An Appearance Based Fast Linear Pose Estimation

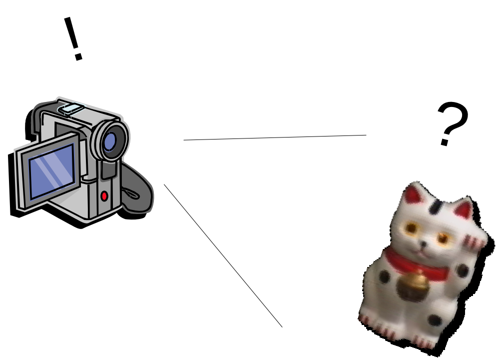
NAIST Toshiyuki Amano
HIROSHIMA UNIVERSITY Toru Tamaki

Thanks to:
Hiroyuki Okugawa, Kengo Harada, Kazufumi Kaneda, Bisser Raytchev

Pose Estimation methods

pose estimation

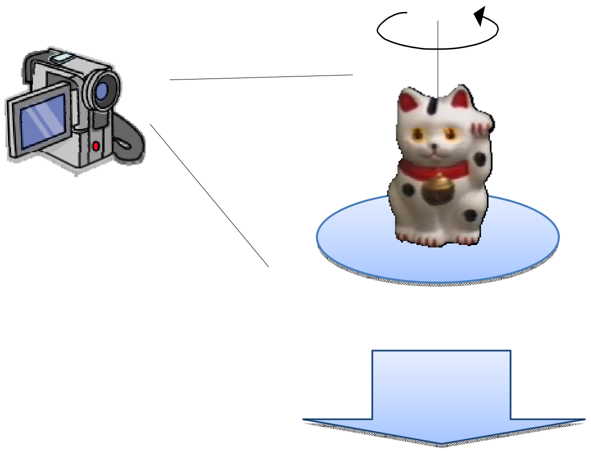
- Geometry-model based
  - (Lowe, 1991)
  - Etc.
- View based
  - Local feature based
    - (Rothganger et al., 2006)
    - (Lowe, 2004)
    - (Ferrari et al., 2006)
    - (Kushal et al., 2006)
    - (Viksten, 2009)
  - **Global appearance based**
    - Parametric Eigenspace (Murase et al., 1995)
    - linear regression (Okatani et al., 2000)
    - kernel CCA (Melzer et al., 2003)
    - SV regression (Ando et al., 2005)
    - Manifold learning



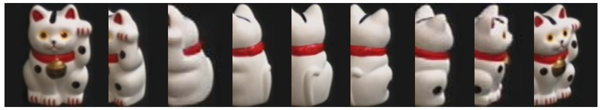
Determining pose of an object relative to the camera

