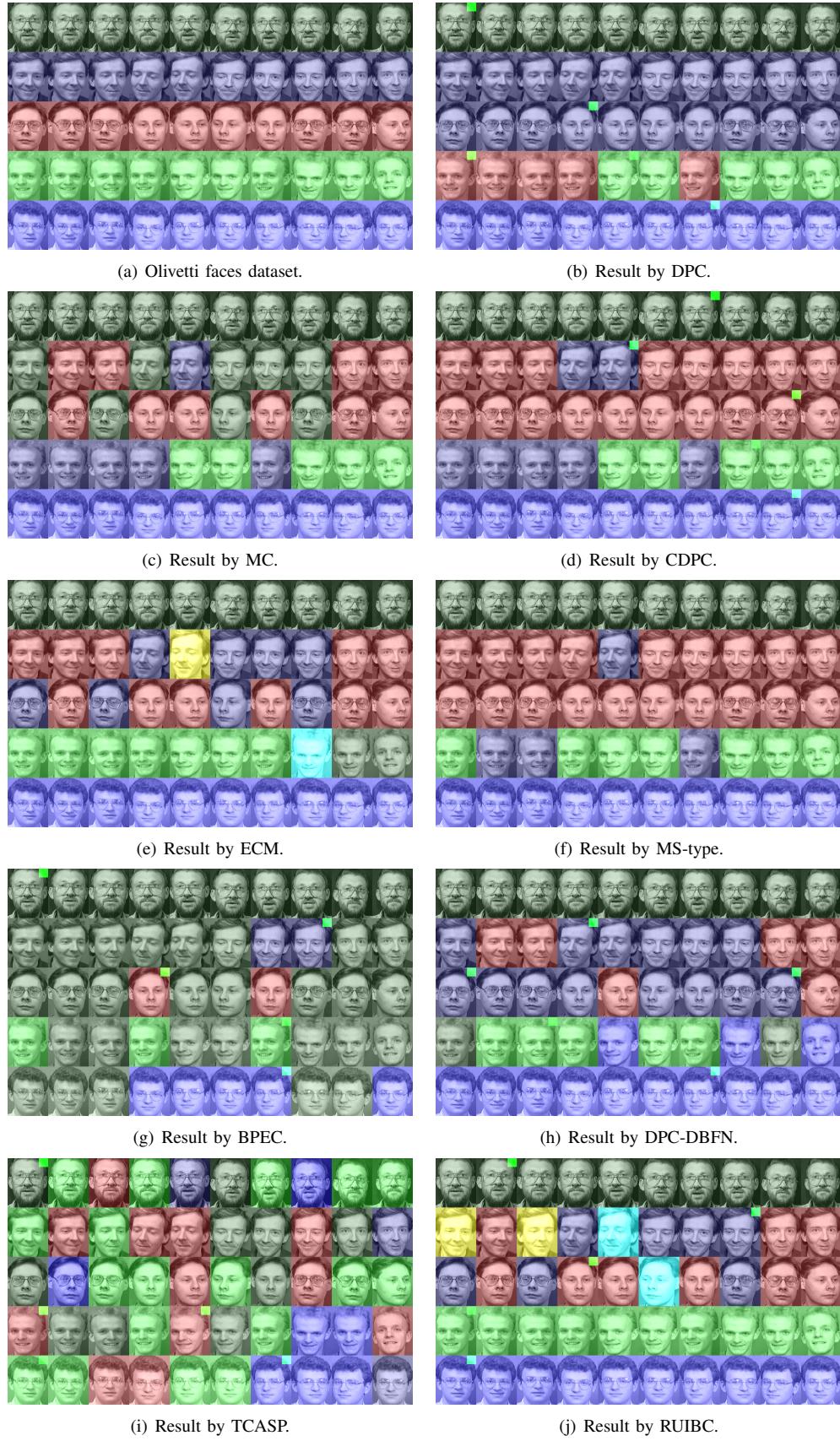


Fig. 9. Clustering results by different methods on the Olivetti faces dataset.

