Interactive Online Learning for Obstacle Classification on a Mobile Robot

Viktor Losing[1,2], Barbara Hammer[1], Heiko Wersing[2]

1 – Research Institute for Cognition and Robotics - CoR-Lab at Bielefeld University,
2 – HONDA Research Institute Europe GmbH

Online Learning

- Motivation:
  - Adaptation to user habits/environment
  - Current methods rather simple
- Benefits:
  - Incremental learning
  - Incorporation of new classes
  - Control of model complexity
  - Handling of drift
- Challenges:
  - Stability - Plasticity

Interactive Scenario

- Random exploration of garden environment
- Grass-segmentation for obstacle detection
- Live-labeling via iPad
- Object specific actions are performed
- Confidence estimation to identify unknown objects [1]

Fig. 1. Typical scene of the interactive scenario.

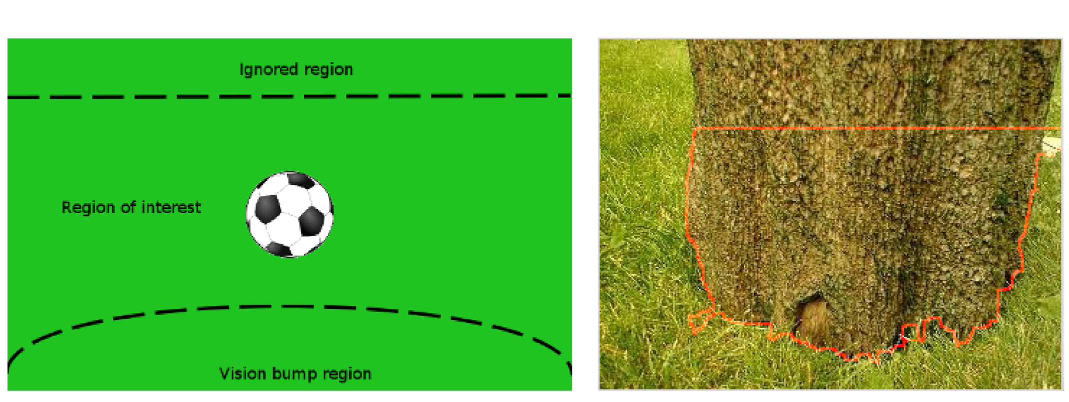

Fig. 2. Left: Partition of the input image. Objects are only examined as long as they are in the region of interest. Overlaps with the vision bump region end the examination and trigger a reaction. Information within the top marked area is ignored completely. Right: Masked area (red) of a close tree stump. The upper part of the image is disregarded even though it belongs to the object.

Feature Representation

- Color-based (simple+robust)
- Rg-Chromaticity histogram
- Intensity invariant
- Size invariant
- 21 dimensions

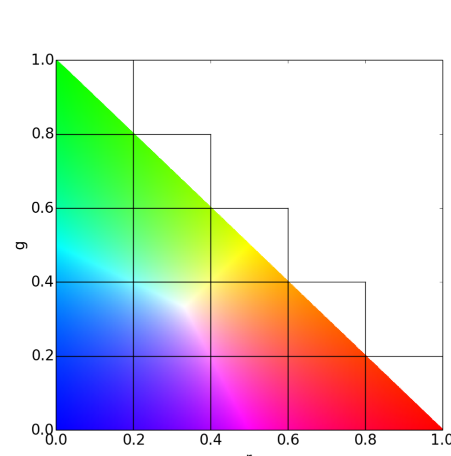

Fig. 3. Histogram binning of the rg-chromaticity space.

Fig. 4. Image in RGB and rg-chromaticity space.

Outdoor Benchmark Data-set

- 40 objects
- 10 sequences per object
- 10 images per sequence
- Cloudy & sunny conditions

Fig. 5. First, fifth and tenth image of some sequences.

