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Subspace transform induced robust similarity measure for facial images

Key words: Subspace analysis; Image similarity measure; Face recognition; Pattern recognition

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Motivation

The motivation of this study is to decrease the gap between the Euclidean distance (Frobenius metric) and some face recognition challenges by removing the related transformation factors that are independent of the intrinsic structural changes of human faces.

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Main idea

1. We propose a fundamental similarity measure technique called the transformation similarity measure (TSM) without a learning process.

2. We present some mathematical features and examples to explain the rationale and robust mechanism of TSM for several face recognition challenges.

3. We perform experiments on several benchmark face databases to verify the TSM performance, and combine TSM with the nearest neighbor rule under different challenges.

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Method

We propose TSM without a learning process, and model the similarity of two facial images as linear regression with the minimum Frobenius norm loss.

Singular value decomposition is adopted to remove some interference related transformations such as illumination changes and block occlusion.

The Frobenius norm distance between the transformation matrix and unit matrix is employed as the similarity of two face images.

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Method

Algorithm 1 Transformation similarity measure

Input: two image matrices A and $B \in \mathbb{R}^{m \times n}$

Output: TSM(A, B)

Main procedure:

1. Solve Eq. (1) and obtain linear transformation $T \in \mathbb{R}^{m \times m}$
2. Perform singular value decomposition of T
3. Remove singular values by Eq. (3) and obtain T^*
4. Obtain TSM(A, B) by Eq. (6)

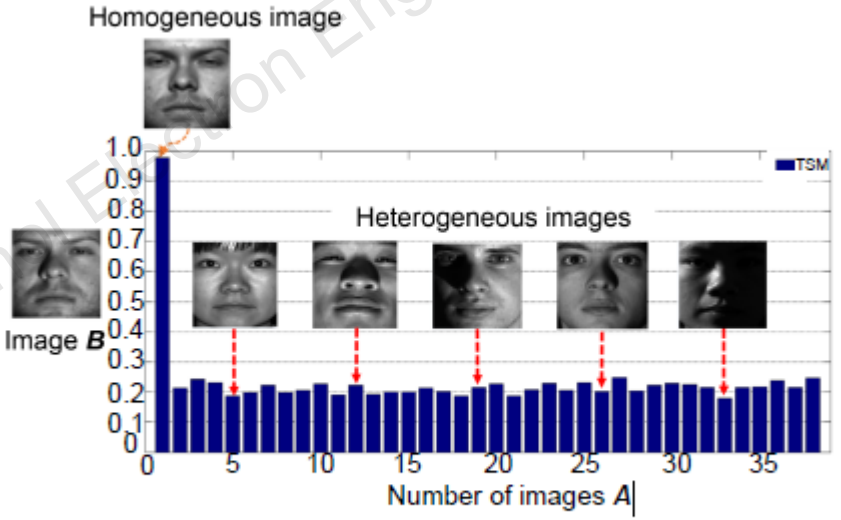


Fig. 2 Illustration of the proposed transformation similarity measure (TSM)

