Ein lernfähiges Vision-System mit KNN in der Medizintechnik

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Übersicht:
- Einführung
- Erkennungsaufgabe im Laborbereich
- Vision-System und MILL-Erweiterung
- Ergebnisse einer Anwendungsstudie
- Zusammenfassung und Ausblick
Introduction
Towards Industrial Use of (Intelligent) Sensor System Design Automation

- **State of the art:** expert driven design, manual, costly, slow, & tedious

- **Emerging alternative:** Automated design by suitable optimization

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Introduction
From Academic/Industrial Lab to Multiple Application Sites & Systems

- Design time solution development commonly bases on single prototype
- Deployment to multiple instances demands for static deviation compensation
- Various dynamic perturbation influences demand for dynamic compensation
- In addition, task variations can take place in the application field
Introduction
From Design to Operation Time: Instance-Specific Compensation

Instance Optimization

- Medical Laboratory Robot DAVID:
- **Task**: Tubes sorting & decapping
- Multiple installation sites in Europe

- **Machine-In-the-Loop-Learning**
- General system development
- Instance training for compensation of **static** non-idealities & deviations
Recognition Task for Medical Laboratory
OLA2500 (top left) with Decapper unit (top right) and tube examples (bottom)
Recognition Task for Medical Laboratory

Recognition Problem

- Automated detection of cap type for decapping unit critical
- Misclassification can lead to sample contamination & destruction
- New challenge by multiple coloured caps (Tiger caps) with blob like colour appearance, with obvious large variety of different colour segment sizes, representing the same type
Recognition Task for Medical Laboratory

Block diagram of the basic robot system with the vision unit & reconfiguration

Symbols:
- Images
- Class data
- Weights/Parameter
  - Tube type 1
  - Tube type 2
  - Tube type 3

(Re-) Configuration of the recognition system

Parameter optimizing

Class data

Datenbase

Weights/Parameter

Machine

Image acquisition

Tube recognition

Decapping
Recognition Task for Medical Laboratory
Analysis of Configuration Activities

- Cost structure in different phases of the product life time

<table>
<thead>
<tr>
<th>Production</th>
<th>Service</th>
<th>Customer</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Recalibration&lt;br&gt;Reteaching</td>
<td></td>
</tr>
<tr>
<td>Costs</td>
<td>Configuration/&lt;br&gt;Teaching</td>
<td>Configuration of&lt;br&gt;scene</td>
</tr>
</tbody>
</table>

- Trade-off of manual/interactive vs. automated (re)configuration tasks

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Vision System with MILL-Extension
Block diagram with design time options

Camera/illumination control

Sensor data

Feature selection/parameter of feature extraction

Selection of classifier and optimisation of parameter

Light

Camera

Feature computation

Selection

Classification

Robot

1

2

\ldots

n

PNN

kNN

\ldots

RNN

Tubes
Vision System with MILL-Extension
Phases and steps of configuring the vision system

Start dialog for configuration of the vision system
Vision System with MILL-Extension

Step 2 of the scene configuration: ROI definition

The Bounds dialog is used to check the mechanical adjustment of the tube inspection unit and to adjust the image regions required for the tube detection. Depending on the program context different sections of this documentation apply:

- Mechanical adjustment
- Adjustment of region of interest
- Adjustment of regions for tube detection

The parameter groups "Basic Settings" and "Region of Interest" are available only in the camera configuration mode since the camera hardware is required to change the parameters for Rotation and Offset X; in parameter setting mode the dialog controls for these parameters are disabled.
Vision System with MILL-Extension

- Step 6 of the scene configuration: Configure the Cap Region

**Note:** If no cap colors are used where color detection is enabled in top view (ColorsFromTop>0 in Tubes.INI), this dialog may be skipped - the parameter settings adjusted with this dialog are relevant only if color detection from top is enabled for at least one cap color in use.

**Note:** The tube holder detection parameters (previous dialog) must be properly adjusted to get good results for the cap region detection. If no suitable setting for proper cap region detection can be found, please re-check the tube holder detection parameters.

