



Figure 3: Recognition performance versus θ in Gaussian kernel size σ . (a) Gaussian function $y = \exp(-x^2/\theta)$ with respect to θ . (b) In indoor environment, the average accuracy under various values of θ on NUST-RF database. (c) In outdoor environment, the average accuracy under various values of θ on NUST-RF database.

Table 2: Recognition accuracy (%) and standard deviation of different methods on traffic video database, where Sparse noise, regular and irregular occlusion are added.

	KNN	ITML	LMNN	FANTOPE	CAP	RML	Proposed
Original	83.48 \pm 3.87	88.09 \pm 2.19	89.37 \pm 2.38	90.16 \pm 2.69	90.16 \pm 2.69	85.05 \pm 5.15	91.34 \pm 1.52
Sparse	68.47 \pm 10.22	72.54 \pm 2.24	74.08 \pm 1.68	77.51 \pm 3.80	75.59 \pm 4.93	71.66 \pm 3.28	81.49 \pm 3.28
Regular	54.75 \pm 4.52	57.09 \pm 1.54	61.83 \pm 4.49	64.91 \pm 1.99	63.01 \pm 4.56	55.13 \pm 3.68	67.32 \pm 3.49
Irregular	58.67 \pm 5.07	66.44 \pm 3.22	69.32 \pm 5.15	69.32 \pm 5.15	69.32 \pm 5.15	60.25 \pm 2.70	73.28 \pm 8.01

Table 3: Recognition accuracy (%) and standard deviation of different methods on OSR dataset, where Sparse noise, regular and irregular occlusion are added.

	KNN	ITML	LMNN	FANTOPE	CAP	RML	Proposed
Original	69.01 \pm 1.96	69.09 \pm 1.18	74.41 \pm 1.20	74.97 \pm 0.88	74.45 \pm 1.19	61.34 \pm 1.62	75.46 \pm 2.15
Sparse	61.83 \pm 1.75	60.93 \pm 0.83	66.67 \pm 1.70	66.70 \pm 1.68	66.67 \pm 1.70	56.57 \pm 2.60	68.67 \pm 1.98
Regular	55.34 \pm 2.72	56.02 \pm 1.20	58.66 \pm 1.31	58.73 \pm 1.43	58.70 \pm 1.27	54.38 \pm 3.26	60.48 \pm 3.42
Irregular	52.25 \pm 1.74	53.45 \pm 2.75	57.02 \pm 1.80	57.10 \pm 1.74	57.13 \pm 1.68	50.45 \pm 2.17	63.99 \pm 2.38

Table 4: Recognition accuracy (%) and standard deviation of different methods on Pubfig dataset, where Sparse noise, regular and irregular occlusion are added.

	KNN	ITML	LMNN	FANTOPE	CAP	RML	Proposed
Original	56.73 \pm 1.12	62.04 \pm 2.19	61.65 \pm 1.63	61.69 \pm 1.60	61.80 \pm 1.72	55.86 \pm 1.54	63.99 \pm 1.60
Sparse	48.46 \pm 1.35	52.52 \pm 0.80	51.35 \pm 1.55	51.39 \pm 1.69	51.39 \pm 1.99	48.23 \pm 1.26	54.59 \pm 1.45
Regular	35.30 \pm 1.14	40.60 \pm 1.42	37.48 \pm 1.64	37.71 \pm 1.56	38.05 \pm 1.57	35.80 \pm 1.59	44.77 \pm 1.09
Irregular	40.94 \pm 2.30	44.27 \pm 1.73	41.73 \pm 3.39	41.88 \pm 2.78	42.33 \pm 2.35	40.23 \pm 2.48	46.09 \pm 2.43

database and PubFig dataset, which exactly works for ITML method. For this classification task, both FANTOPE and CAP methods are based on LMNN method. Since they all have similar results, which indicates the low-rank regularization for Mahalanobis distance metric learning is not particularly effective in this case. Especially for regular occlusion that replace a randomly selected local region with “baboon” image and irregular occlusion that replace local region with “tiger” image, LMNN, FANTOPE and CAP achieve almost the same result.

4.3 Facial Kinship Verification

In this section, we evaluate our methods on facial kinship verification task, which is to determine whether there is a kin relation between a pair of given face images [19]. We use KinFaceW-I dataset without adding extra sparse noise or contiguous occlusion. Some example pairs from KinFaceW-I dataset are shown in Fig. 6.

- **KinFaceW-I dataset** - KinFaceW-I dataset consists of four representative types of kin relations: Father-Daughter (F-D), Father-Son (F-S), Mother-Daughter (M-D) and Mother-Son (M-S), respectively. In the KinFaceW-I dataset, there are