Global appearance based

Learning

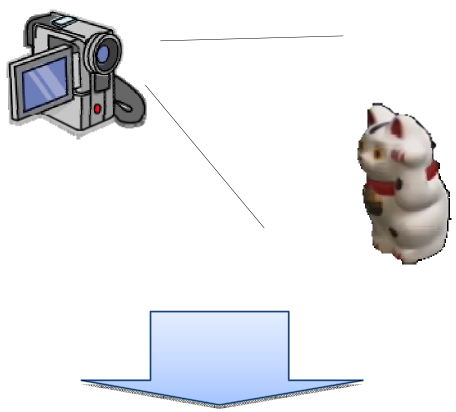


$x_1, x_2, \ldots$

Images 

poses $\theta_1\ \theta_2 \quad \cdots \quad \theta_n$

Estimation



 x

$\hat{\theta}$

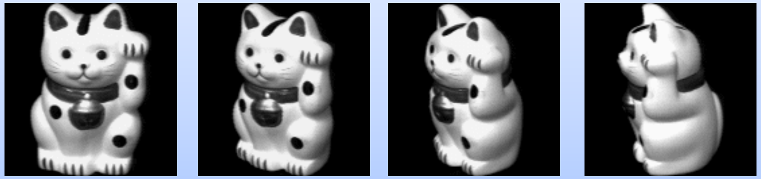
Fast

Easy

supervised
object-specific
not robust to clutter

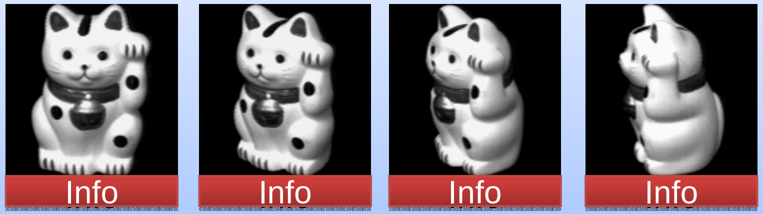
Idea: Embedding Information

Difficult …



Adding additional information tracks to images

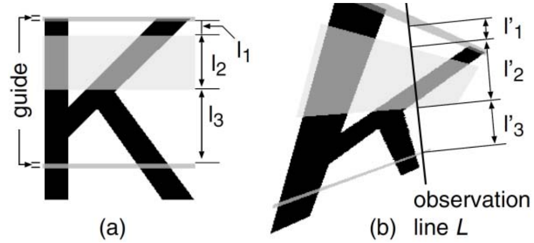
Easy!



