Pattern Recognition Lecture
“Summary, Applications, and Conclusions”

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Topics

No	Topic
01	Introduction and Outline
02	Classifiers Based on Bayes Decision Theory
03	Linear Classifiers
04	Nonlinear Classifiers
05	Feature Selection
06	Feature Generation I
07	~~Feature Generation II~~
08	Template Matching
09	Context-Dependent Classification
10	~~Supervised Learning: The Epilogue~~
11	Clustering: Basics Concepts
12	Clustering Algorithms I: Sequential Algorithms
13	Clustering Algorithms II: Hierarchical Algorithms
14	Clustering Algorithms III: Schemes Based on Function Optimisation
15	Summary, Applications, and Conclusions

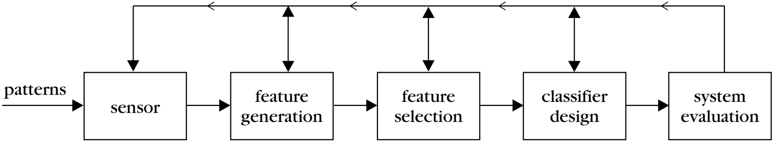
Adaptive Learning of Context

for Pattern Recognition

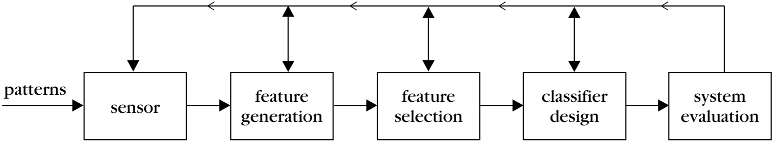
Overview

Overview

Basic Stages of Pattern Analysis

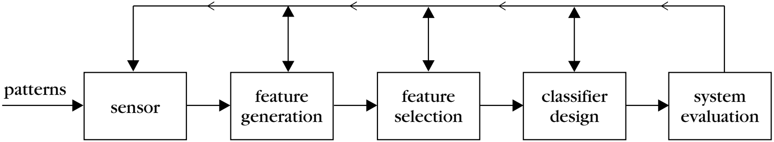


Basic Stages of Pattern Analysis



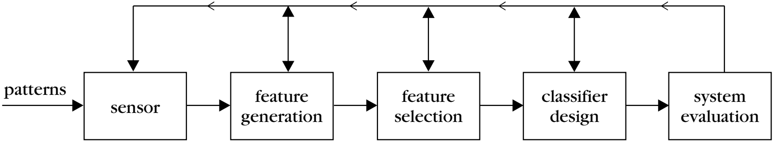
- Adaptive Runtime Optimisation

Basic Stages of Pattern Analysis



- Adaptive Runtime Optimisation
- Integration of Background Knowledge

Basic Stages of Pattern Analysis

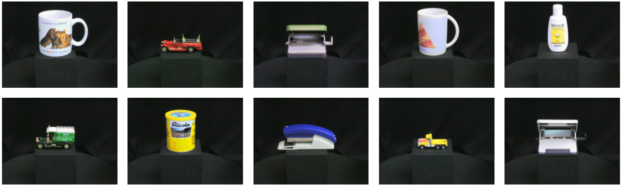


- **Adaptive Runtime Optimisation**
- Integration of Background Knowledge

Scientific Methods for Pattern Recognition

Example

- Generic Appearance-Based Statistical Object Recognition



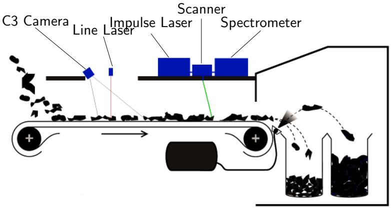
Properties

- Generic Methodology without Fixing the Application
- Limited Robustness in Real-World Environments

Industrial Systems for Pattern Recognition

Example

- Automatic Sorting of Aluminium Alloys



Properties

- Concrete Application Domain
- Problem-Specific Features
- Limited Portability

Development Phase

- Generic System for Pattern Recognition
- Multiple Sensors, Features, and Classifiers

Adaptive Learning for Pattern Recognition

Development Phase

- Generic System for Pattern Recognition
- Multiple Sensors, Features, and Classifiers

Supervision Phase

- Application for a Concrete Task
- Labelling of Misclassified Patterns by a Supervisor
- Adaptive Optimisation of the Processing Chain

Adaptive Learning for Pattern Recognition

Development Phase

- Generic System for Pattern Recognition
- Multiple Sensors, Features, and Classifiers

Supervision Phase

- Application for a Concrete Task
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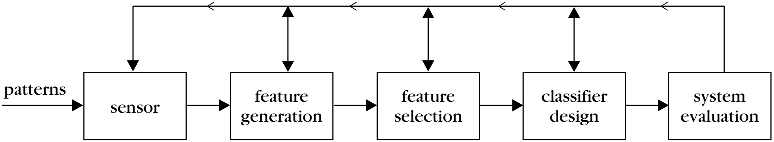
- Adaptive Optimisation of the Processing Chain

Recognition Phase

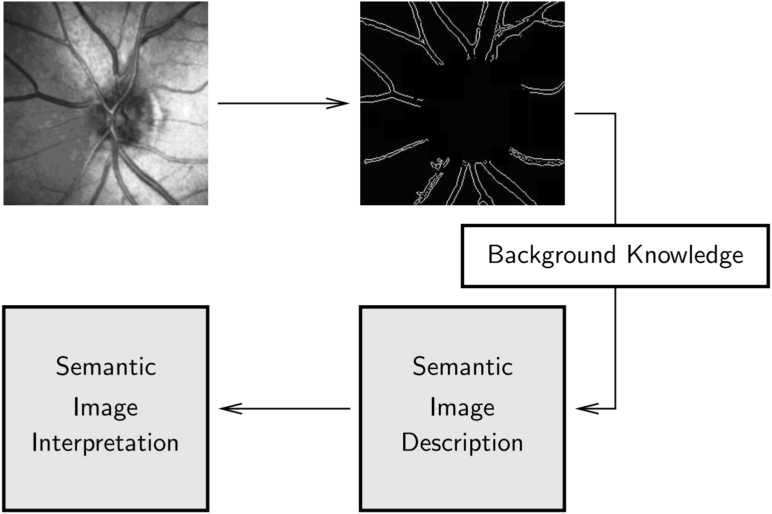
- Further Application without Supervision

