A Study of the Region Covariance Descriptor

Impact of Feature Selection and Image Transformations

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Innovation and education in visual information processing

INTRODUCTION

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

- 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
  - distance between covariance matrices

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

$$\boldsymbol{\Lambda}_R = \frac{1}{|R|-1}\sum_{\boldsymbol{x}\in R}(\phi(\boldsymbol{x})-\mu_R)(\phi(\boldsymbol{x})-\mu_R)^\intercal$$

$$\mu_R = \frac{1}{|R|}\sum_{\boldsymbol{x}\in R}\phi(\boldsymbol{x})$$ mean feature

$|R|$ number of pixels in R

FEATURE MAPPINGS


spatial x coordinate


spatial y coordinate


red channel


green channel


blue channel


magnitude of first-order partial derivative in horizontal direction


magnitude of first-order partial derivative in vertical direction


magnitude of second-order partial derivative in horizontal direction


magnitude of second-order partial derivative in vertical direction

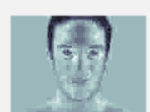

magnitude of second-order mixed partial derivative


magnitude of edge response


edge orientation


luminance (LAB colour space)

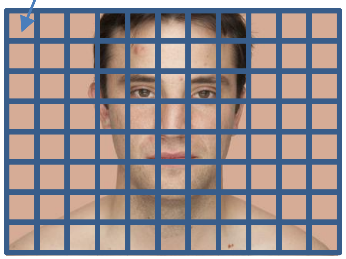

a channel (LAB colour space)


b channel (LAB colour space)

REGION COVARIANCE DESCRIPTOR EXAMPLE

$\boldsymbol{x} \in \mathbb{R}^2, \phi(\boldsymbol{x}) \rightarrow$ R G B

R



Ω_1

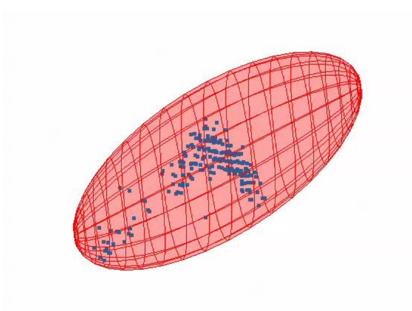
$\boldsymbol{x} \in \mathbb{R}^2, \phi(\boldsymbol{x}) \rightarrow$ R G B

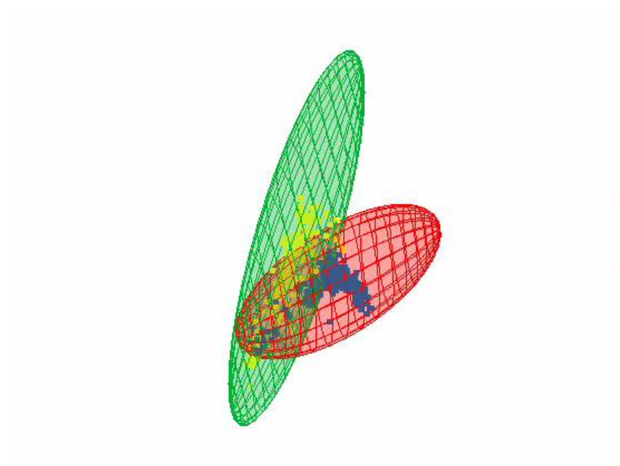
R

Ω_2

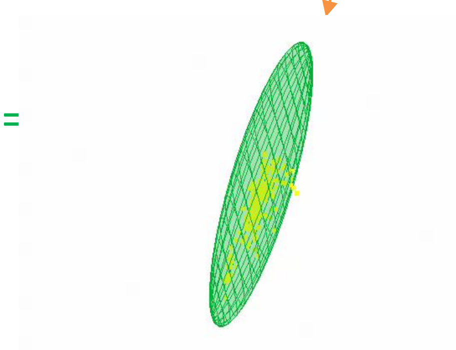
$$dist(\Omega_1, \Omega_2) \triangleq dist(\Lambda_R, \Lambda_R)$$

