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

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#### INTRODUCTION

A modern computer vision pipeline for generic image classification and recognition consists of three broad conceptual steps:

- selecting suitable (region covariance descriptors )
- defining a measure of similarity between feature descriptor (distance between covariance matrices)
- learning a classification rule that uses the feature descriptors and corresponding similarity measure to determine what the image represents

#### 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
$\phi \colon \Omega  o \mathbb{R}^n$	mapping from pixels to length-n feature vectors
$\Lambda_R$	n-by-n covariance matrix

$$\Lambda_{R} = \frac{1}{|R| - 1} \sum_{x \in R} (\phi(x) - \mu_{R}) (\phi(x) - \mu_{R})^{T}$$

mean feature

$$u_R = \frac{1}{|R|} \sum_{\mathbf{x} \in R} \phi(\mathbf{x})$$
$$|R|$$

number of pixels in R

### FEATURE MAPPINGS

	spatial x coordinate		magnitude of sec derivative in hori
	spatial y coordinate		magnitude of sec derivative in vert
C.	red channel		magnitude of sec partial derivative
T	green channel		magnitude of edg
T	blue channel		edge orientation
	magnitude of first-order partial derivative in horizontal direction		luminance (LAB c
Contraction of the second	magnitude of first-order partial derivative in vertical direction		a channel (LAB co
		(T)	b channel (LAB co

# **REGION COVARIANCE DESCRIPTOR EXAMPLE**



 $dist(\Omega_1, \Omega_2) \triangleq dist(\Lambda_R, \Lambda_R)$ 

cond-order partial izontal direction cond-order partial ical direction cond-order mixed

e response

colour space)

olour space)

nnel (LAB colour space)

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

#### Humanae © Angelica Dass



# 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



# TRANSFORMATIONS

saturation brightness blur noise rotation





### EXPERIMENTS

within: comparable set  $\triangleq$  transformed base images



Features: Distance: Transform:

x, y, r, g, b Euclidean Blur





RESULTS







**among**: comparable set  $\triangleq$  transformed base images + + entire dataset

Features:				Same					
Distance:				Same					
Transform:				S	Sam	е			
0	0	0.245142	0.262897	0.296667	0.347761	0.4 12424	0.489637	0.57461	0.6645
U	P	6	3	P	P.	Y	P	Y	P)
0.758948	0.855618	0.954695	0.985737	1.05593	1.15713	1.26058	1.36586	1.44916	1.47016
1.57909	1.62252	1.68794	1.80079	1,91384	1.9591	2.03078	2.14787	2.19591	2.26714

_									
48	0.855618	0.954695	0.985737	1.05593	1.15713	1.26058	1.36586	1.44916	1.4701
	1		1 1.00	3	ð	ð	0	100	Ø
09	1.62252	1.68794	1.80079	1,91384	1.9591	2.03078	2.14787	2.19591	2.2671
	1	ø	ÿ	ø	100	ø	Ø	at a	
55	2.43552	2.50901	2.69112	2.75301	2.87637	2.99778	3.00777	3.04753	3.1188
	a co	1	ø		1	0	300	P.C.	
57	3.29746	3.35699	3.47417	3.58325	3.5881	3.69997	3.80981	3,91631	3.9779
	S	ø		100	ł,				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 0 75.4844 194.677 283.383 356.474 468.927 593.964 623.123 696.163
	697.376       712.49       729.064       742.982       823.84       828.609       958.588       972.814       980.614       1005.58         Image: Second state       Image: Second stat
	1056.87 1078.81 1087.8 1097.28 1099.38 1109.35 1111.73 1121.15 1126.59 1130.13 1056.87 1078.81 1087.8 1097.28 1099.38 1109.35 1111.73 1121.15 1126.59 1130.13 1050 1050 1050 1050 1050 1050 1050 1050
	$ \begin{bmatrix} 1134.81 \\ 1135.68 \\ 1145.51 \\ 1148.71 \\ 1156.51 \\ 1182.38 \\ 1198.16 \\ 1205.08 \\ 1212.89 \\ 1222.04 \\ 1222.04 \\ 1025 \\ 1222.04 \\ 1025 \\ 102$
	Features: Same Distance: Log-Euclidean Transform: Same
	0 0 0.04856060.139414 0.24966 0.371492 0.498175 0.622633 0.713578 0.747574
	0.821965 0.836859 0.83911 0.840103 0.857541 0.876827 0.88018 0.961587 1.00586 1.0279
	1.03328 1.04048 1.05809 1.06239 1.12469 1.12832 1.13248 1.13536 1.13713 1.14973
	1.15563 1.20082 1.20392 1.26394 1.27553 1.33599 1.35142 1.35201 1.36998 1.37211
	1.37466       1.39075       1.39948       1.41231       1.41982       1.4627       1.46909       1.51741       1.55186       1.59428         Image: State St
	Features: Same
	Distance: Same Transform: Rotation
	0 0 0.637245 1.00718 1.16818 1.21767 1.23766 2.10752 2.52668 2.74606
	2.87018       3.2862       3.8027       3.84154       4.39553       5.00039       5.13381       5.2463       5.50922       5.98914         Image: Straight Straigh
	6.28043       6.54537       6.59532       6.69685       6.99746       7.17224       7.69688       7.88903       8.12413       8.69154         Image: Im
	8.70867 8.72736 9.33361 9.40536 9.49675 10.09 10.2189 10.2345 10.2673 10.2876
	10.6887 10.7191 10.772 10.7999 10.8501 11.1999 11.9897 11.6803 11.7285 11.8174
$-1\left(\frac{ I_{\mathcal{Y}} }{ I_{\mathcal{X}} }\right)$	Features: Same Distance: Affine-invariant
	Transform: Same
	2.465 19e2.465 19e3010 1955660.02175680.03360970.03799740 05285350.0572637 0.060305 0.06 16843
	0.06301720.06548230.0678440.06969580.0715470.07222010.0725770.07408160.07444270.0748393
	0.07802670.07865820.07973580.08410280.08697810.08713080.090554 0.106875 0.107575 0.110603
	0.112028 0.112195 0.113452 0.120926 0.122182 0.122618 0.148528 0.162714 0.164389 0.16461
	0.169201 0.171908 0.175291 0.179292 0.183273 0.204877 0.219453 0.227922 0.228739 0.235419 $ \begin{array}{c} \hline \\ \hline $

### DISCUSSION

- Excellent retrieval performance observed for the  $dist_E$  measure for Gaussian noise and blur transformations when the position feature (xy) was combined with a colour feature (rgb or lab).