For cap color recognition in top view the program needs to find the exact position of the tube's cap in the mirror image. This is a more complex task.
Training of the vision system

Configure Database with tube information:
- Name
- Number of colors to detect from side and top
- Cap type (ID only, no additionally information in Database)

For each tube type (cap, cap color):
- pre-sort tube into racks
- pre-select the cap type and color
- Process the tubes in normal operation in the machine

Start the training process:
- Press the „Training“-Button
- Check the result in the confusion matrix
Vision System with MILL-Extension

- Step 5 of the teaching: Training of the vision system
Vision System with MILL-Extension
Flow of feature extraction process

Feature Extraction

Find position of cap in side and top view

Extract Tube Height
Extract Cap-Features
Filter invalid pixel

RGB → HSB
Hue-Saturation-Histogram
Search peaks in Histogram

Extract features for each peak:
- center
- size
- Volume

Tube Height
Cap-Features
Colour features (Side view)
Colour features (Top view)
Vision System with MILL-Extension

Example of feature space from contour information for five tube types
Vision System with MILL-Extension

Tube with tiger cap and corresponding color blob segmentation
Vision System with MILL-Extension
Probabilistic-Neural Network (PNN) of Specht

Resolving of class affiliation, e.g., Max-of-L
Class 1
Class L

Output
(Classification)
Layer

Kernel-Layer

Input Layer

- Each training data vector is stored as Gaussian kernel with fixed global $\sigma$
- According to class labels, kernel are wired to pdf summation nodes
- Explicit cost or a priori weighting can be employed before pdf max-of-L
Hierarchical classification of tubes with two-level rejection mechanism

Hierarchical Classification of tubes

- Classify Cap Geometry
- Classify Tube Height
- Classify Color from side
- Classify Color from top

Feature extraction

- Probability for each cap
- Probability for each tube
- Probability for each color (side)
- Probability for each color (top)

Database with allowed combinations

Rating for all allowed combinations

Recognised tube type (with cap type and cap color)
Results of Large-Scale Application Study
Motivation of Classifier Choice

- Results of classifier selection (Parameters: \( m \) = dimension of feature vector, \( s \) = width of gaussian kernel of the PNN classifier, \( k \) = number of considered nearest neighbours of the kNN classifier)
- Data from one installation, 27,744 tubes, six different cap geometries

<table>
<thead>
<tr>
<th>Classifier</th>
<th>parameters</th>
<th>Recognition Rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>PNN</td>
<td>( \sigma = 2 ) ( m = 80 )</td>
<td>99.1 %</td>
</tr>
<tr>
<td>PNN</td>
<td>( \sigma = 2 ) ( m = 5 )</td>
<td>94.4 %</td>
</tr>
<tr>
<td>PNN</td>
<td>( \sigma = 10 ) ( m = 80 )</td>
<td>98.8 %</td>
</tr>
<tr>
<td>PNN</td>
<td>( \sigma = 10 ) ( m = 5 )</td>
<td>98.4 %</td>
</tr>
<tr>
<td>kNN</td>
<td>( k = 10 ) ( m = 80 )</td>
<td>98.4 %</td>
</tr>
<tr>
<td>kNN</td>
<td>( k = 10 ) ( m = 5 )</td>
<td>90.9 %</td>
</tr>
</tbody>
</table>
Results of Large-Scale Application Study
Selected Date from Multiple Relevant Installations

- **Summary of the investigated data:**

<table>
<thead>
<tr>
<th>Description</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total Analysed tubes in test sets</td>
<td>19,993</td>
</tr>
<tr>
<td>Number of sample sets</td>
<td>17</td>
</tr>
<tr>
<td>Number of different machines</td>
<td>16</td>
</tr>
<tr>
<td>Size of sample sets</td>
<td>168-3856</td>
</tr>
<tr>
<td>Number of samples per class in training sets</td>
<td>20 - 100</td>
</tr>
<tr>
<td>Number of Cap-Types per sample set</td>
<td>5-18</td>
</tr>
<tr>
<td>Number of combinations of Cap and Colour</td>
<td>7-37</td>
</tr>
</tbody>
</table>
Overall classification results for the sample sets mentioned on previous slide

<table>
<thead>
<tr>
<th></th>
<th>Correct</th>
<th>Wrong</th>
<th>Rejected</th>
<th>Correct Total</th>
<th>Wrong Total</th>
<th>Rejected Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tube types</td>
<td>98.97</td>
<td>0.03</td>
<td>1.00</td>
<td>19'993</td>
<td>6</td>
<td>202</td>
</tr>
<tr>
<td>CapsColors</td>
<td>98.78</td>
<td>0.06</td>
<td>1.16</td>
<td>19'955</td>
<td>12</td>
<td>234</td>
</tr>
</tbody>
</table>
Conclusions and Outlook

- The system in its state of evolution until recent updates has been field application on more than 250 installations all over the world!
- The subjective user satisfaction was high in the majority of cases
- Several pathological cases could be identified and led to the recent system state summarized in this contribution
- The remaining error rate is so small, that it is absolutely sufficient for the requirement of this application and the satisfaction of users
- Currently, the potential of computational intelligence methods and the basic learning architecture has only be fractionally exploited, more to come....