$\Lambda_R =$





$\Lambda_R =$



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 $Sym(n)$
$\boldsymbol{P}, \boldsymbol{Q}$	covariance matrices in $Sym_+(n)$
$\|\cdot\|_F$	Frobenius norm

$$dist_E(\boldsymbol{P}, \boldsymbol{Q}) = \|\boldsymbol{P} - \boldsymbol{Q}\|_F$$ Euclidean metric

$$dist_L(\boldsymbol{P}, \boldsymbol{Q}) = \|log\boldsymbol{P} - log\boldsymbol{Q}\|_F$$ Log-Euclidean metric

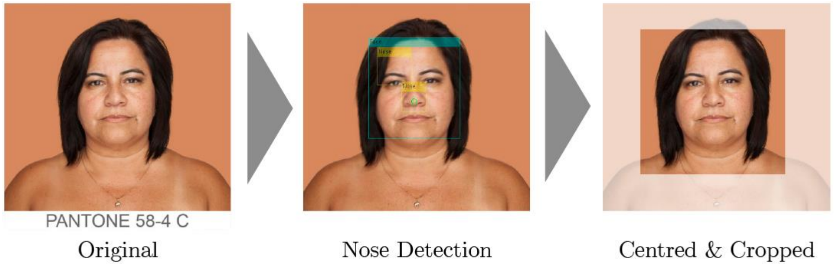
$$dist_A(\boldsymbol{P}, \boldsymbol{Q}) = \|log(\boldsymbol{P}^{-1}\boldsymbol{Q})\|_F = \left\|log\left(\boldsymbol{P}^{-1/2}\boldsymbol{Q}\boldsymbol{P}^{-1/2}\right)\right\|_F$$ Affine-invariant metric

