# A Study of the Region Covariance Descriptor Impact of Feature Selection and Image Transformations

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- selecting suitable image descriptors
- defining a measure of similarity between feature descriptors
- learning a classification rule that uses the feature descriptors and corresponding similarity measure to determine what the image represents

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   region covariance descriptor
- the definition of a measure of similarity between feature descriptors

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# MOTIVATION

- Region covariance descriptor has proven to be useful in numerous computer vision applications.
- The properties of the descriptor are not well understood or documented.

# **REGION COVARIANCE DESCRIPTOR**

Ω	image

- *x* spatial coordinates of a pixel in image
- *R* rectangular region of interest in image
- $\phi: \Omega \to \mathbb{R}^n$  mapping from pixels to length-n feature vectors
- $\Lambda_R$  n-by-n covariance matrix

$$\boldsymbol{\Lambda}_{R} = \frac{1}{|R| - 1} \sum_{\boldsymbol{x} \in R} (\phi(\boldsymbol{x}) - \mu_{R}) (\phi(\boldsymbol{x}) - \mu_{R})^{\mathsf{T}}$$

$$\mu_R = \frac{1}{|R|} \sum_{x \in R} \phi(x) \qquad \text{mean feature}$$
$$|R| \qquad \text{number of pixels in R}$$

# FEATURE MAPPINGS





b channel (LAB colour space)

## REGION COVARIANCE DESCRIPTOR EXAMPLE



How should one define  $dist(\Lambda_R, \Lambda_R)$ ?

#### DISTANCE BETWEEN COVARIANCE MATRICES

- Sym(n) set of all  $n \times n$  symmetric real matrices
- $Sym_+(n)$  subset of positive definite matrices in Sym(n)
- **P**, **Q** covariance matrices in  $Sym_+(n)$
- $\|\cdot\|_F$  Frobenius norm

 $dist_{E}(\boldsymbol{P}, \boldsymbol{Q}) = \|\boldsymbol{P} - \boldsymbol{Q}\|_{F}$   $dist_{L}(\boldsymbol{P}, \boldsymbol{Q}) = \|log\boldsymbol{P} - log\boldsymbol{Q}\|_{F}$   $dist_{A}(\boldsymbol{P}, \boldsymbol{Q}) = \|log(\boldsymbol{P}^{-1}\boldsymbol{Q})\|_{F}$   $= \|log(\boldsymbol{P}^{-1/2}\boldsymbol{Q}\boldsymbol{P}^{-1/2})\|_{F}$ Euclidean metric Log-Euclidean metric Affine-invariant metric

#### How do features and distance measures influence the similarity between two images?

### DATASET



- Diverse images of human faces  $500 \times 500$  pixels
- Processing by centering all images on the nose and cropping to  $319 \times 319$  pixels



Original



Nose Detection



Centred & Cropped

PANTONE 70-5 C

PANTONE 49-6 C PANTONE 62-5 C

Humanae © Angelica Dass

#### TRANSFORMATIONS



#### **EXPERIMENTS**

• within: *comparable set* ≜ transformed base images



# EXPERIMENTS (Cont.)

• **among**: *comparable set* ≜ transformed base images + entire dataset



## **RESULTS: Different Base Image**



#### **RESULTS: Different Feature Set**

Features: x, y, r, g, b, l, a, b Distance: Euclidean Transform: Blur

0	0	12,9837	22.2503	33.7466	46.1978	58.7937	71.1652	83.0871	94.3892
6-16	6-10	(s - t)	(	(	6-10	1			
105.194	115.367	125.069	134.266	143	151.382	159.447	167.332	174.96	182.417
189.806	197.032	204.116	211.103	217.976	224,689	231.324	237.849	244.326	250.75
ė.									
257.082	263.209	269.305	275.219	280.967	286.521	291.855	297.143	302.151	306.986
			1			1			1
307.636	311.704	316.283	320.674	324.948	329.155	393.279	337.223	341.142	344.926
2									

Features: x, y, r, g, b,  $\sqrt{I_x^2 + I_y^2}$ ,  $tan^{-1} \left( \frac{|I_y|}{|I_x|} \right)$ , I, a, b Distance: Same Transform: Same

0	o	75.4844	194.677	283.383	356.474	468.927	593.964	623.123	696.163
6-16	1	10-10	1		6-6	6-6	1	3	
697.376	712.49	729.064	742.982	823.84	828.609	958.588	972.814	980.614	1005.58
(II)	(Carl	(Ca)			D		(15.)	90	(1)
1056.87	1078.81	1087.8	1097.28	1099.38	1109.35	1111.73	1121.15	1126.59	1130.13
		C State			(E-31)			00	10
1134.81	1135.68	1145.51	1148.71	1156.51	1182.38	1198.16	1205.08	1212.89	1222.04
	(H)		P			1	10.0		S
1222.47	1227.93	1249.42	1259.02	1279.78	1305.27	1308.92	1317.43	1320.86	1323.32
	11.0	32.0					1- 3)	11 3	1 - 1)