Basic Stages of Pattern Analysis



- Adaptive Runtime Optimisation
- **Integration of Background Knowledge**

Semantic Gap in Image Understanding



Overview

Research Areas

Multimodal Object Recognition and Scene Analysis

- Origin: University of Erlangen-Nuremberg
- Finalised: Appearance-Based Statistical Object Recognition
- Ongoing: Object Recognition in Multimodal Sensory Data
- Ongoing: Skeleton-Based Representation of Articulating Objects
- Ongoing: Matching of 3D Objects Based on 3D Curves
- Ongoing: Adaptive Learning of Context for Object Recognition

Research Areas

Semantic Multimedia Analysis and Retrieval

- Origin: Queen Mary, University of London
- Finalised: Content-Based Video Retrieval
- Ongoing: Classification of Environmental Organisms in Microscopic Images
- Ongoing: Event Detection in Video Data
- Ongoing: Adapting to User Preferences based on Relevance Feedback

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- Origin: University of Koblenz-Landau
- Finalised: Spacial Reasoning for Medical Image Understanding
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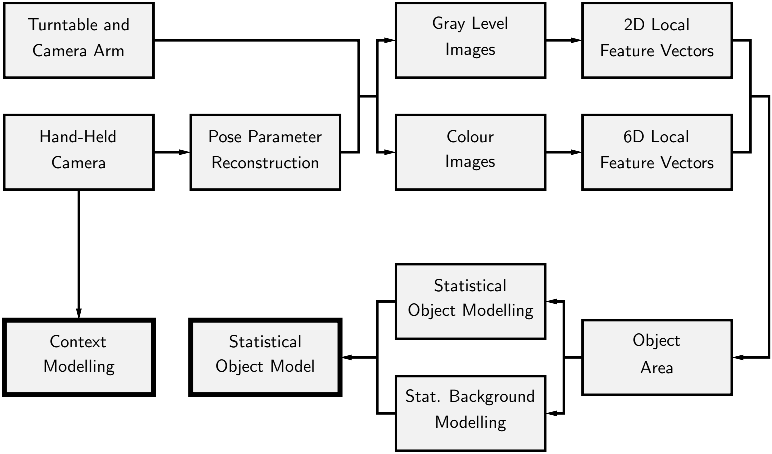
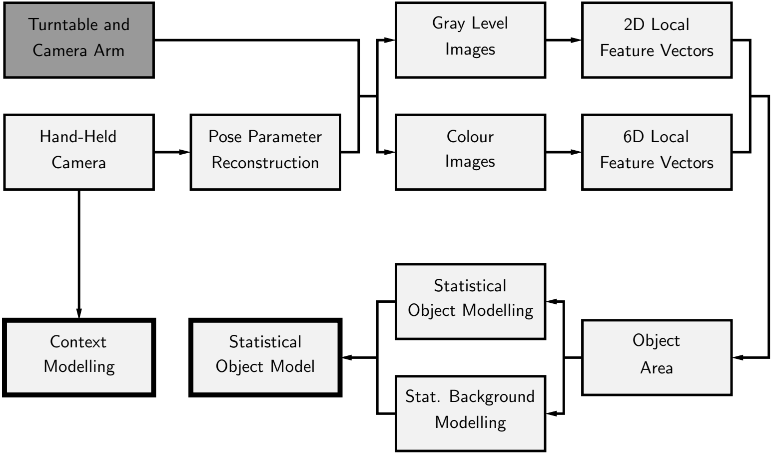
- Ongoing: Ontology-Based Medical Image Processing

Overview

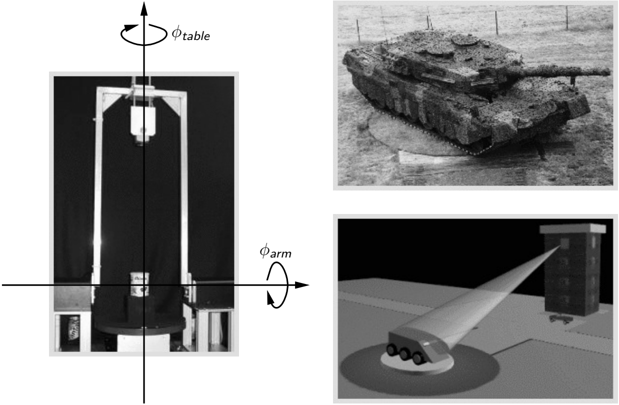
Training Phase



Turntable and Camera Arm



Turntable and Camera Arm

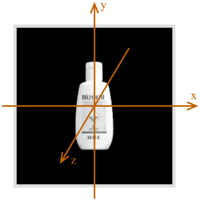


Object poses $(\phi_\rho, \mathbf{t}_\rho)$ for all N_ρ training images $\mathbf{f}_{\rho=1,\dots,N_\rho}$ are known.

Object Pose

$\mathbf{t}_{int} = (t_x, t_y)^{\mathrm{T}}$

$\phi_{int} = \phi_z$



$\mathbf{t} = (t_x, t_y, t_z)^{\mathrm{T}} = (0, 0, 100)^{\mathrm{T}}$
$\boldsymbol{\phi} = (\phi_x, \phi_y, \phi_z)^{\mathrm{T}} = (0, 0, 0)^{\mathrm{T}}$

$\mathbf{t} = (50, 25, 100)^{\mathrm{T}}$
$\boldsymbol{\phi} = (0, 0, 0)^{\mathrm{T}}$

$\mathbf{t} = (50, 25, 100)^{\mathrm{T}}$
$\boldsymbol{\phi} = (0, 0, -30)^{\mathrm{T}}$

$t_{ext} = t_z$

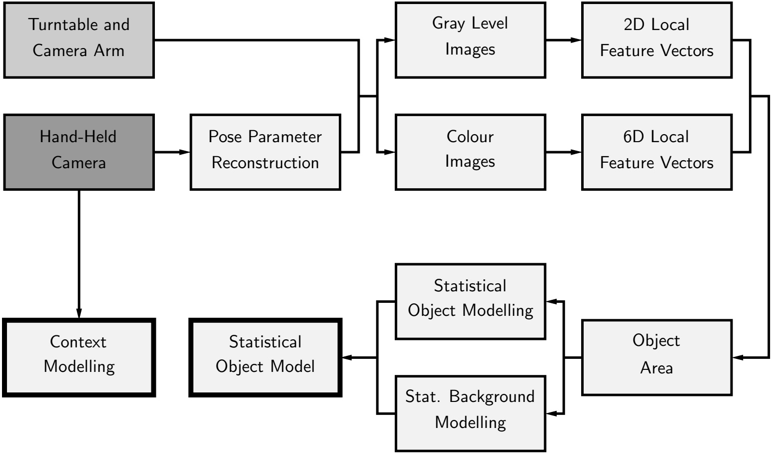
$\boldsymbol{\phi}_{ext} = (\phi_x, \phi_y)^{\mathrm{T}}$