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

DATASET

Humanae © Angelica Dass

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



TRANSFORMATIONS

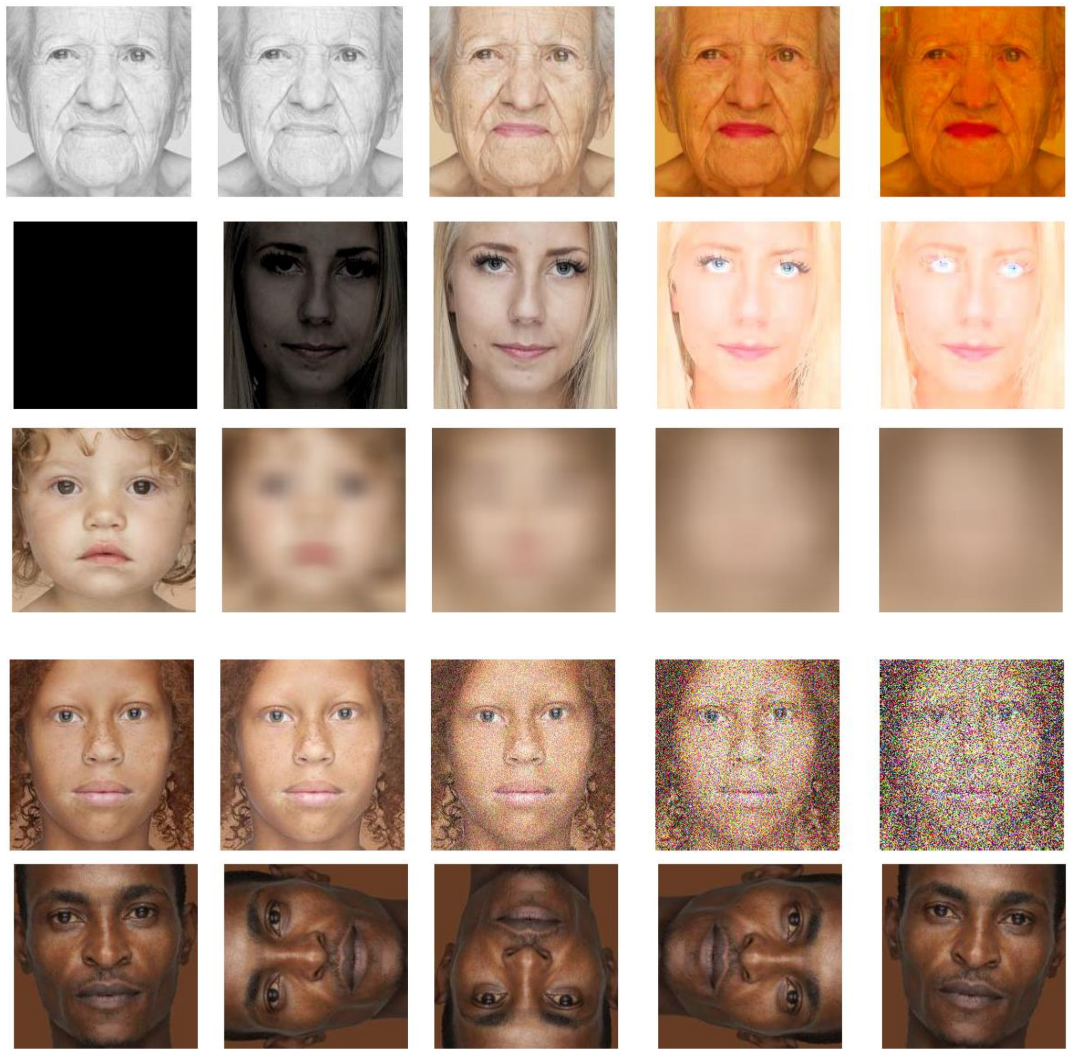
saturation

