Table 2: Classification accuracy (%) on the original CMU-PIE with low-level shadow corruptions.

Dataset	Standard Learning		Transfer Learning					
	NN	CESR	GFK	TrFLDA	JDA	LSDT	DTSL	RIDA
P1 *vs* P2	26.09	44.81	26.15	39.23	58.81	26.21	**65.87**	60.10
P1 *vs* P3	26.59	48.41	27.27	35.48	54.23	26.53	**64.09**	62.32
P1 *vs* P4	30.67	61.07	31.15	51.46	84.50	30.64	**82.03**	75.46
P1 *vs* P5	16.67	27.51	17.59	27.21	49.75	16.91	**54.90**	48.22
P2 *vs* P1	24.49	38.39	25.24	31.36	57.62	24.43	45.04	**58.31**
P2 *vs* P3	46.63	68.75	47.37	33.95	62.93	46.57	53.49	**71.02**
P2 *vs* P4	54.07	**84.53**	54.25	61.67	75.82	54.10	71.43	80.29
P2 *vs* P5	26.53	43.32	27.08	25.12	39.89	26.53	47.94	**52.51**
P3 *vs* P1	21.37	32.80	21.82	40.40	50.96	21.40	52.49	**54.89**
P3 *vs* P2	41.01	56.66	43.16	34.56	57.95	41.07	55.56	**65.25**
P3 *vs* P4	46.53	**82.94**	46.41	66.60	68.45	46.53	77.50	80.84
P3 *vs* P5	26.23	43.50	26.78	37.62	39.95	26.23	54.11	**60.60**
P4 *vs* P1	32.95	50.36	34.24	74.04	80.58	32.89	**81.54**	78.45
P4 *vs* P2	62.68	84.47	62.92	78.45	82.63	62.74	85.39	**88.34**
P4 *vs* P3	73.22	90.38	73.35	78.13	87.25	73.10	82.23	**91.12**
P4 *vs* P5	37.19	57.60	37.38	58.64	54.66	37.38	72.61	**75.12**
P5 *vs* P1	18.49	31.33	20.35	42.74	46.46	18.46	**52.19**	48.56
P5 *vs* P2	24.19	38.37	24.62	38.43	42.05	24.19	49.41	**52.67**
P5 *vs* P3	28.31	49.33	28.49	46.02	53.31	28.31	58.45	**62.01**
P5 *vs* P4	31.24	61.16	31.33	57.49	57.01	31.21	64.31	**68.58**
Mean	34.76	54.78	35.35	47.93	60.24	34.78	63.53	**66.73**

Table 3: Classification accuracy (%) on CMU-PIE under added contiguous occlusions

Dataset	Standard Learning		Transfer Learning					
	NN	CESR	GFK	TrFLDA	JDA	LSDT	DTSL	RIDA
P1 *vs* P2	19.15	37.69	19.28	27.93	29.96	19.28	48.13	**50.03**
P1 *vs* P3	20.53	41.54	20.53	24.63	34.80	20.53	46.20	**49.26**
P1 *vs* P4	24.33	52.60	24.36	37.13	53.17	24.30	65.70	**69.21**
P1 *vs* P5	12.93	21.63	13.24	19.06	24.26	12.81	38.66	**39.15**
P2 *vs* P1	18.52	33.28	18.67	20.89	35.32	18.58	36.40	**43.64**
P2 *vs* P3	30.09	**58.21**	30.21	20.89	35.91	30.09	38.48	52.63
P2 *vs* P4	40.04	**79.81**	40.25	43.77	49.23	40.19	61.97	71.52
P2 *vs* P5	19.49	36.52	19.67	16.36	22.49	19.49	38.05	**42.52**
P3 *vs* P1	16.81	28.24	16.93	26.20	28.93	16.84	38.81	**40.76**
P3 *vs* P2	28.48	47.89	28.55	22.41	31.31	28.42	40.09	**48.99**
P3 *vs* P4	34.09	**75.73**	34.15	46.80	39.53	34.09	63.35	69.39
P3 *vs* P5	19.06	38.24	19.30	23.16	24.75	18.93	39.52	**46.81**
P4 *vs* P1	25.03	43.86	25.27	48.56	52.49	24.94	63.69	**64.89**
P4 *vs* P2	44.14	77.66	44.32	51.26	53.22	44.26	73.05	**78.82**
P4 *vs* P3	51.59	83.64	51.53	52.45	58.09	51.59	70.28	**84.65**
P4 *vs* P5	27.33	51.16	27.82	38.24	34.80	27.45	58.21	**61.15**
P5 *vs* P1	14.26	25.75	14.26	27.55	30.70	14.26	36.42	**38.49**
P5 *vs* P2	18.48	32.97	18.48	25.29	22.77	18.48	40.39	**43.19**
P5 *vs* P3	20.40	42.22	20.65	28.31	27.70	20.59	45.04	**45.53**
P5 *vs* P4	25.20	55.00	25.32	40.01	33.34	25.14	49.05	**55.60**
Mean	25.50	48.18	25.64	32.05	36.14	25.51	49.57	**54.81**