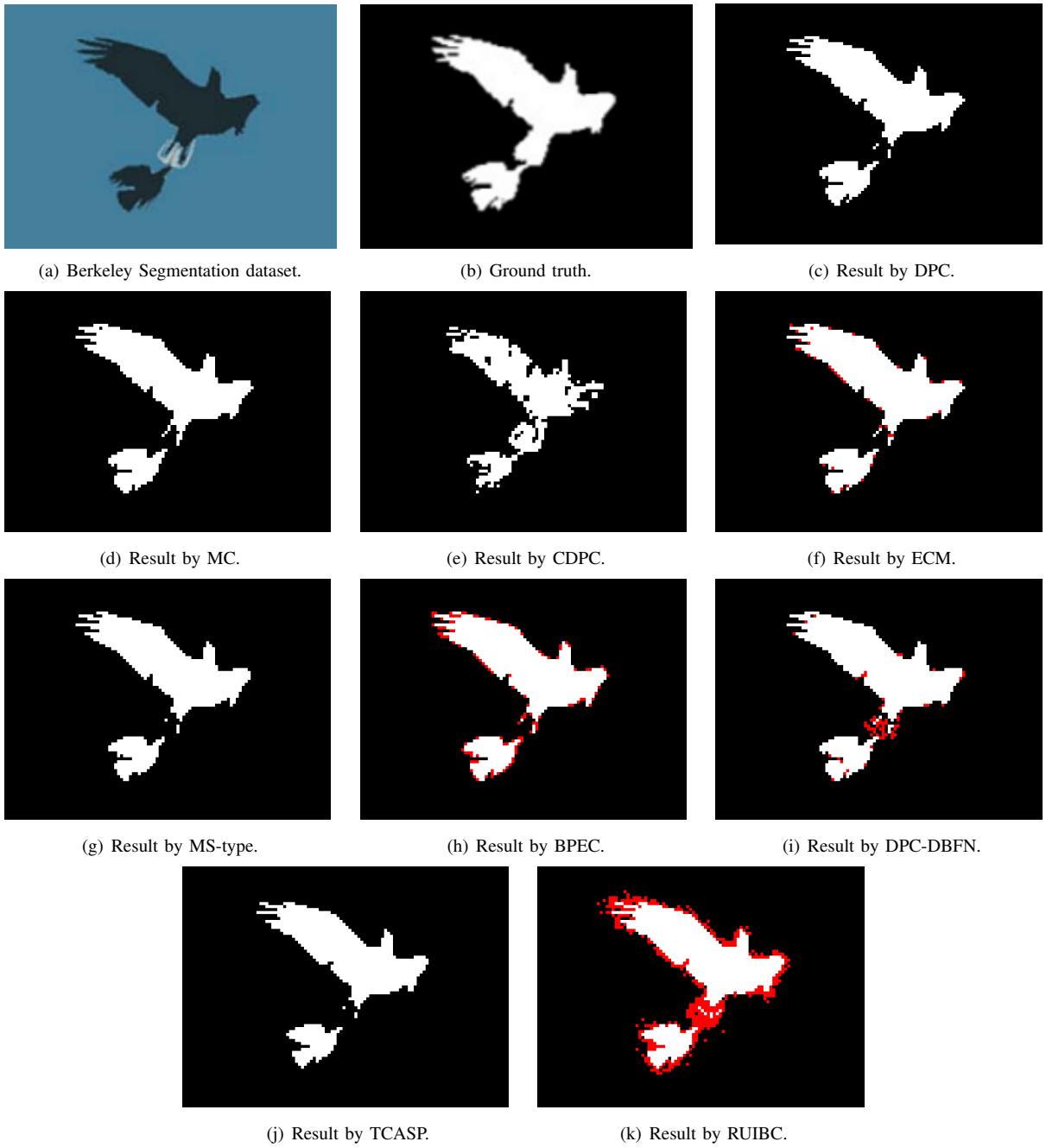


Fig. 10. Clustering results by different methods on the Berkeley Segmentation dataset.