brightness

blur

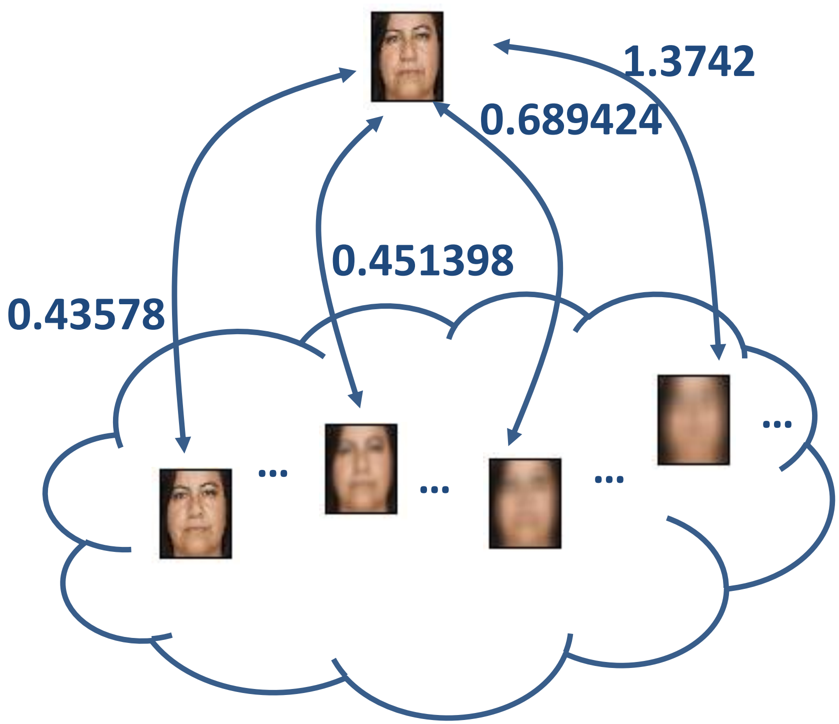
noise

rotation



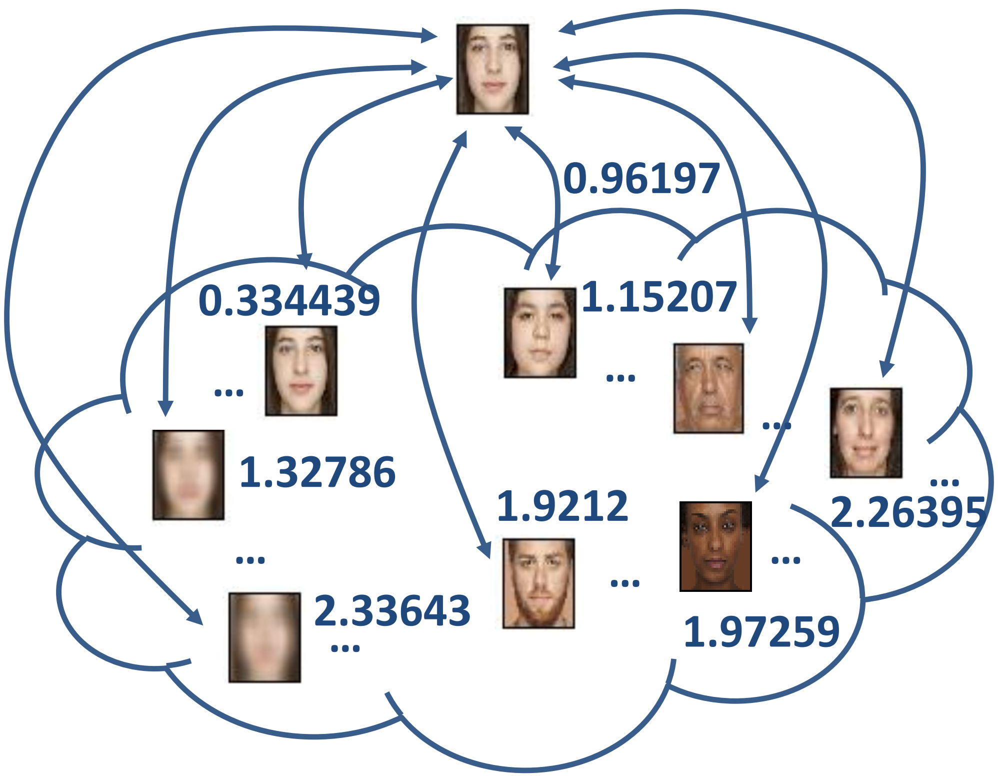
EXPERIMENTS

- **within**: *comparable set* ≜ transformed base images



EXPERIMENTS (Cont.)