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Method

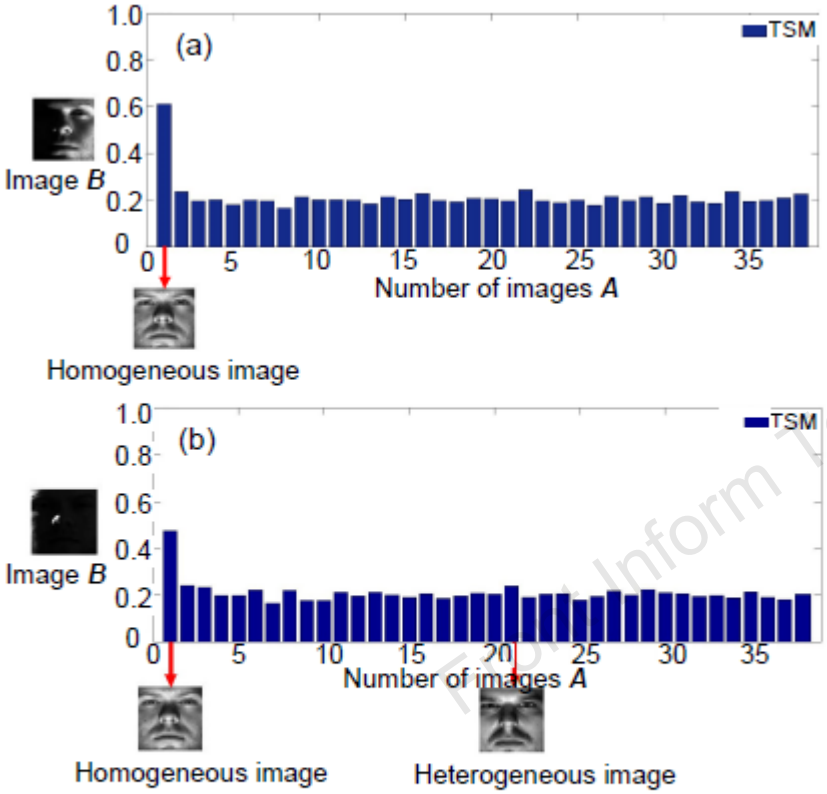


Fig. 4 An intuitive illustration of the insensitivity of TSM to the illumination variation conditions: (a) extreme illumination condition 1; (b) extreme illumination condition 2

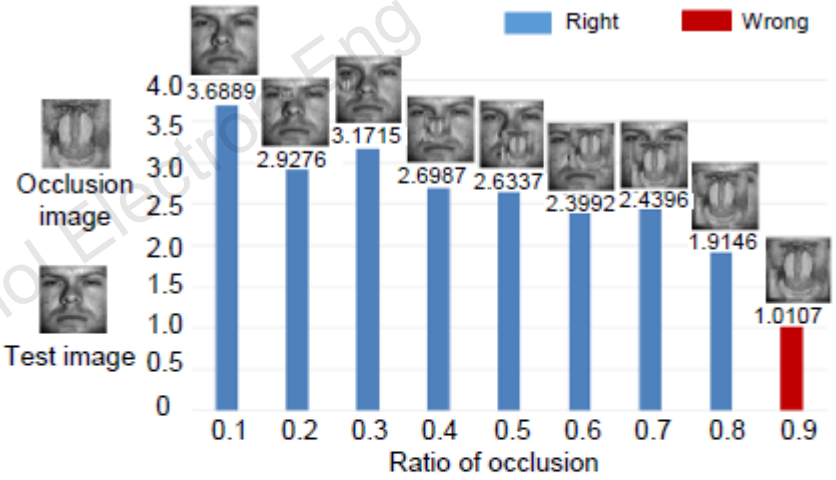


Fig. 5 Intuitive illustration of the insensitivity of TSM to the block occlusion condition

Blue bars mean that the test image is correctly classified and red bars mean misclassification. Numbers above the bars indicate the ratios between the largest and the second-largest TSMs. References to color refer to the online version of this figure

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Major results

Table 1 Average recognition rate and test sample running time on the Extended Yale B database with known sample size variation

Similarity measure	Average recognition rate (%)					Test sample running time (ms)				
	k=1	k=4	k=8	k=16	k=32	k=1	k=4	k=8	k=16	k=32
Euclidean distance	9.67	35.21	61.42	66.93	69.73	3	11	27	45	99
Manhattan distance	9.58	33.92	57.31	62.71	69.14	6	17	41	73	137
Nuclear norm	14.82	57.48	80.00	84.26	86.24	68	162	402	786	1342
Angle distance	13.18	44.36	79.75	86.41	90.12	17	28	47	88	157
Hausdorff distance	6.78	18.30	35.58	52.17	79.86	257	694	1456	2238	3967
Mahalanobis distance	14.36	45.16	82.51	87.65	89.18	637	234	4783	8876	15 736
LRM-L1 (SRC)	19.18	63.17	84.68	92.03	95.06	105	113	122	340	253
LRM-L2 (LRC)	21.46	66.23	86.43	92.67	95.51	0.37	0.56	0.72	1.19	1.32
Proposed TSM	73.72	91.30	96.80	98.41	98.95	139	447	834	1521	2986