other cross-domain datasets with larger distribution differences. (2) Note that the source data on CMI-PIE are mildly corrupted as well. RIDA and DTSL are shown to outperform the remaining transfer methods, since they can generally reconstruct each uncorrupted target point (or recovered point) by its uncorrupted neighbors in the source domain and transfer the discriminating information accurately. (3) Our method achieves higher accuracy rates than DTSL on 14 datasets. For instance, our method achieves almost 10% improvements compared to DTSL on P2 *vs* P4 and P4 *vs* P3. Moreover, the average performance of our method is much better than all the other competitors. These results illustrate the reliable cross-domain performance of our method.

Contiguous Occlusions with an Unrelated Image We further randomly occlude 50 percent of the number of the target data using the unrelated monkey image shown in Figure 2(e). Contiguous occlusions and shadows may exist simultaneously on these target images, leading to large outliers. The average classification results over 10 random repetitions are shown in Table 3 and the following observations can be concluded. First, with the added occlusions, the accuracy of all the methods decreases, especially JDA. Second, our method outperforms all the other domain adaptation methods in terms of average accuracy. RIDA can assign small weights to the large outliers, and put more emphasis on the uncontaminated points during learning the reconstruction and the transformation. As a result, the learnt transformation can explicitly reduce the distribution difference.

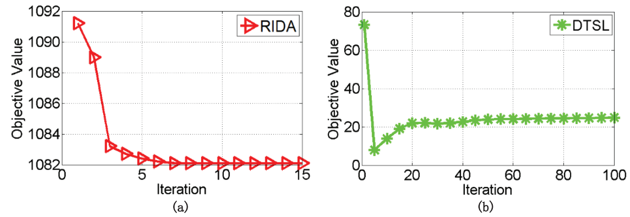

Figure 4: Convergence of RIDA and DTSL on C1 *vs* C2.

Convergence Analysis

The convergence of RIDA has been proven in Section 3. In this section, we experimentally plot its convergence on C1 *vs* C2 in Figure 4(a). For comparison, the convergence of DTSL has also been shown in Figure 4(b). As can be seen, our objective function decreases in every iteration and the optimization process converges after less than 10 iterations. In contrast, the objective value of DTSL is volatile and there is still no convergence after 100 steps of iterations. Similar observations can be drawn from other datasets as well.

Conclusion

In this paper, we have proposed a novel domain adaptation method inspired from correntropy. The key idea is to seek a shared feature space based on cross-domain reconstruction and incorporate the removal of contaminated target data into this seeking process, resulting in an accurate alignment between two domains. Without any specific assumptions on noise, the proposed method achieves its main advantage in the strong robustness for the challenging domain adaptation problems where the target data are contaminated by different kinds of severe and complex noise. Furthermore, an effective half-quadratic technique has been developed, guaranteeing the convergence of RIDA. Comprehensive experimental results validate the effectiveness and the noise suppression ability of the proposed method. In the future, we plan to facilitate the robustness by exploring more knowledge (e.g., class information) from two domains.

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