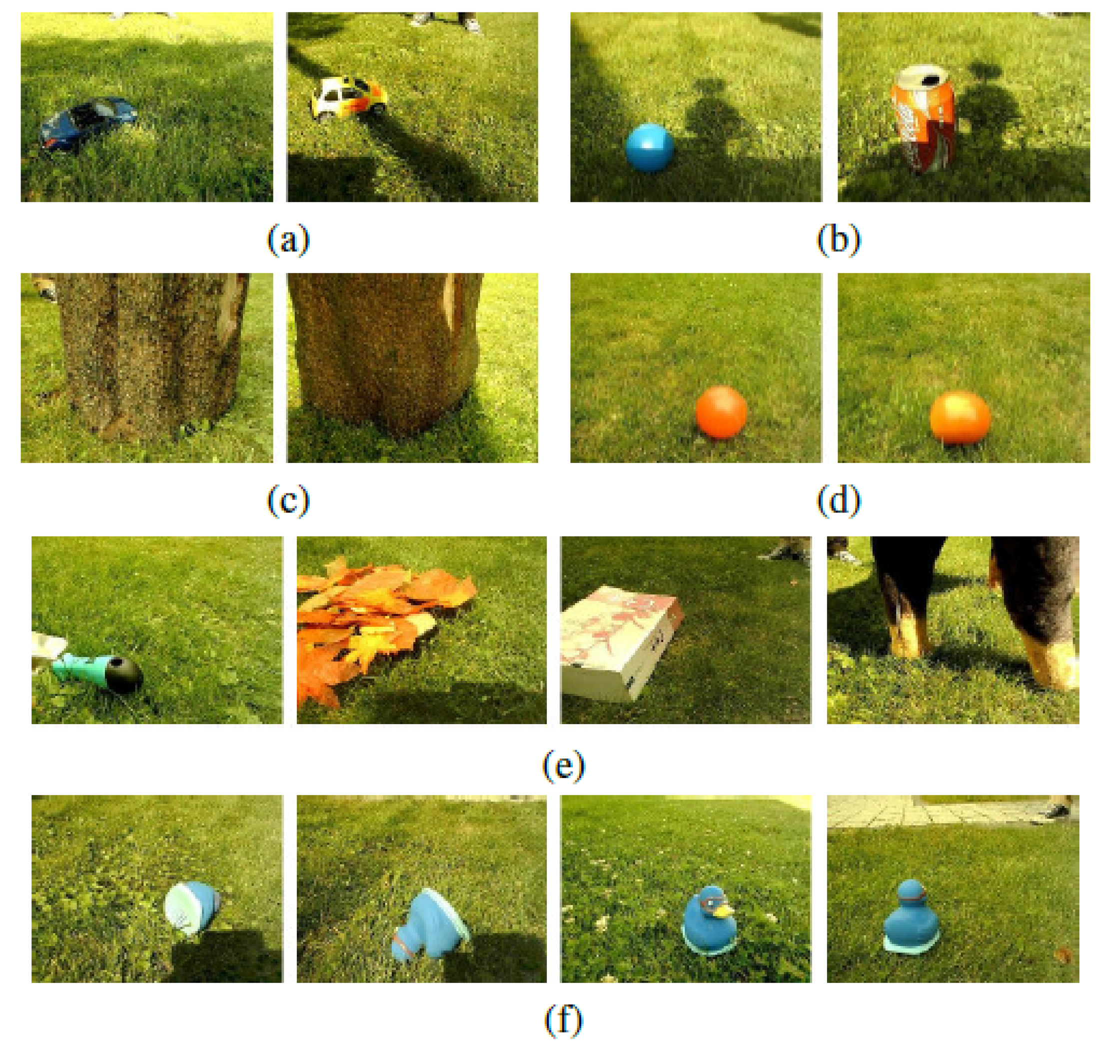

Fig. 6. Challenges of the Outdoor data set. Objects covered in various degrees by shadows cast by environmental obstacles such as trees or buildings (a) or by the robot itself (b). Sunlight and auto-exposure cause a darker object representation (c). Specular highlights (d). Occlusions by the image border (e). Various object poses (f).

