

DCT BASED REGION LOG-TIEDRANK COVARIANCE MATRICES FOR FACE RECOGNITION Cong Jie Ng, Andrew Beng Jin Teoh, Cheng Yaw Low

$\begin{bmatrix} C \\ A \\ S \\ S \\ P \\ 2016 \end{bmatrix}$

Introduction

- I. Gabor-based Region Covariance Matrix (GRCM) has been den as a promising descriptor for face recognition.
 - GRCM requires large number of filters to achieve satisfactory performance.
 - Complex-valued Gabor filter requires double convolution operations for each filter that makes the computation more expensive.
- II. Region Covariance Matrix (RCM) offers spatial information that is useful for recognition tasks
 - **Overly small** RCM region renders **poor covariance estimation**, which can affect the recognition performance drastically especially when both gallery and probe set have **very different distributions**.

DCT as Filter Bank for Region Covariance Matrix

DCT Property as Filter Bank

- For real valued basis and input signal, convolution can be viewed as projecting overlapped (i.e. stride one) local signals onto a *flipped basis*.
- Both are equivalent for symmetric basis, hence preserves the decorrelation characteristic.

$$X = \langle c, x \rangle = c^{T} x = \sum_{m=0}^{N-1} c[m] x[m]$$

Inner Product

$$(f * x)[N] = \sum_{m=-M}^{M} f[N]$$

Convolution

DCT and RCM

- DCT an *orthogonal transform*, transforms a signal into *decorrelated spectrum*.
- Decorrelated spectrum is *not suitable* for RCM construction.
- **Non-linear operation** breaks the decorrelation among filter responses.



Correlation Matrix 49 7x7 DCT Basis on a Face Image



Absolute Operation Energy spread to off diagonal entries

Without Non-Linear Operation Energy are concentrated only in diagonal entries

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V - m]x[m]

Region Log-TiedRank Covariance Matrix (RLTRCM)

RCM Descriptor

- RCM is capable of implicitly encoding *spatial information* of local image regions with covariance matrix.
- Smaller region gives better spatial precision, but poorer covariance estimation.
- Covariance matrix is also known to be very *sensitive to outliers*.

Tied Ranking

- Motivated by Spearman's rank correlation matrix (SRCM) ranking method.
- Spearman's rank correlation matrix computes *Pearson correlation* among *ranked variables*.
- Eliminates disparity between variables, more robust against undersampling and outliers.

Log-TiedRank Covariance Matrix (LTRCM)

- Construction
- symmetric matrix, S' which lies on **vector space**.
- 2. S' is then *simplified* and *vectorized*.
- 3. LTRCM vector is obtained by applying **Tied Ranking** on $\vec{S}' = [S'_{1,1}, \sqrt{2}S'_{1,2}, \sqrt{2}S'_{1,3}, \dots, \sqrt{2}S'_{n,n-2}, \sqrt{2}S'_{n,n-1}, S'_{n,n}]^T$



• Non-singular covariance matrix is a Symmetric Positive Definite matrix that lies on *Riemannian Manifold*. • Regulating SPD matrix is *not trivial* and replacing Covariance Matrix with SRCM *computation expensive*.

1. Embeds nonsingular covariance matrix into its tangent space with respect to origin (Identity Matrix) to form a

Ex	periment
A) I	Evaluation on
	Filter
	Gabor
	DCT
5) E	valuation on
	Filter
	Gabor
	DCT
C) C	Comparison w
	Method
	RCM [1] Sigma Sets [19] GRCM [2] GWRCM [6]
	DCT (AIRM) DCT (Log-TR + WF
Со	nclusion a
• F	From the exper
	convolution o



Results

Various Variations (AR Dataset)



Metric	Expression	Illumination	Occlusion	Average
AIRM [2]	97.643	99.663	92.845	96.717
Log-Euc	94.781	96.465	82.828	91.358
Log-TR	99.327	100	99.327	99.551
AIRM	98.822	98.990	93.014	96.942
Log-Euc	97.980	98.148	85.606	93.911
Log-TR	98.485	99.832	98.317	98.878

Pose Variations (FERET Bc ~ Bh)



Metric	Bc	Bd	Be	Bf	Bg	Bh	Average
AIRM [2]	50.5	94.0	99.0	99.0	88.5	48.0	79.83
Log-Euc	45.0	86.0	97.5	98.0	83.5	43.5	75.58
Log-TR	81.5	99.5	99.5	100	96.5	76.0	92.17
AIRM	61.0	94.5	99.5	99.5	94.5	70.0	86.50
Log-Euc	52.5	89.0	99.0	99.5	91.5	62.5	82.33
Log-TR	94.5	100	100	100	99.0	89.0	97.08

with other RCM Based methods (FERET Fb, Fc, Dup-I, Dup-II)

85.19 27.84 44.04 29.06 46.5 89.62 91.75 50.55 44.87 69.2 91.72 93.30 61.77 63.25 77.5 91.63 93.30 62.19 64.10 77.8 93.72 95.36 68.56 70.94 82.1	age
89.62 91.75 50.55 44.87 69.2 91.72 93.30 61.77 63.25 77.5 91.63 93.30 62.19 64.10 77.8 93.72 95.36 68.56 70.94 82.1	53
91.72 93.30 61.77 63.25 77.5 91.63 93.30 62.19 64.10 77.8 93.72 95.36 68.56 70.94 82.1 PC(A) 93.32 100 93.90 93.61	20
91.63 93.30 62.19 64.10 77.8 93.72 95.36 68.56 70.94 82.1 PC(A) 02.80 02.21 06.1	51
93.72 95.36 68.56 70.94 82.1 DCA 00.33 100 03.80 03.31 06.1	81
	15
PCA) 99.35 IU 92.60 92.51 90.1	11

and Discussion

eriment real-valued DCT with 30 filters which requires less than half of the operations outperforms complex-valued *Gabor* with 40 filters in most cases. • It is also shown that, **DCT** method is more robust against **occlusions** and **pose changes**. • With **RLTRCM**, both Gabor and DCT methods shows **significant boost** over **RCM** especially when *probe set* is *far deviated* from *gallery set* (Pose Variations and Occlusions) Oppose to **AIRM** and **Log-Euclidean** which uses actual value representation, **LTRCM** that uses rank representation is *insensitive to precision difference*, only rank order matters.