$\mathbf{t} = (0, 0, 100)^{\mathrm{T}}$
$\boldsymbol{\phi} = (22.5, 0, 0)^{\mathrm{T}}$

$\mathbf{t} = (0, 0, 100)^{\mathrm{T}}$
$\boldsymbol{\phi} = (0, 45, 0)^{\mathrm{T}}$

$\mathbf{t} = (0, 0, 80)^{\mathrm{T}}$
$\boldsymbol{\phi} = (0, 0, 0)^{\mathrm{T}}$

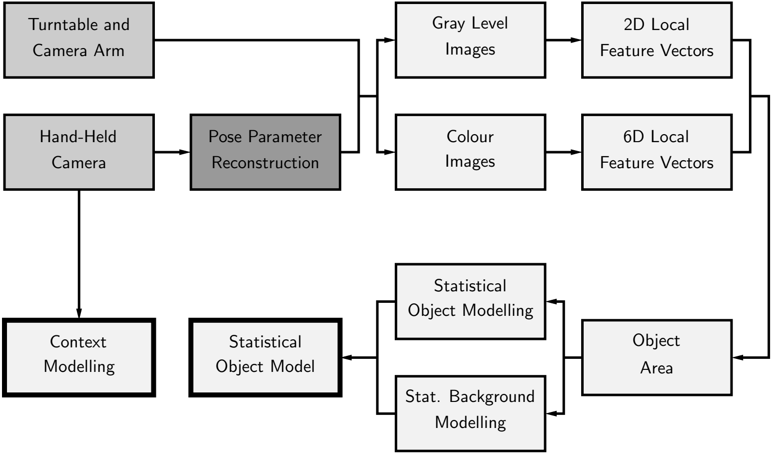
Hand-Held Camera



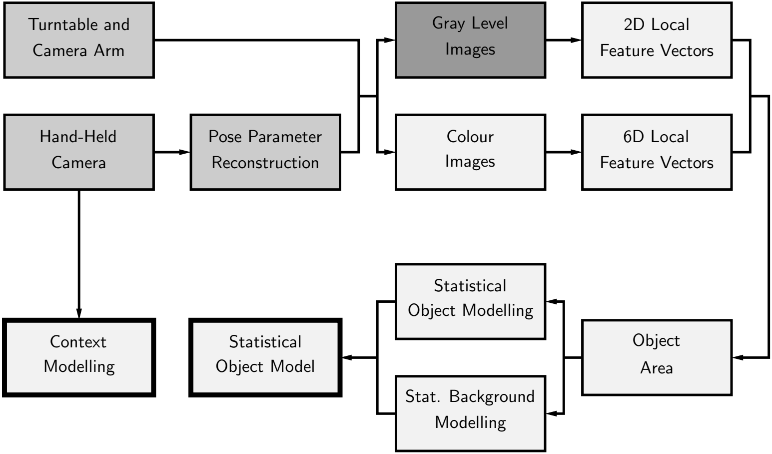
Hand-Held Camera

Object poses $(\phi_\rho, \mathbf{t}_\rho)$ for the training images $\mathbf{f}_\rho$ are unknown.