Estimating the *information track*

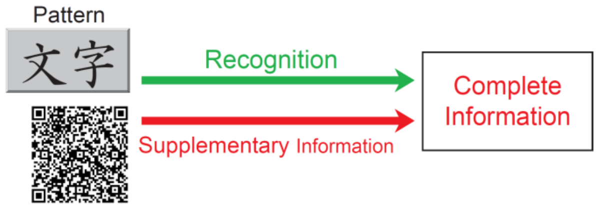
Related work

Cross ratio



Uchida et al., ICPR2006/ICDAR2007

Barcode

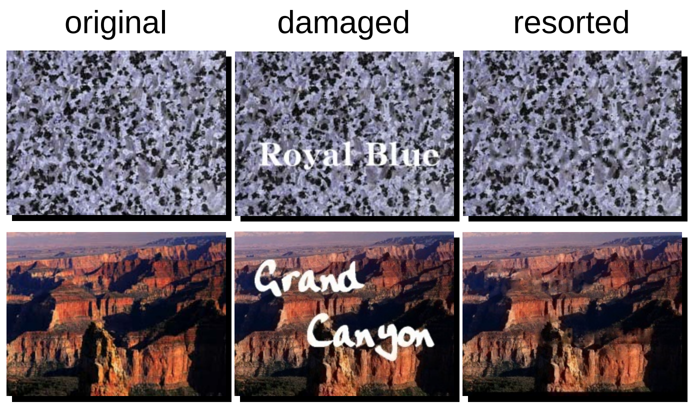


Iwamura et al., CBDAR2005

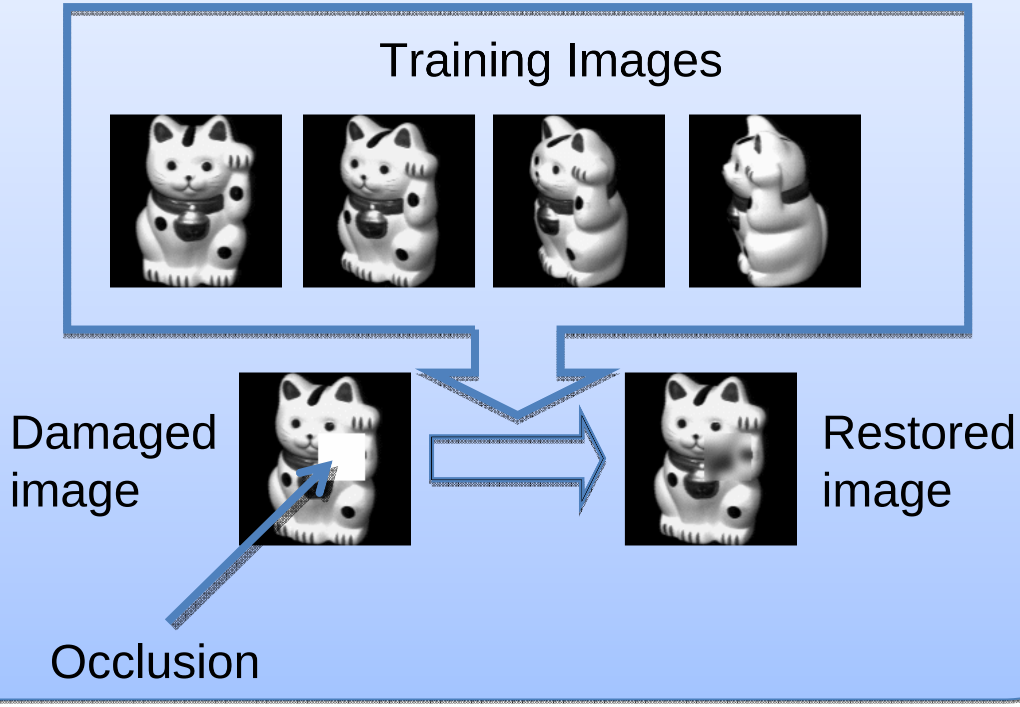
Recognition with Embedded information

How? Using BPLP!

BPLP (Back Projection for Lost Pixels, Amano and Sato 2002)
- Restoring an image damaged by occlusion
- Learning the image
- Estimating the pixel values



In our case …



Learning

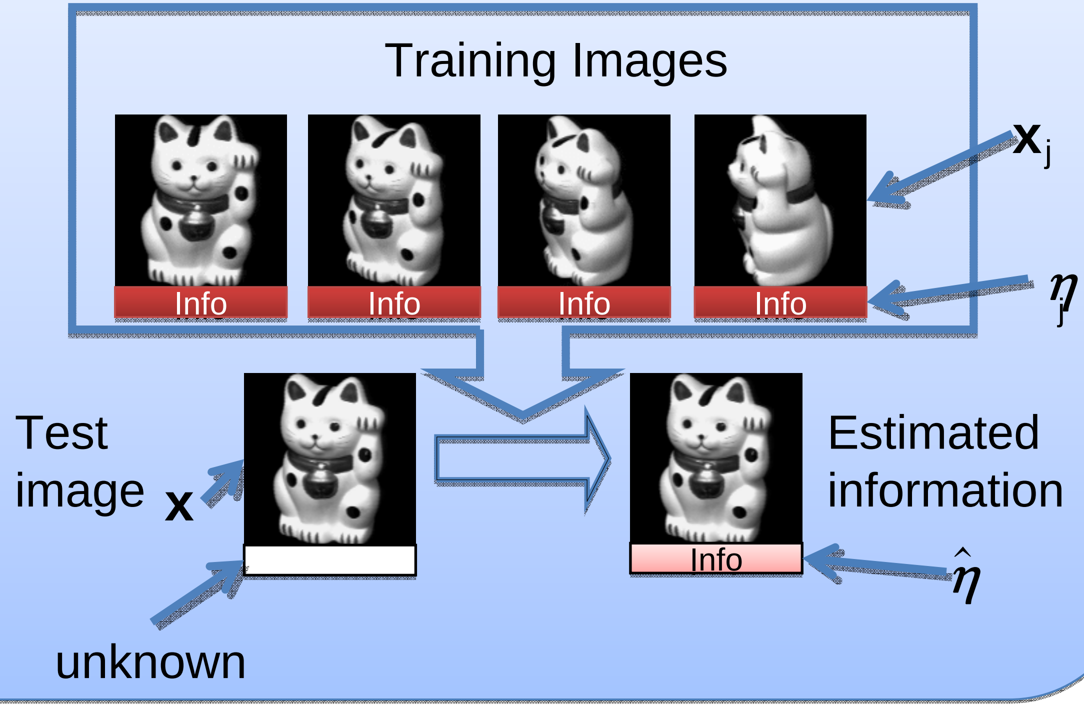
- Image part
- Parameter part (information track)