Learning Architecture

- Generalized LVQ [2]
- Supervised, prototype based
- $E(X,W)=\sum_{i=1}^{m}\Phi\left(\frac{(d_i^+)-d_i^-)}{(d_i^+ + d_i^-)}\right)$
- Minimized in stochastic gradient descent scheme

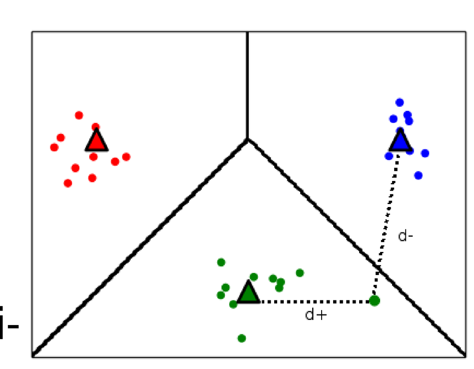

Fig. 7. Simple three class problem. Black lines represent the class borders.

Prototype Insertion - Current Methods

- Based on heuristics
- Use misclassifications only

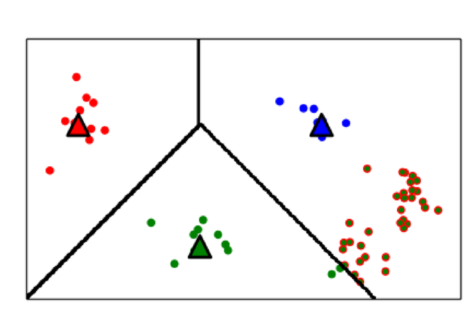

Fig. 8. Situation before a new prototype is inserted.

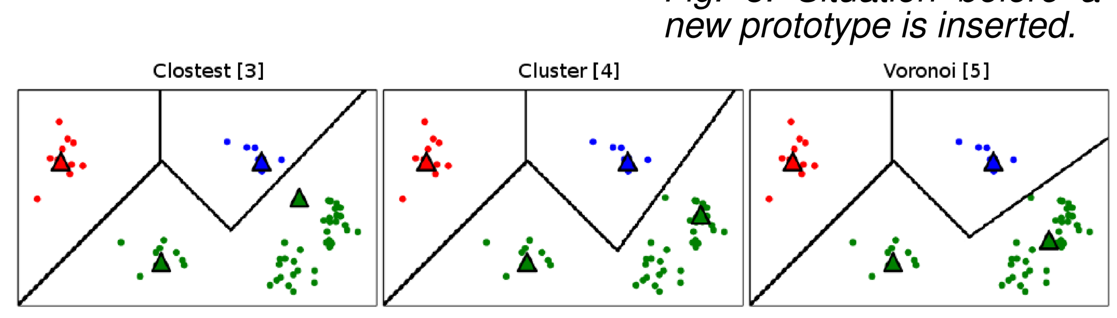

Fig. 9. Situation after a new prototype is inserted by each heuristic.

Prototype Insertion - SamplingCost

- Store a window of recent t samples in a list Ψ
- Choose a random subset $\hat{\Psi} \subseteq \Psi$ of size $|\hat{\Psi}| = \hat{t}$
- Evaluate each sample (x_i, y_i) in $\hat{\Psi}$ as prototype:
  - Add sample as prototype $\hat{W}_i := \{W \cup (x_i, y_i)\}$
  - Calculate the cost $E(\Psi, \hat{W}_i)$
- Choose $\hat{W}_i$ s.t. $E(\Psi, \hat{W}_i)$ is minimized