### **RESULTS: Different Distance**

Features: x, y, r, g, b Distance: Euclidean Transform: Blur

0	0	0.140917	0.142351	0.149038	0.158431	0.167529	0.178474	0.190019	0.201923
6-10	6-6	(E - 1)	10-10	1	6-6	6-16	6-10		10
0.218686	0.235663	0.256928	0.277966	0.302496	0.329692	0.361277	0.3966	0.434741	0.477814
			(C)						
0.524224	0.575118	0.627226	0.683711	0.742173	0.803391	0.868795	0.937089	1.00931	1.08409
1.16183	1.23813	1.31689	1.39421	1.46964	1.54303	1.6122	1.6816	1.74553	1.80714
						4			
1.86757	1.92634	1.98206	2.03615	2.09076	2.14555	2.19799	2.25055	2.90257	2.35252
0							-		

Features: Same Distance: Log-Euclidean Transform: Same



### **RESULTS: Different Distance**

Features: x, y, r, g, b Distance: Euclidean Transform: Blur

0	0	0.140917	0.142351	0.149038	0.158431	0.167529	0.178474	0.190019	0.201923
6-0	6-6	(F	10-10	1	6-6	10	6-6	9	
0.218686	0.235663	0.256928	0.277966	0.302496	0.329692	0.361277	0.3966	0.434741	0.477814
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1.86757	1.92634	1.98206	2.03615	2.09076	2.14555	2.19799	2.25055	2.90257	2.35252
							1		

Features: Same Distance: Affine Invariant Transform: Same



### **RESULTS: Different Transform**

Features: x, y, r, g, b Distance: Euclidean Transform: Blur

0	0	0.140917	0.142351	0.149038	0.158431	0.167529	0.178474	0.190019	0.201923
6	6-6	(E	10-10	1	6-6	10-10	6-6	9	(1) (1)
0.218686	0.235663	0.256928	0.277966	0.302496	0.329692	0.361277	0.3966	0.434741	0.477814
			(1)						
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						1			
1.86757	1.92634	1.98206	2.03615	2.09076	2.14555	2.19799	2.25055	2.30257	2.35252
							-		

Features: Same Distance: Same Transform: Rotation

0	0	0.637245	1.00718	1.16818	1.21767	1.23766	2.10752	2.52668	2.74606
	S	000	0	65		620	626	6-10	C.
2.87018	3.2862	3.8027	3.84154	4.39553	5.00039	5.13381	5.2463	5.50922	5.98914
	C.	10-10	20	Co	20	1000	Ľ	and a	00
6.28043	6.54537	6.59532	6.63685	6.99746	7.17224	7.69688	7.88903	8.12413	8.69154
te le	15-16-	25)	(B - 1)	(F.)		A COLO	and and		( Sel
8.70867	8.72736	9.33361	9.40536	9.49675	10.09	10.2189	10.2345	10.2673	10.2876
	20)	11.2		No.	6-10	Y	3		1-1
10.6887	10.7191	10.772	10.7939	10.8501	11.1999	11,3897	11.6803	11.7285	11.8174
Y	29	100	1	10.0	123	S.	20	J.	N

#### **RESULTS:** Different Distance for **Different Problems**

 $|I_{\chi\chi}|, |I_{\chiy}|, |I_{\chi\chi}|, \sqrt{I_{\chi}^2 + I_{\chi}^2}, \tan^{-1}\left(\frac{|I_y|}{|I_{\chi\chi}|}\right)$ Features: Distance: Euclidean

Transform: Rotation



Features: Same Distance: Affine Invariant Transform: Same

2.46519e-2.46519e-30.01955660.02175680.03360970.03799740.05285350.05726370.0603050.0616843



.0715470.07222010.0725770.07408160.07444270.0748393 0.06301720.06548230.0678440



0.07802670.07865620.07973590.08410280.08697810.08713080.090554 0.106875 0.107575 0.110603



0.113452 0.120926 0.122182 0.122618 0.148528 0.162714 0.164389 0.112028 0 16461















0.169201 0.171908 0.175291 0.179232 0.183273 0.204877 0.219453 0.227922 0.228739 0.235419



- No distance measure works best in all situations.
- Inclusion or exclusion of a single feature can have a dramatic impact.
- Selection of features must be guided by extensive empirical analysis.
- Excellent retrieval performance observed for the dist<sub>E</sub> measure for Gaussian noise and blur transformations when the position feature (xy) was combined with a colour feature (rgb or lab).

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# CONCLUSION

- Our work has explored various aspects of the region covariance descriptor.
- We discussed three different distance measures that are frequently utilised and explained their significance.
- We also explored the efficacy of the distance measures through extensive targeted experiments in which we investigated numerous feature combinations.
- Our findings suggest that no specific distance measure is best for all scenarios, and that the choice of features can have a dramatic impact on performance.

## QUESTIONS