Estimating

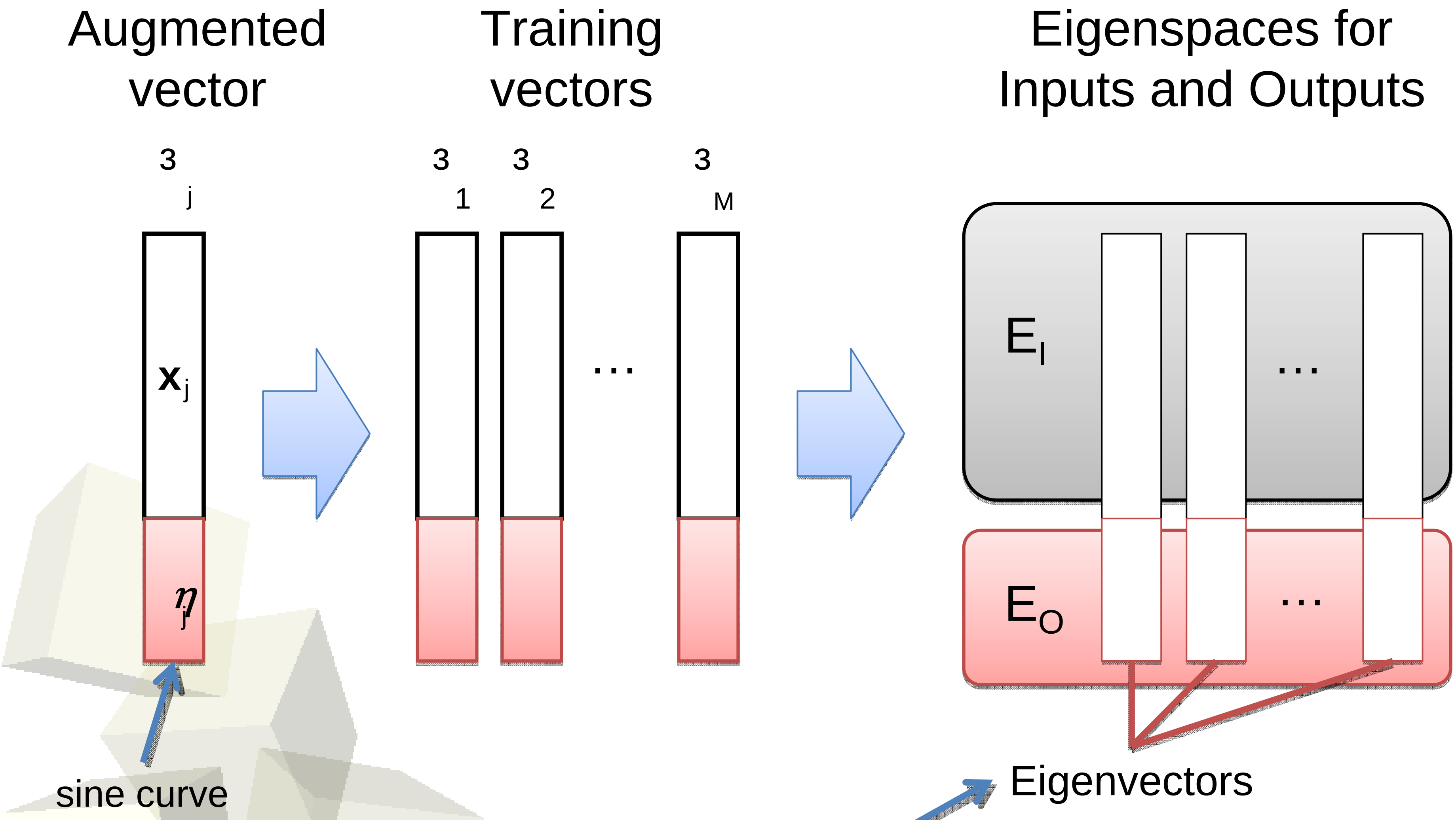
- Restoring as an occluded area from a test image with no information track

Proposed method

- ✓ Easy !
- ✓ Fast !