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

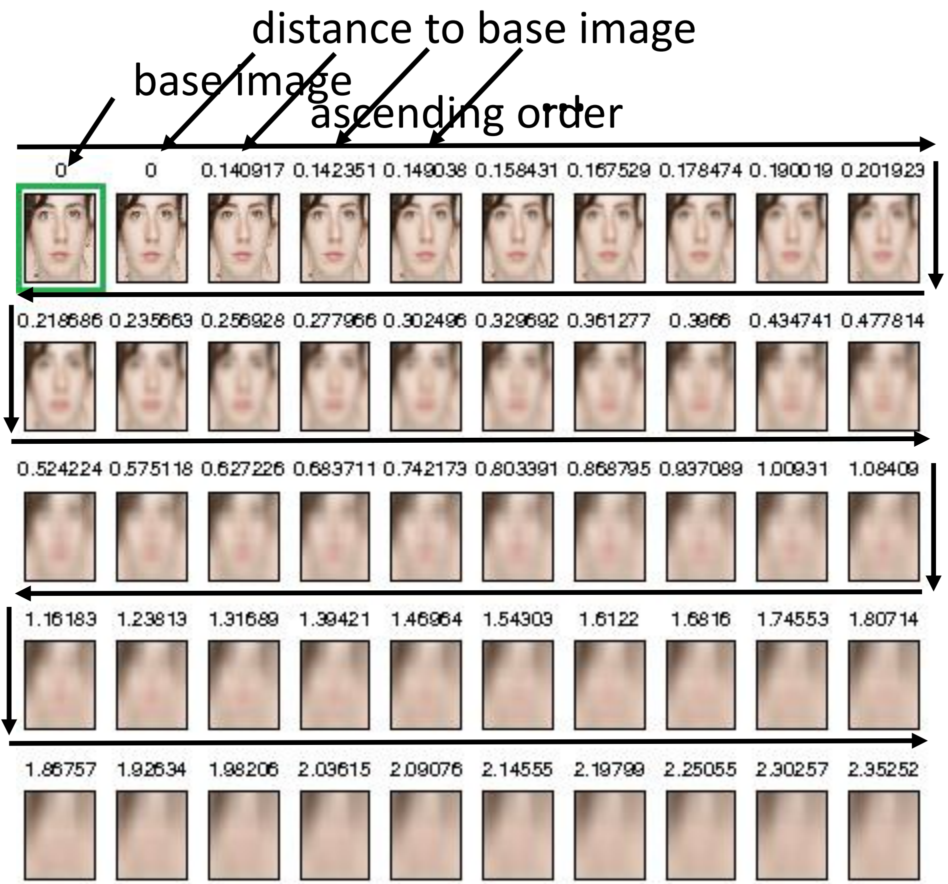


RESULTS: Different Base Image

Features: x, y, r, g, b

Distance: Euclidean

Transform: Blur



Features: Same

Distance: Same

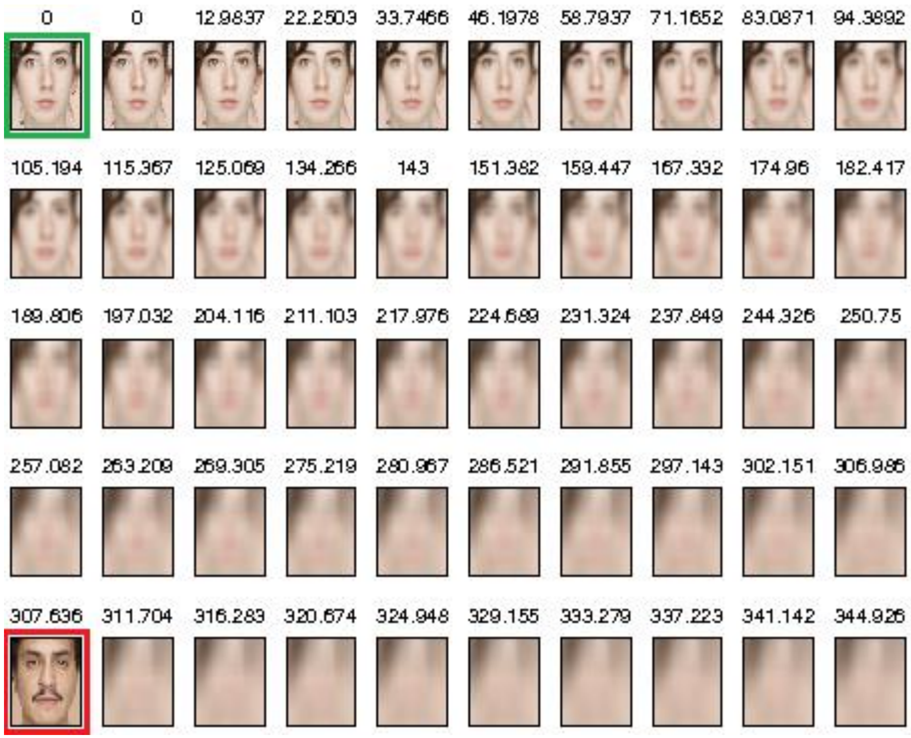
Transform: Same

RESULTS: Different Feature Set

Features: x, y, r, g, b, l, a, b

Distance: Euclidean

Transform: Blur