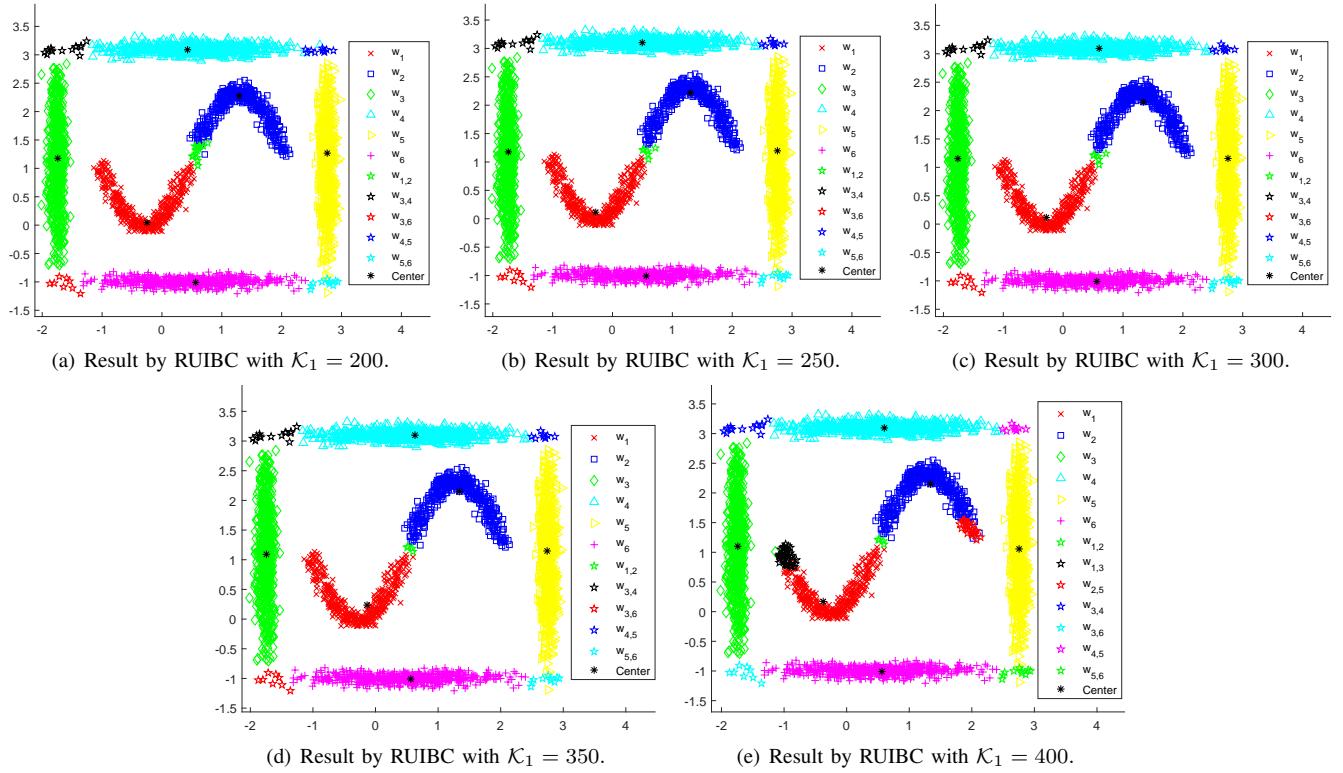


Fig. 11. Clustering results by RUIBC with different \mathcal{K}_1 on the SD1 dataset.