Learning Eigenspace



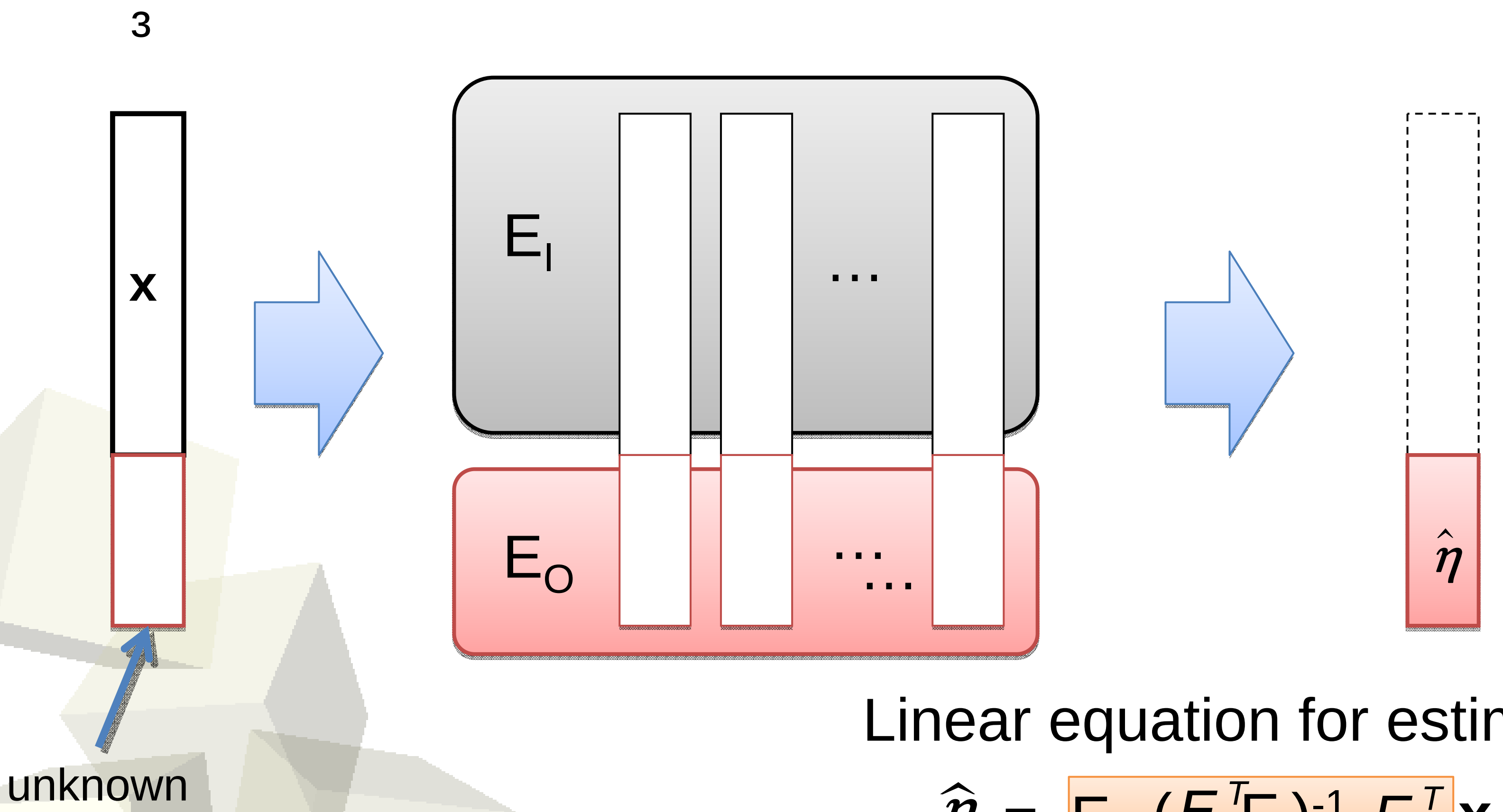
Also, these are sine curves that are linear combinations of sine curves !