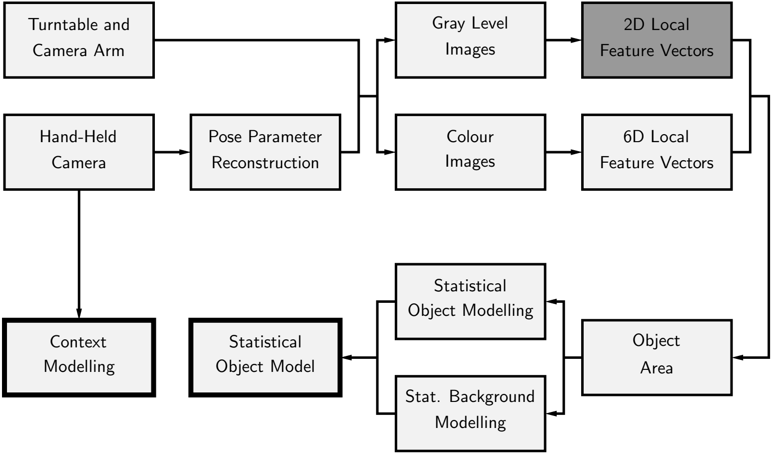
Pose Parameter Reconstruction



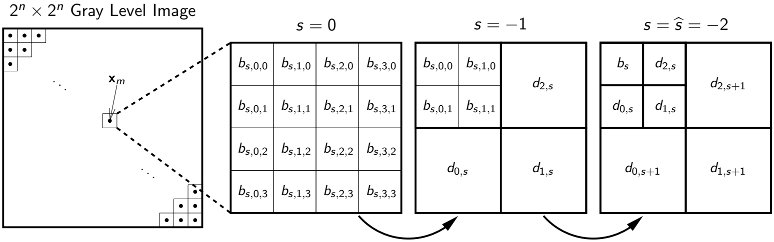
Grey Level Images



2D Local Feature Vectors

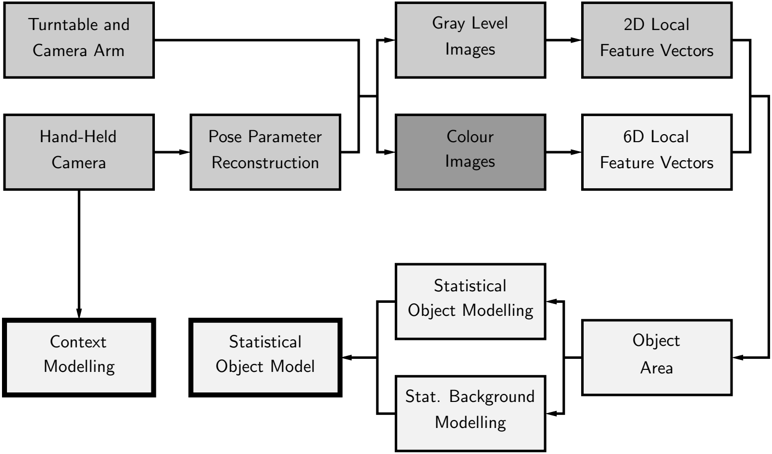


2D Feature Extraction with Wavelet Transform

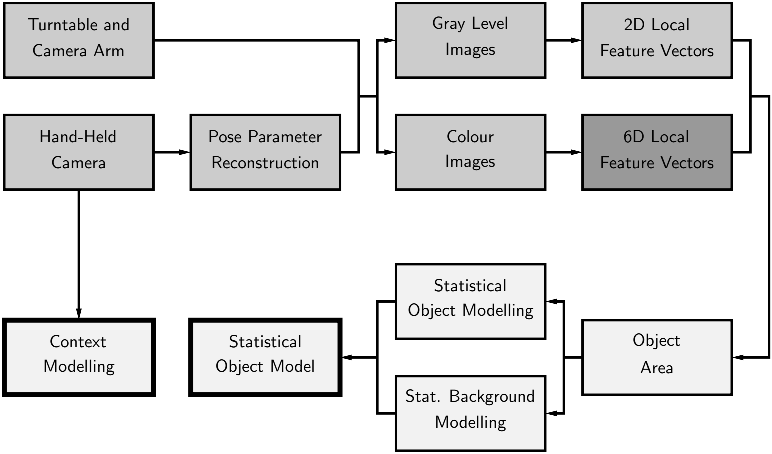


$$\mathbf{c}_m = \mathbf{c}(\mathbf{x}_m) = \begin{pmatrix} c_{m,1} \\ c_{m,2} \end{pmatrix} = \begin{pmatrix} \ln(2^s|b_s|) \\ \ln[2^s(|d_{0,s}| + |d_{1,s}| + |d_{2,s}|)] \end{pmatrix}$$

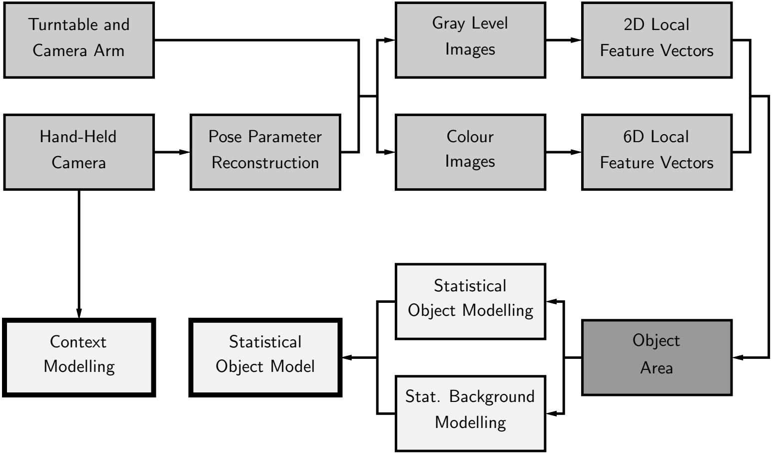
Colour Images



6D Local Feature Vectors

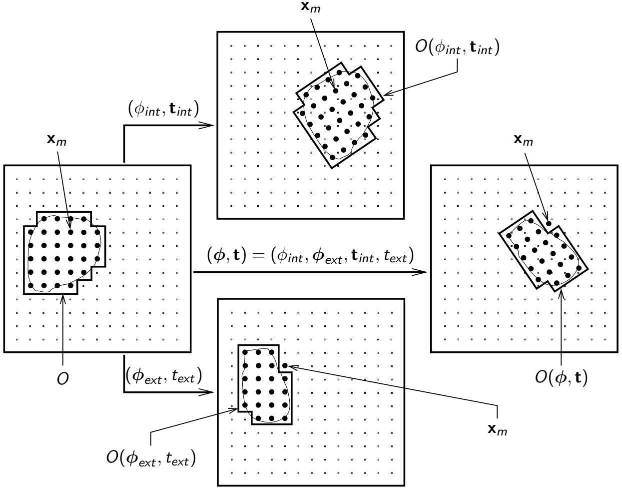


Object Area

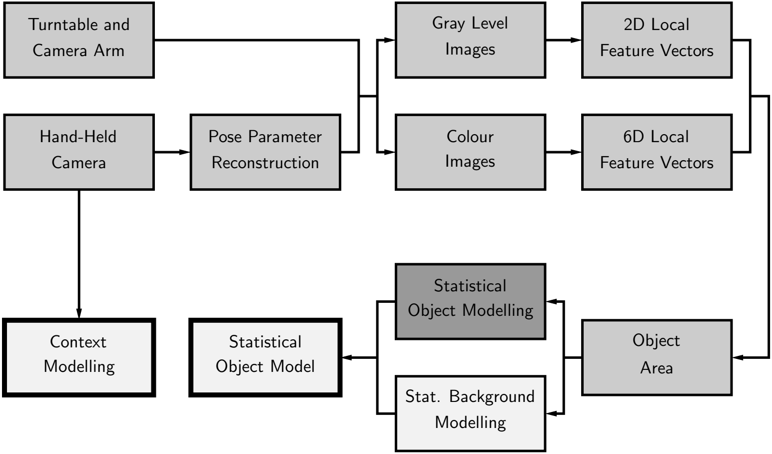


Turntable and Camera Arm
Hand-Held Camera
Pose Parameter Reconstruction
Gray Level Images
Colour Images
2D Local Feature Vectors
6D Local Feature Vectors
Context Modelling
Statistical Object Model
Statistical Object Modelling
Stat. Background Modelling
Object Area