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

Distance: Same

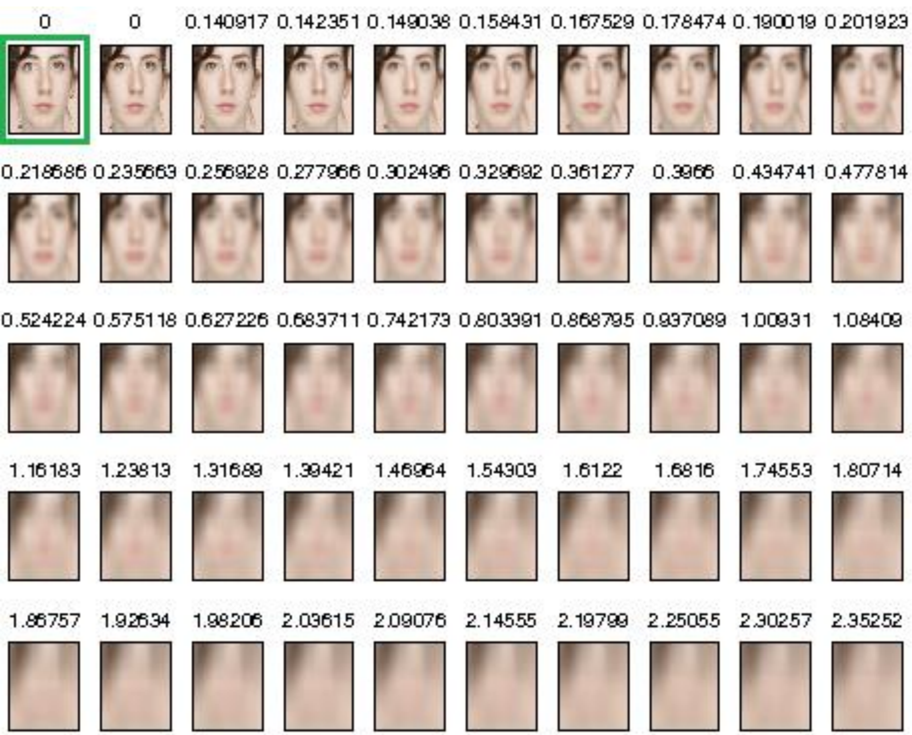
Transform: Same

RESULTS: Different Distance

Features: x, y, r, g, b

Distance: Euclidean

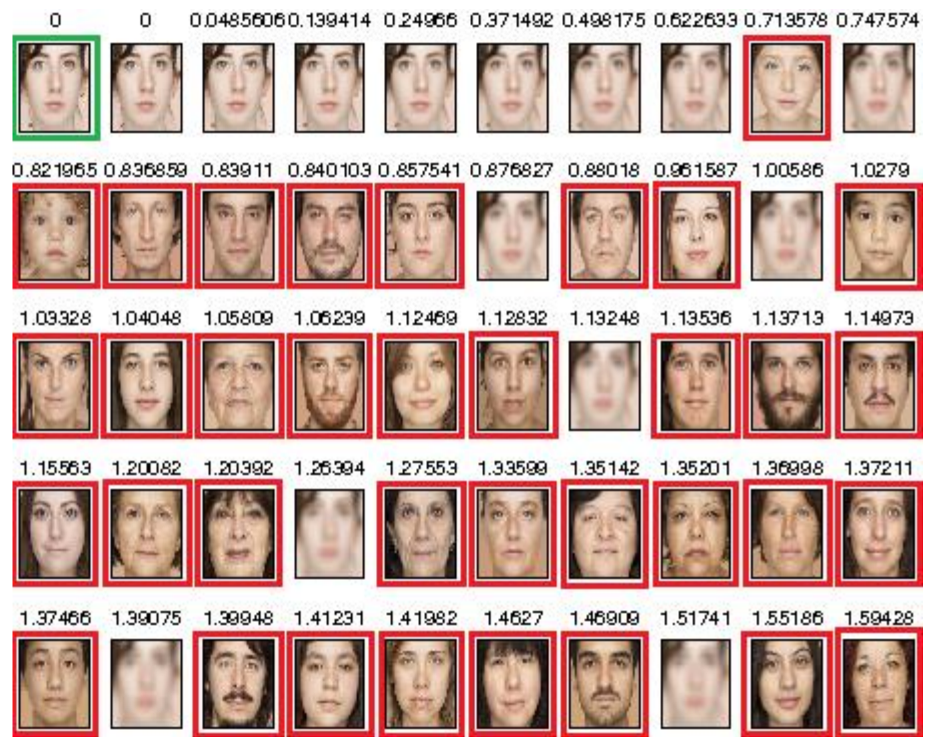
Transform: Blur



Features: Same

Distance: Log-Euclidean

Transform: Same

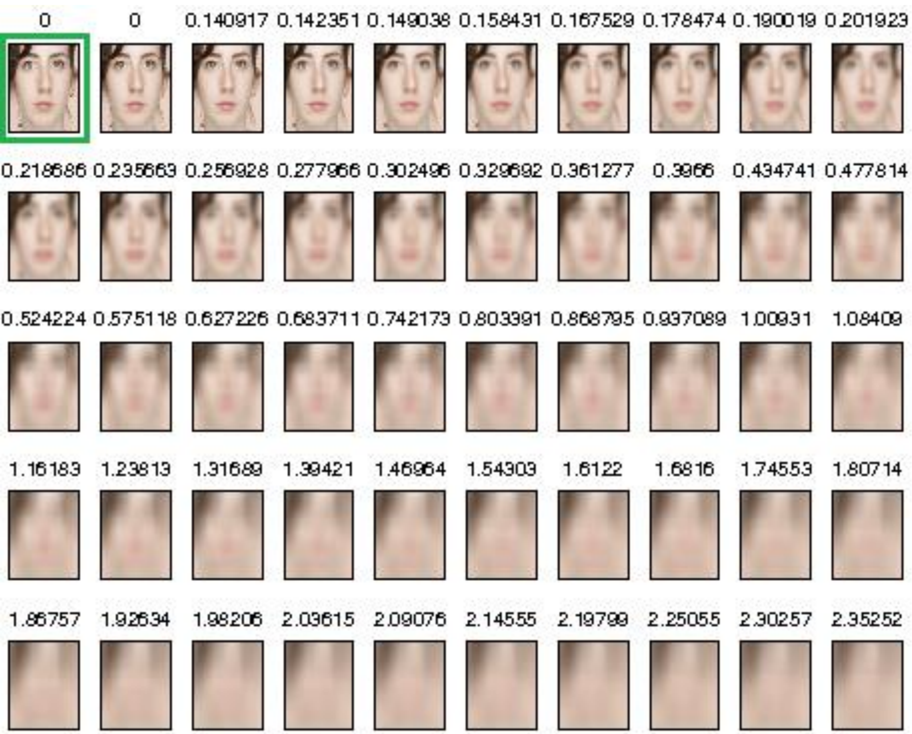


RESULTS: Different Distance