Estimation by projection

Augmented vector

Eigenspaces for Inputs and Outputs

Estimated Information track



Linear equation for estimation

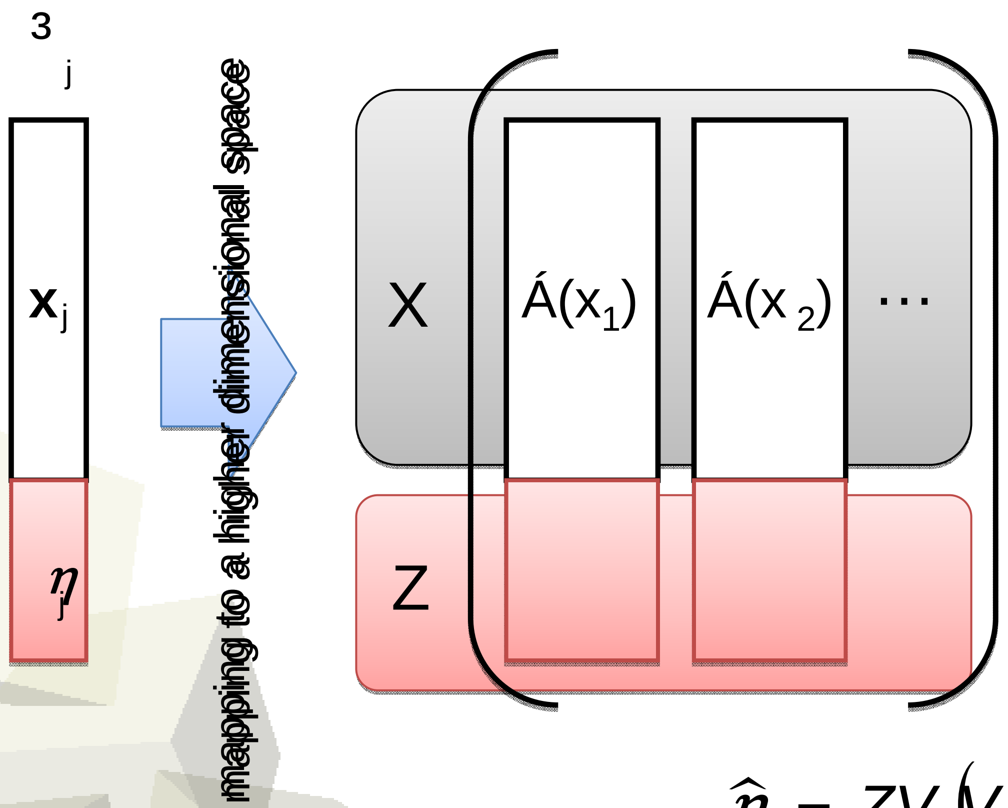
$$\hat{\eta} = \boxed{E_O (E_I^T E_I)^{-1} E_I^T} \mathbf{x}$$

Precomputed!

Kernelization (not implemented)

Augmented vector

Training vectors

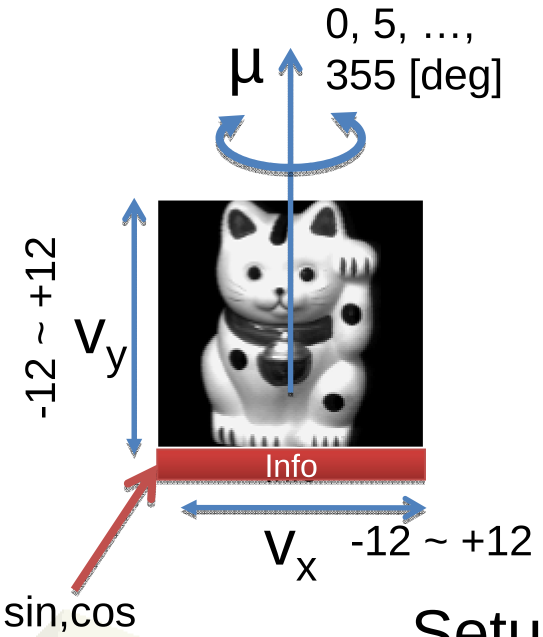


$= EDV^T$ with SVD

$$\hat{\eta} = ZV\left(V^T K(X,X)V\right)V^T K(X,x)$$

Non-linear equation for estimation by using kernel BPLP (Amano and Sato 2003)