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Major results

Table 2 Average recognition rate on the Extended Yale B database with inverse images

Similarity measure	Average recognition rate (%)				
	k=1	k=4	k=8	k=16	k=32
Euclidean distance	2.43	2.51	2.68	2.34	2.71
Manhattan distance	2.54	2.86	3.02	3.21	3.24
Nuclear norm	1.26	2.38	2.28	2.74	2.62
Angle distance	2.43	2.28	2.54	2.67	2.68
Hausdorff distance	1.12	2.28	2.18	2.24	2.37
Mahalanobis distance	3.15	3.26	3.46	4.25	5.38
LRM-L_1 (SRC)	3.47	3.61	3.65	4.17	4.28
LRM-L_2 (LRC)	3.48	3.62	3.65	4.12	4.32
Proposed TSM	71.96	92.91	97.13	97.96	98.16

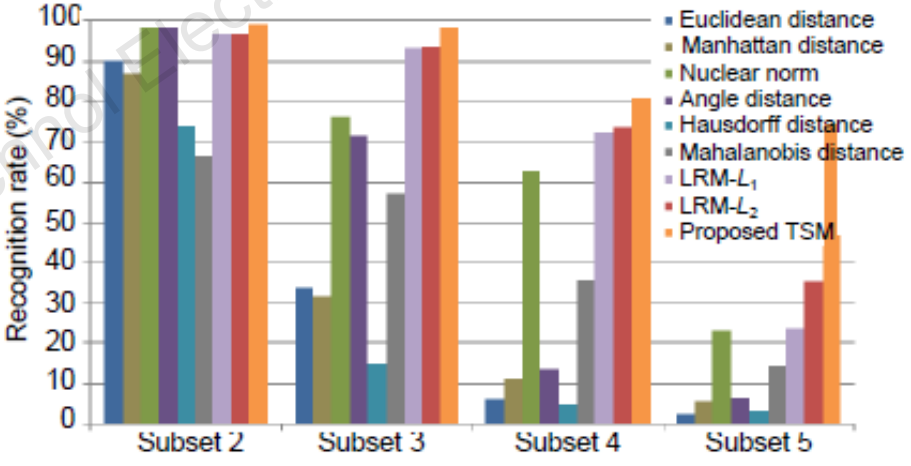


Fig. 11 Recognition rate on the Extended Yale B database under various lighting conditions

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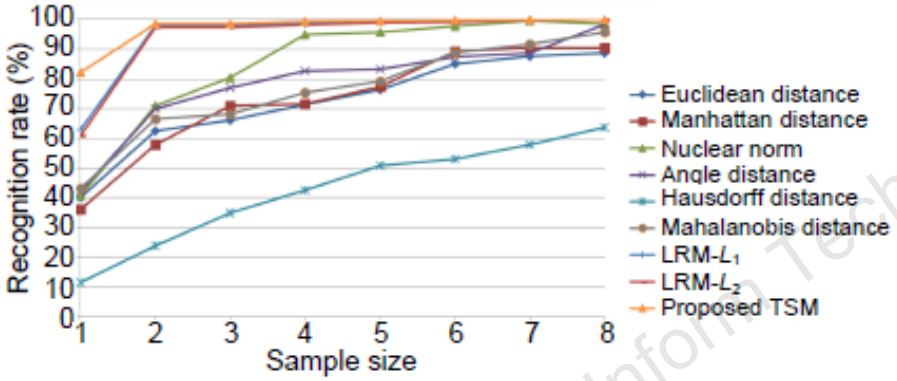