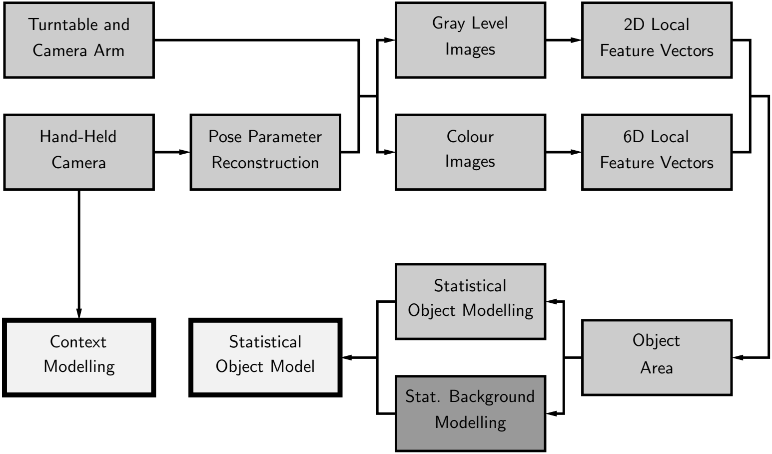
Object Area $O = O(\phi, \mathbf{t})$



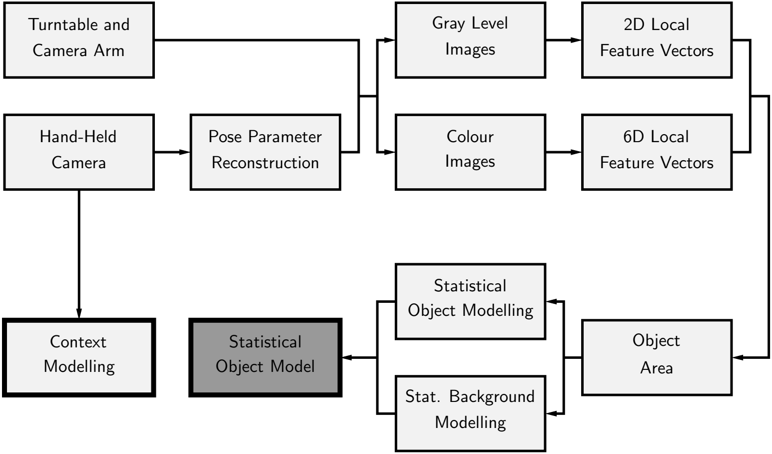
Statistical Object Modelling



Statistical Background Modelling



Statistical Object Model

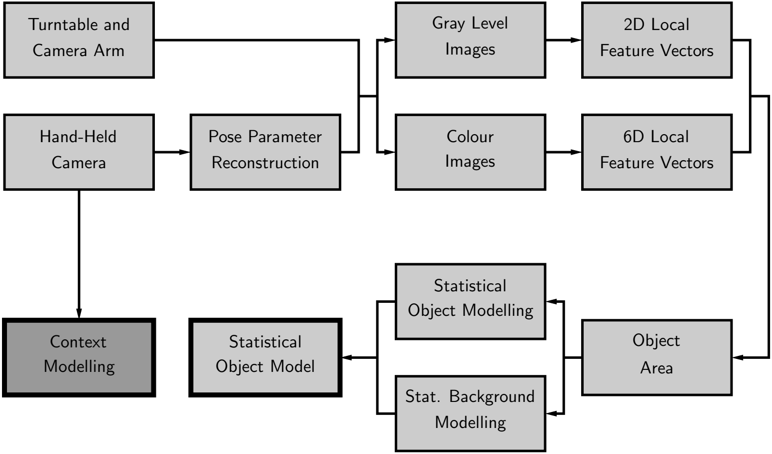


Statistical Object Model - Summary

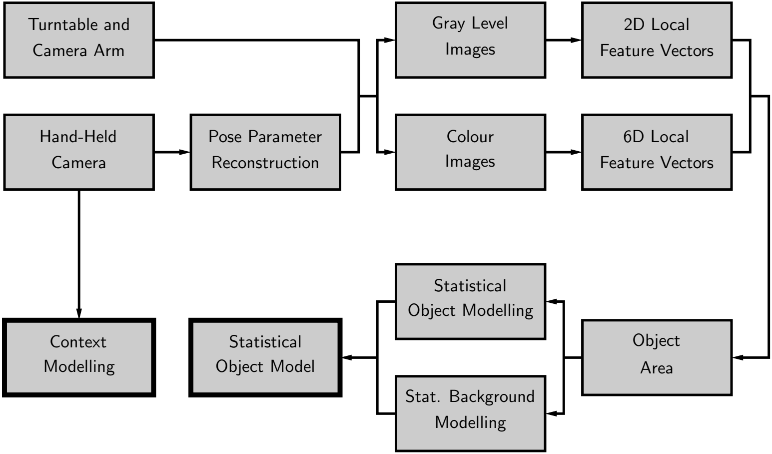
$$\Omega_\kappa \quad \longrightarrow \quad \mathcal{M}_\kappa = \mathcal{M}_\kappa(\phi, \mathbf{t})$$

1. Object Area $\qquad O_\kappa = O_\kappa(\phi, \mathbf{t})$
2. Densities for Object Features $\qquad p(\mathbf{c}_m) = p(\mathbf{c}_m | \boldsymbol{\mu}_m, \boldsymbol{\sigma}_m, \phi, \mathbf{t})$
3. Densities for Background Features $\qquad p(\mathbf{c}_m) = p_b$