Features: x, y, r, g, b

Distance: Euclidean

Transform: Blur



Features: Same

Distance: Affine Invariant

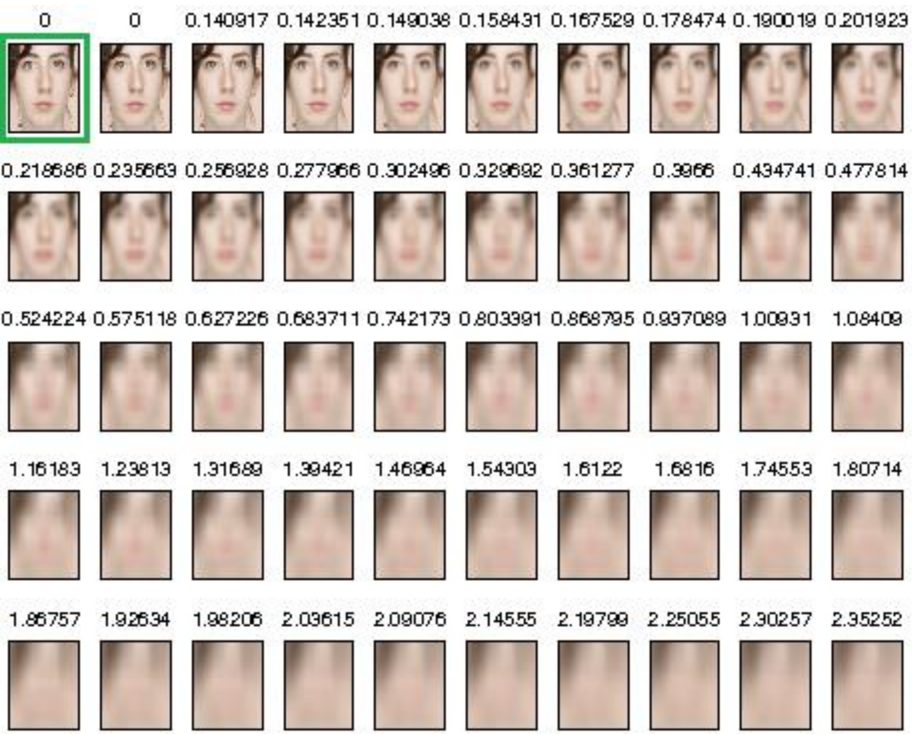
Transform: Same

RESULTS: Different Transform

Features: x, y, r, g, b

Distance: Euclidean

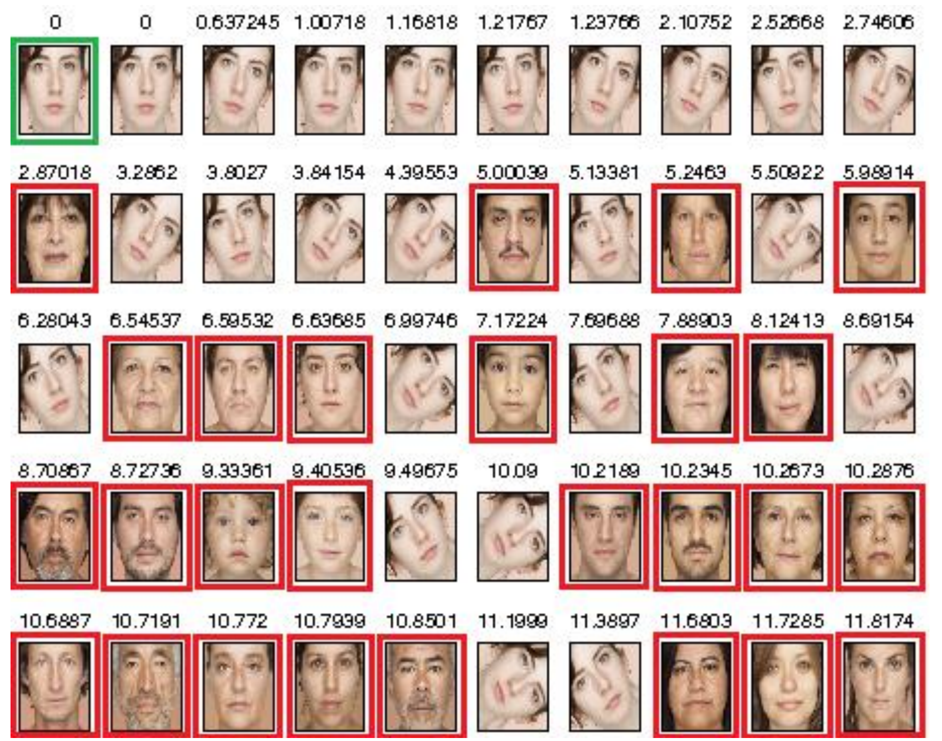
Transform: Blur



Features: Same

Distance: Same

Transform: Rotation

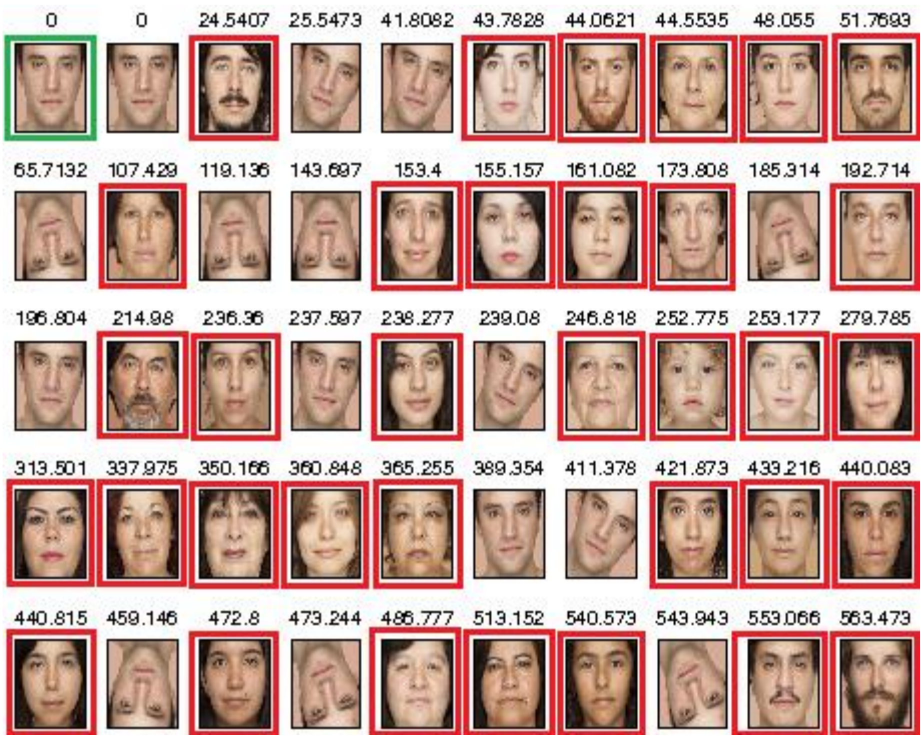


RESULTS: Different Distance for Different Problems

Features: $|I_{xx}|, |I_{yy}|, |I_{xy}|, \sqrt{I_x^2 + I_y^2}, tan^{-1}\left(\frac{|I_y|}{|I_x|}\right)$

Distance: Euclidean

Transform: Rotation



Features: Same

Distance: Affine Invariant

Transform: Same

DISCUSSION

- 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 $dist_E$ 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