Fig. 12 Average recognition rate on the CMU PIE face database

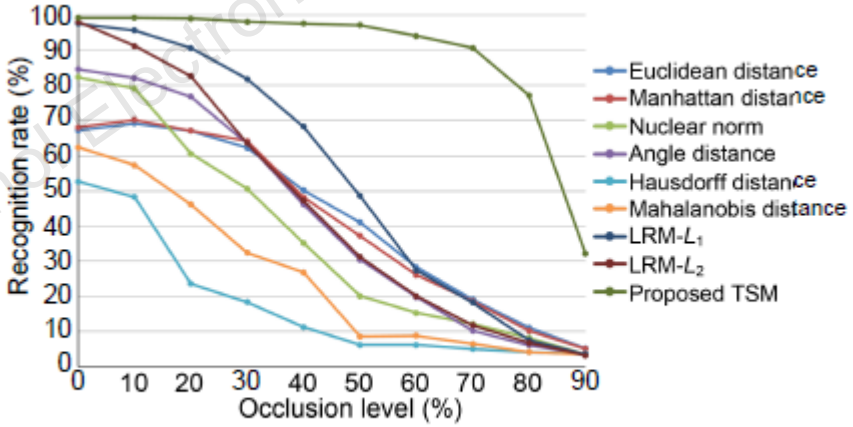


Fig. 14 Recognition rate under different occlusion levels

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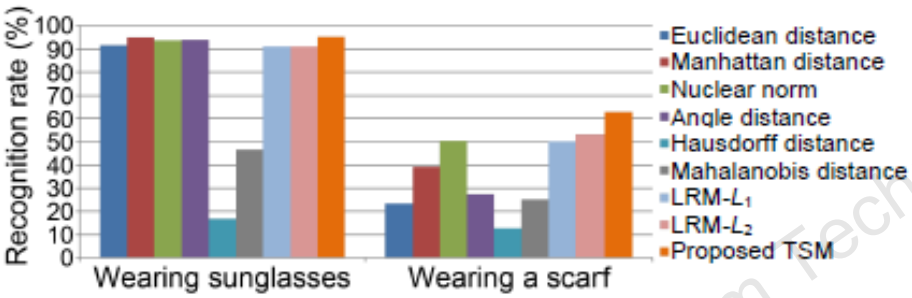


Fig. 15 Average recognition rate on the AR database with real face disguise

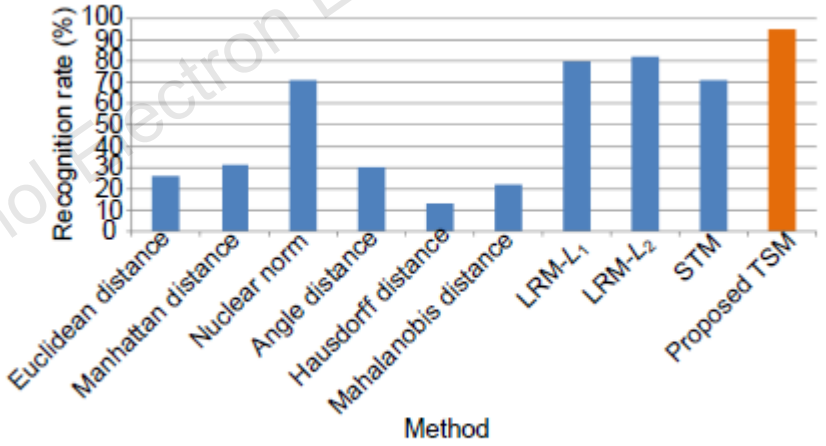


Fig. 16 Recognition rate on the CUHK sketch face database

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Conclusions

We have proposed the TSM to enhance the robustness of the metric method under lighting and occlusion conditions. The proposed method is both simple and practical since it does not involve a learning process. Experimental results indicated that the proposed TSM achieves encouraging performance compared with the general similarity measure methods with respect to some robustness issues, such as alternating illumination, structural noise caused by occlusion, and heterogeneous pattern.

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