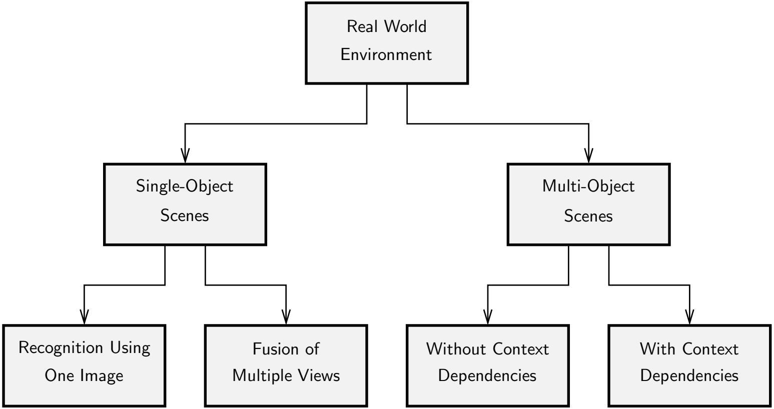
Context Modelling



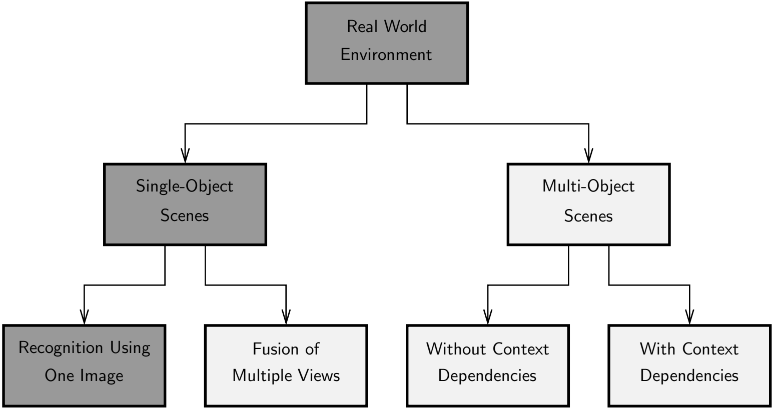
Training Phase Completed



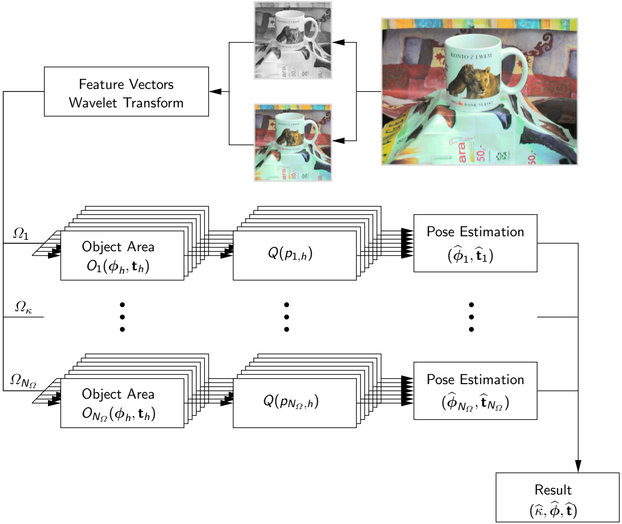
Recognition Phase



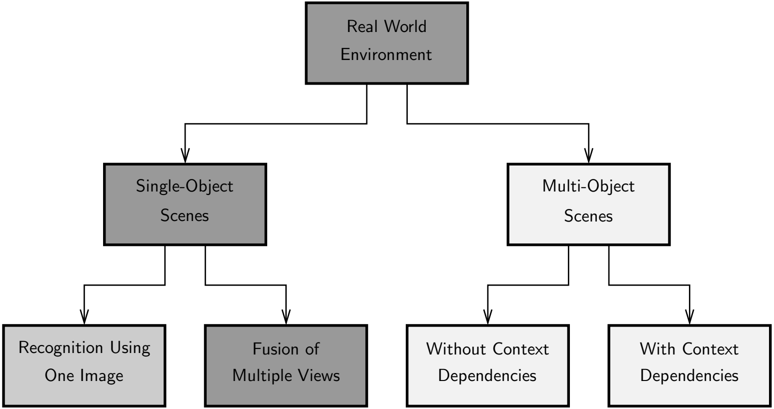
Single-Object, One Image



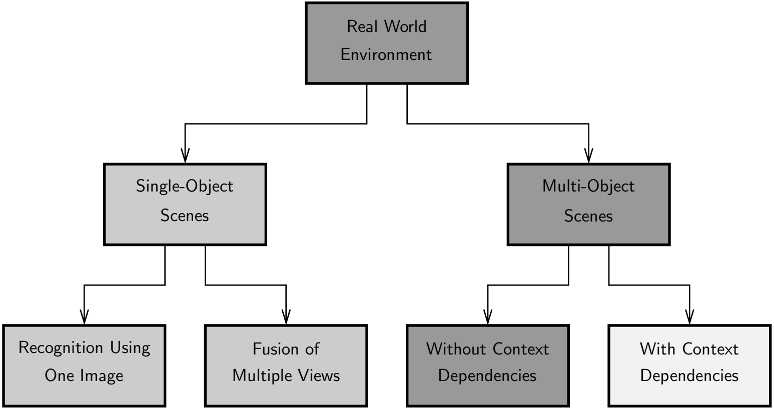
Classification and Localisation Algorithm