Exp. 1: Accuracy and speed



Using COIL-20 dataset

3DOF estimation

- 1 rotation
- 2 translations

Setup					Average error		
μ	v_x	v_y	M	D	μ	v_x	v_y
36 steps	3 steps	3 steps	324 images	131 dim.	24.8 [deg]	1.11 [pix]	1.53 [pix]
36	5	5	900	252	7.76	0.833	0.724
36	7	7	1764	337	5.86	0.692	0.490
36	9	9	2916	388	5.31	0.696	0.450

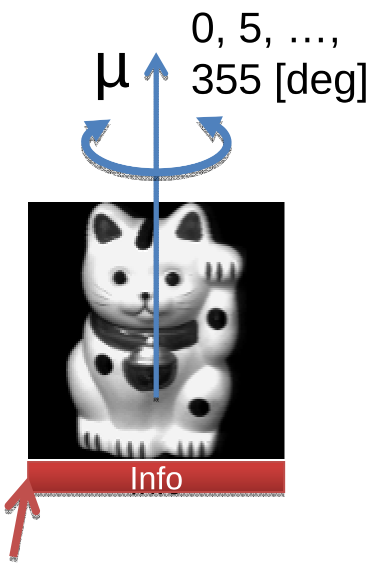
D: Dimensionality of Eigenspace
M: Number of training images

Speed

533 [μsec]

for one estimation

Exp. 2: Effect of number of samples



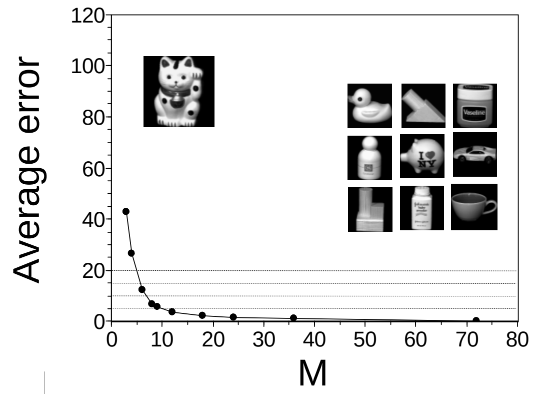
Using COIL-20 dataset

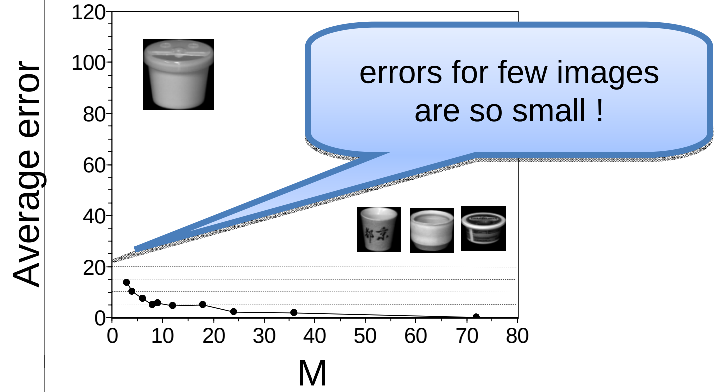
1DOF estimation
- 1 rotation

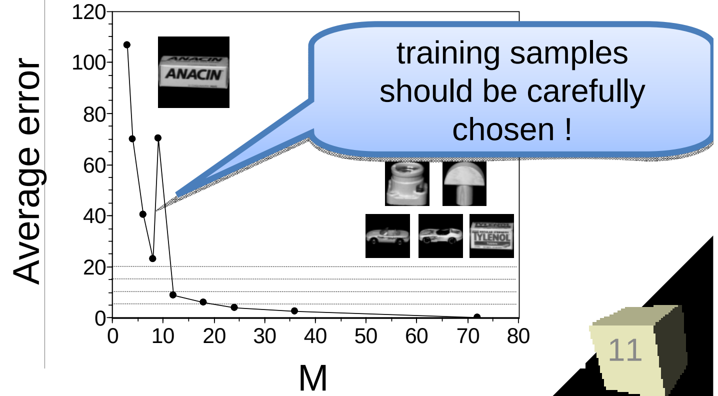
Setup

μ	v_x	v_y	M	D
36 steps	1 steps	1 steps	36 images	36 dim.
24	1	1	24	24
…				
3	1	1	3	3