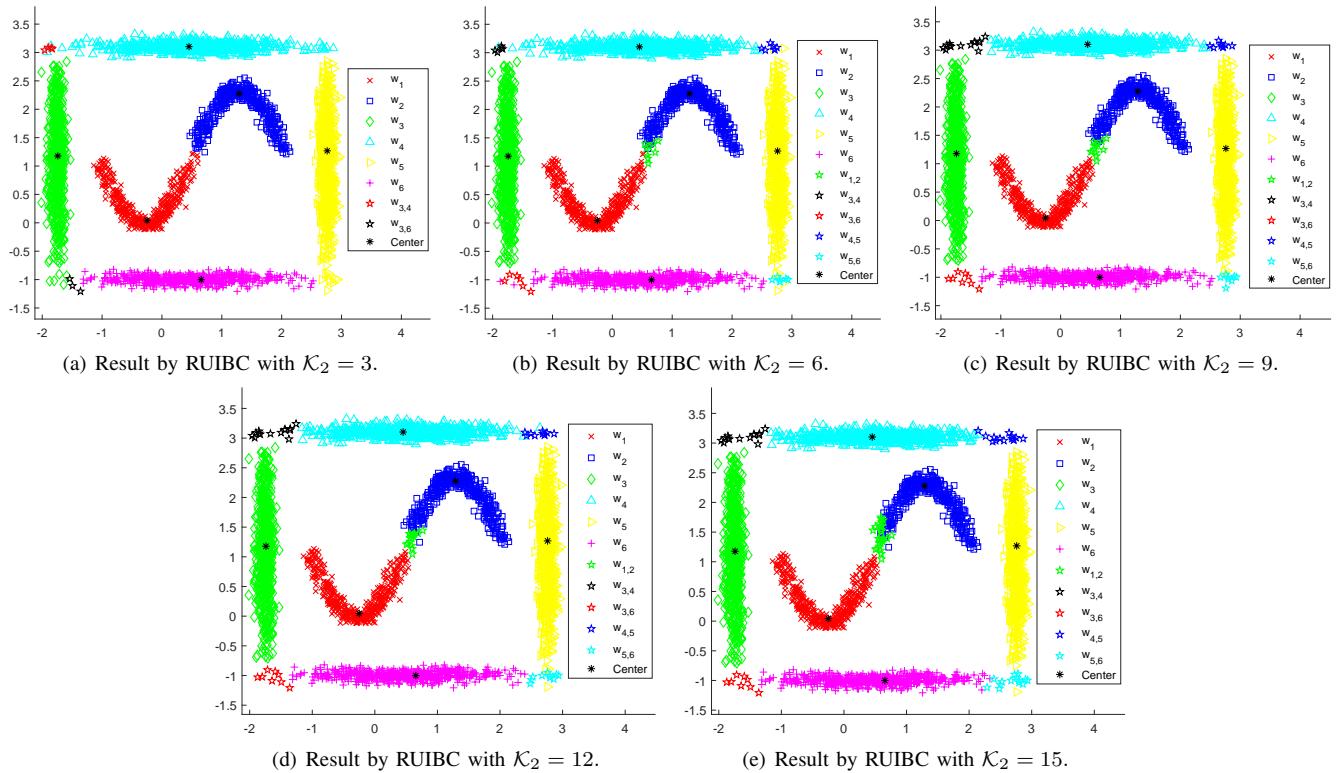


Fig. 12. Clustering results by RUIBC with different \mathcal{K}_2 on the SD1 dataset.

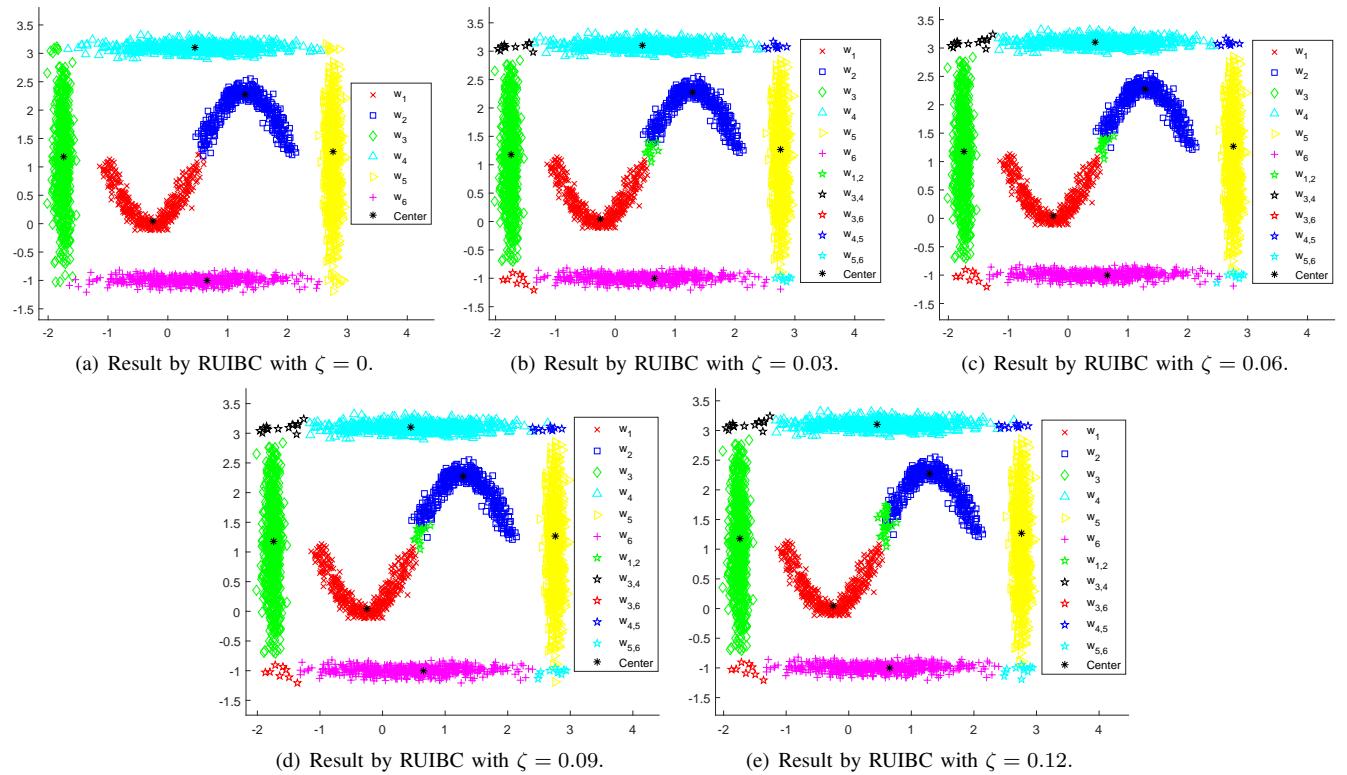


Fig. 13. Clustering results by RUIBC with different ζ on the SD1 dataset.