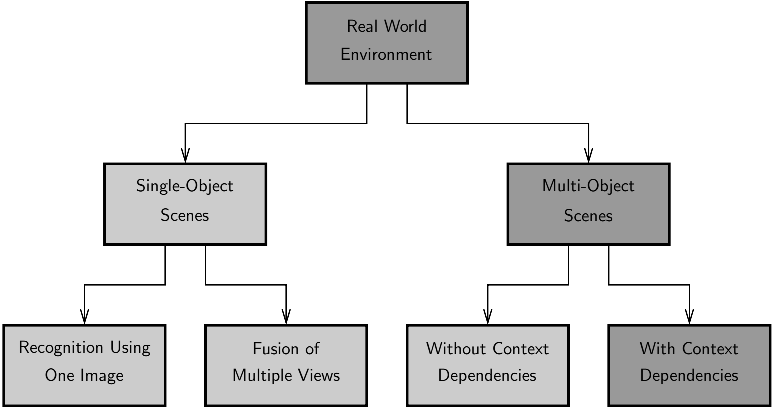
Single-Object, Multiple Views



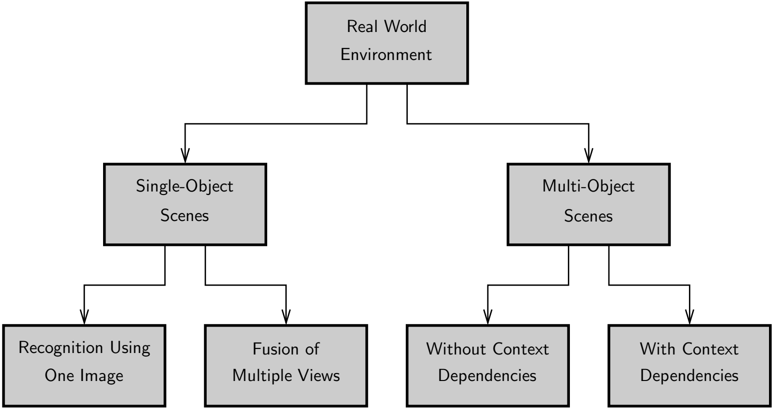
Multi-Object Scenes without Context



Multi-Object Scenes with Context



Recognition Phase Completed



Experiments and Results

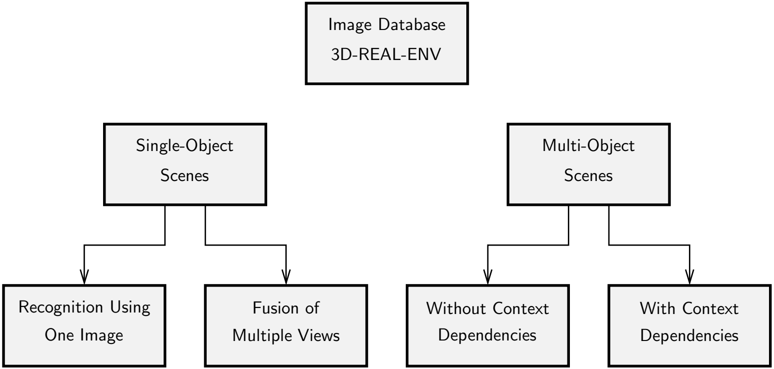
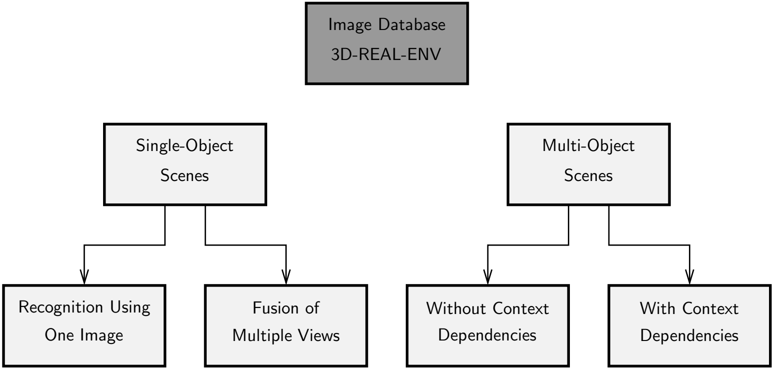
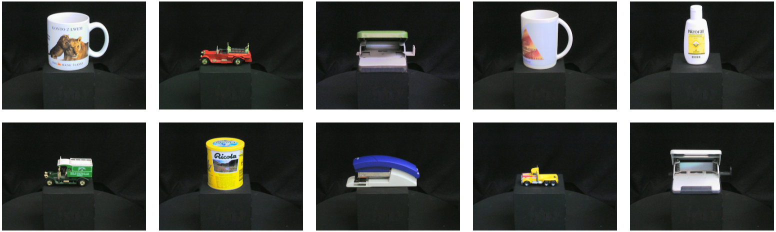


Image Database 3D-REAL-ENV



Training Images

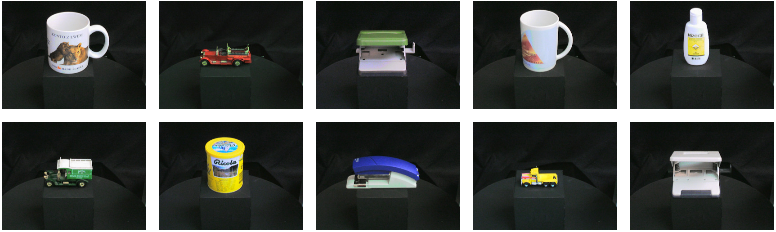


1680 Training Viewpoints, 33600 Images

$$\phi_{x,\rho} = (0.0^\circ, 4.5^\circ, 9.0^\circ, \ldots, 85.5^\circ, 90.0^\circ)$$

$$\phi_{y,\rho} = (0.0^\circ, 4.5^\circ, 9.0^\circ, \ldots, 351.0^\circ, 355.5^\circ)$$

Test Images HomBack

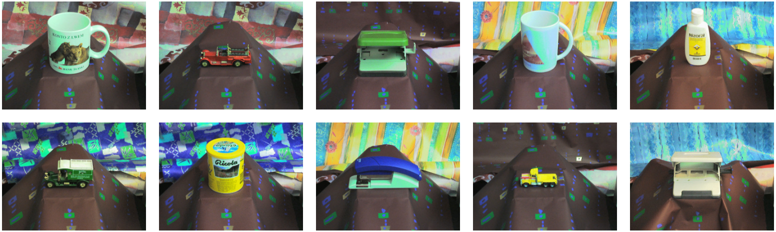


288 Test Viewpoints, 2880 Images

$$\phi_{x,\tau} = (0.00^\circ, 11.25^\circ, 22.50^\circ, \ldots, 78.75^\circ, 90.00^\circ)$$

$$\phi_{y,\tau} = (0.00^\circ, 11.25^\circ, 22.50^\circ, \ldots, 337.50^\circ, 348.25^\circ)$$

Test Images LessHetBack



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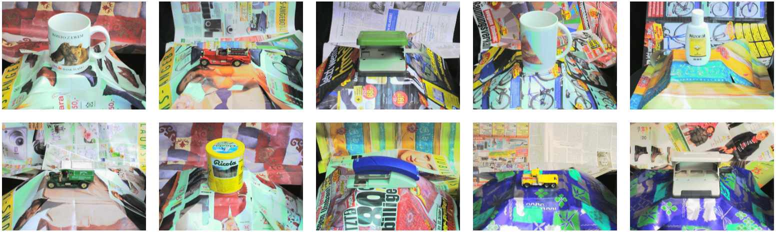
Test Images MoreHetBack



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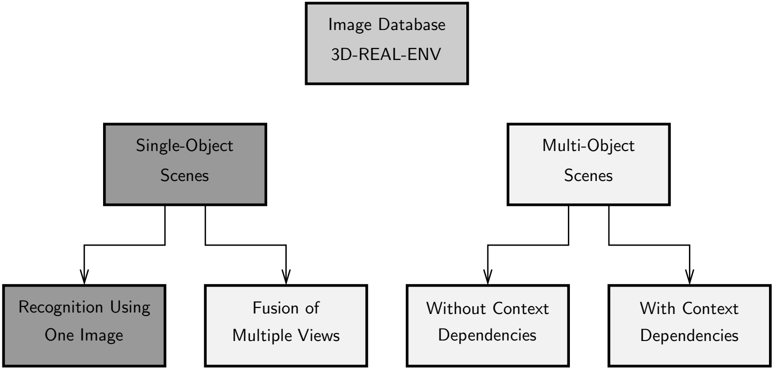
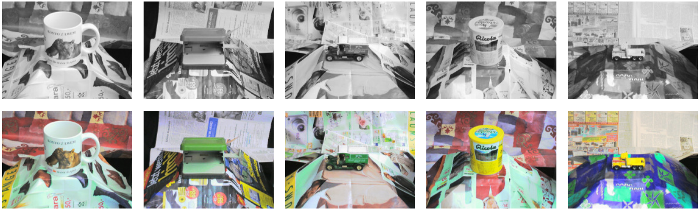
Single-Object, One Image