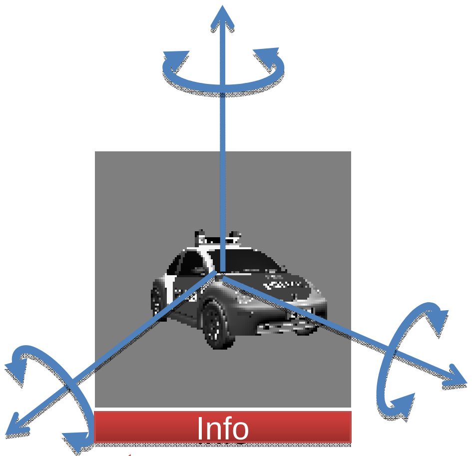
No dimensionality reduction







Exp. 3: Estimation of 3DOF rotation

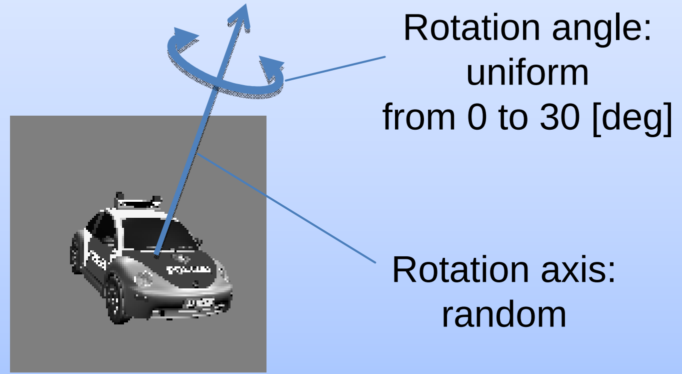


Elements in a rotation matrix

Using a CG object

3DOF estimation
- 3 rotations

Generating by angle-axis rotation



Setup

R	M	D
Randomly generated	100 images	100 dim.

Result

Error
2.26±2.07 [deg]

No dimensionality reduction

Conclusion

- Pose estimation with global appearance of an object
- Linear equation for estimation
- Experimental results
  - 1DOF rotation + 2 translations
  - 1DOF rotation
  - 3DOF rotation

- Future work
  - Implementation of kernelized method
  - More experiments with real images

Subspace 2009
Workshop in conjunction with ICCV2009
Kyoto, Japan
Sep. 27, 2009

GOAL OF THE WORKSHOP

The goal of the workshop is to share the potential of subspace methods with researchers working on various problems in computer vision, and to encourage interactions which could lead to further developments of subspace methods. The fundamental theories of subspace methods and their applications in computer vision will be discussed at the workshop.

SUBSPACE METHODS

Subspace methods are important for solving many theoretical problems in pattern recognition and computer vision. Also they have been widely used as a practical methodology in a large variety of real applications. Subspace methods have been studied intensively, in particular, in the field of character recognition, contributing to a number of commercial optical character recognition systems. During the last three decades, the area has become one of the most successful underpinnings of diverse applications such as classification, recognition, pose estimation, motion estimation. At the same time, there are many new and evolving research topics: nonlinear methods including kernel methods, manifold learning, subspace update and tracking.

PREVIOUSLY ORGANIZED WORKSHOPS

Prior to this workshop, we have successfully organized three related workshops: an international workshop on subspace methods, Subspace 2007 in conjunction with ACCV2007, and two Japanese workshops, Subspace 2006 and 2008. The number of attendees and submissions for these workshops demonstrate their success. Especially, the Proceedings of the Subspace2007 workshop have been downloaded more than 800 times from the workshop's website from 38 different countries for the first six months. We believe that Subspace 2009 in conjunction with ICCV will stimulate fruitful discussions among the participants and provide novel ideas for future research in computer vision.