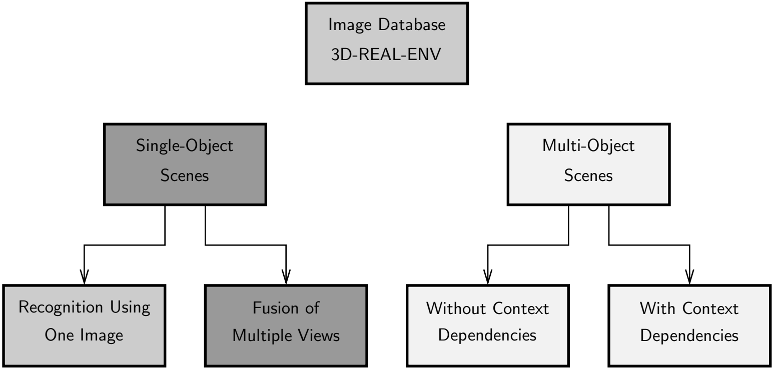


Classification and Localisation Rates

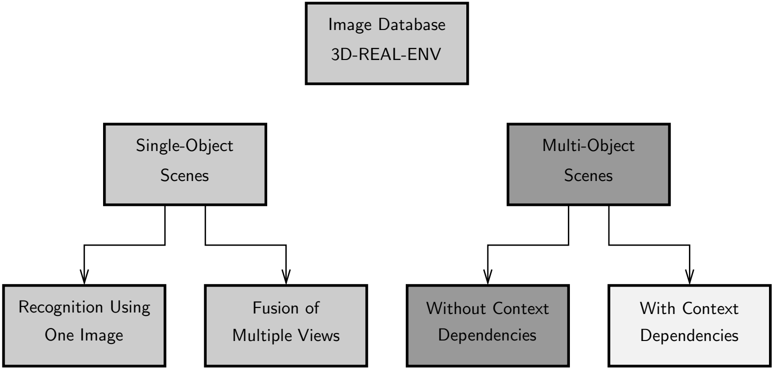
Distance of Training Views 4.5°	Classification			Localisation		
	Hom. Back.	Less Het. Back.	More Het. Back.	Hom. Back.	Less Het. Back.	More Het. Back.
Gray Level	100%	92.2%	54.1%	99.1%	80.9%	69.0%
Colour	100%	88.0%	82.3%	98.5%	77.8%	73.6%



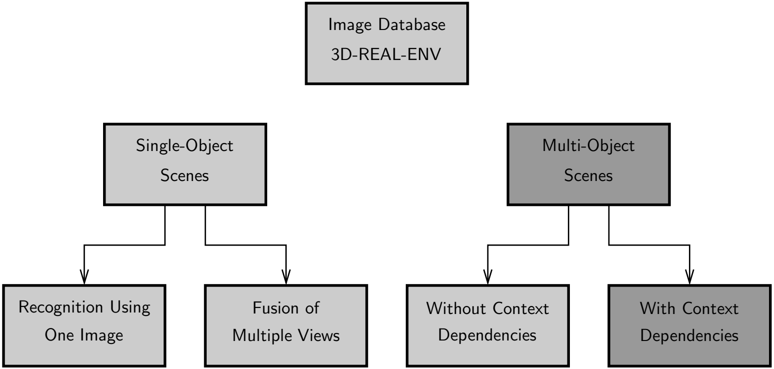
Single-Object, Multiple Views



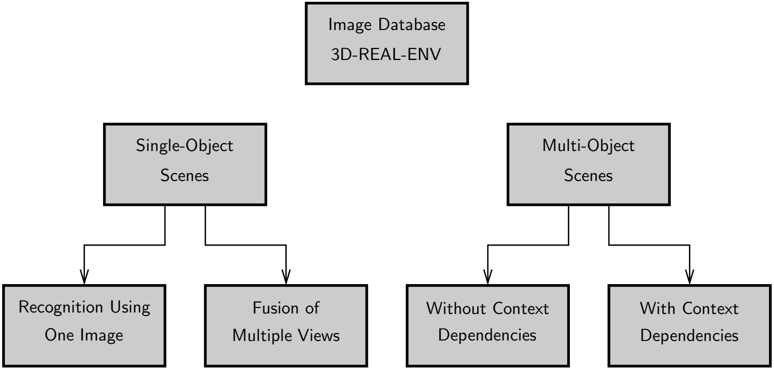
Multi-Object, Without Context



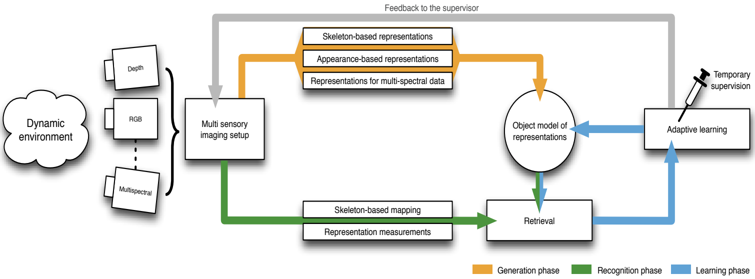
Multi-Object, With Context



Evaluation Completed



Adaptive Learning for Object Recognition



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- Finalised: Spacial Reasoning for Medical Image Understanding
- Ongoing: Depression Screening Based on Multi-Sensory Smartphone Data
- Ongoing: Ontology-Based Medical Image Processing

Existing Collaborations

Multimodal Object Recognition and Scene Analysis

- Prof. Ryszard Tadeusiewicz, AGH Krakw
- Prof. Longin Jan Latecki, Temple University in Philadelphia
- Prof. Walter Kropatsch, Vienna University of Technology
- Prof. Andreas Kolb, University of Siegen
- Prof. Rolf Lakaemper, Temple University in Philadelphia
- Prof. Dietrich Paulus, University of Koblenz-Landau
- Prof. Zygmunt Pizlo, Purdue University
- Prof. Frank Deinzer, University of Applied Sciences Würzburg

Existing Collaborations

Semantic Multimedia Analysis and Retrieval

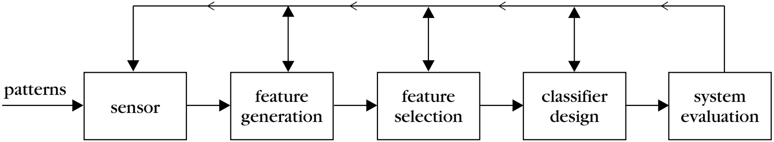
- Prof. Grzegorz Nalepa, AGH Krakw
- Prof. Volker Blanz, University of Siegen
- Prof. Stefan Rüger, The Open University
- Prof. Christoph Ruland, University of Siegen
- Prof. Kuniaki Uehara, Kobe University
- Prof. Beihai Zhou, University of Technology Beijing

Existing Collaborations

Behavioural Biometry and Medical Image Processing

- Prof. Jarek Krajewski, University of Wuppertal
- Prof. Elmar Nöth, University of Erlangen-Nuremberg
- Prof. Steffen Staab, University of Koblenz-Landau
- Prof. Veit Braun, Neurosurgery Department, Jung-Stilling Hospital Siegen

Long-Term Scientific Vision



- Adaptive Runtime Optimisation
- Integration of Background Knowledge