Results

Artificial Data

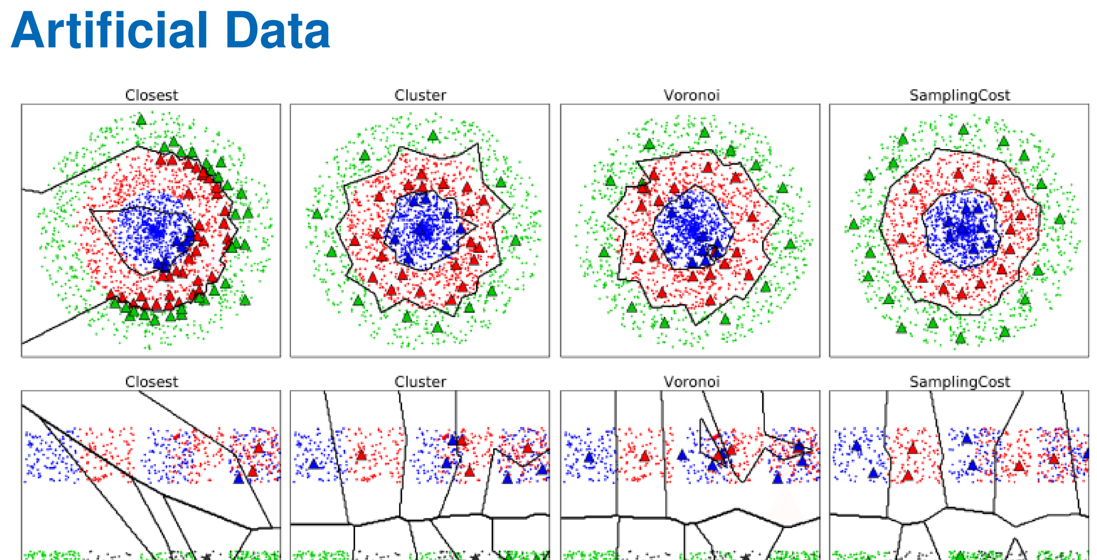

Fig. 10. Networks of each placement strategy after the training of the data sets Border (top) and Overlap (bottom).

Border-DS	Acc.	Nodes
SamplingCost	**93.51**	**38.2**
Closest	90.17	58.2
Cluster	91.93	42.9
Voronoi	91.71	46.4

Overlap-DS	Acc.	Nodes
SamplingCost	**78.74**	**21.3**
Closest	65.76	29.8
Cluster	74.85	25.6
Voronoi	74.08	26.4

Real Data

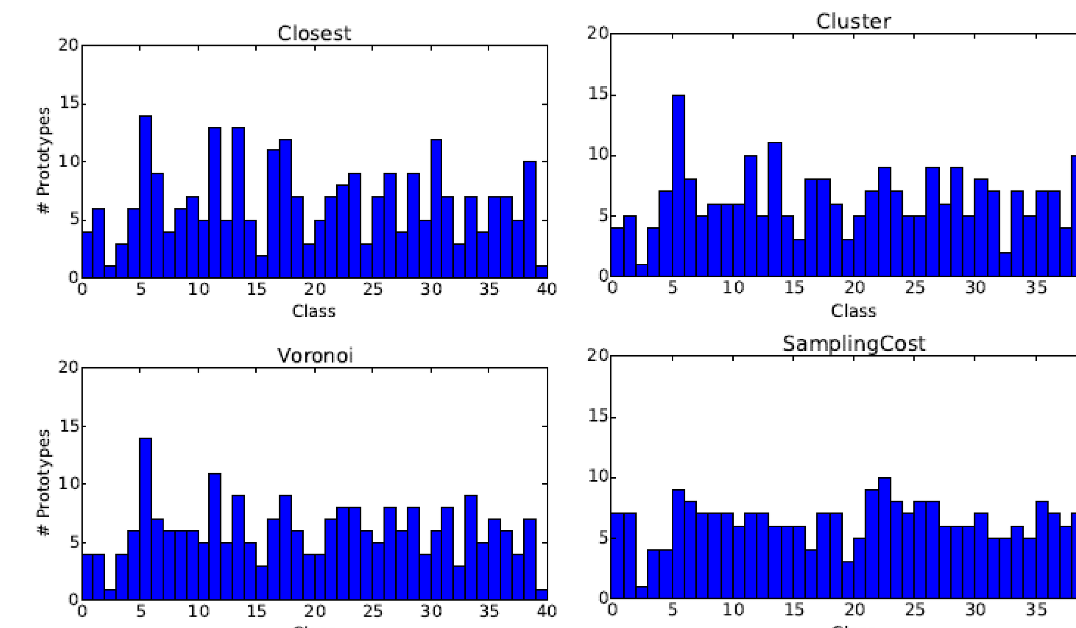

Fig. 11. Prototype distributions for the Outdoor data set.

Random-order	Test acc.	Train acc.	Nodes
SamplingCost	**81.58**	85.94	**234.8**
Closest	78.03	83.23	253.4
Cluster	78.55	83.06	247.0
Voronoi	81.18	85.62	236.6

Sequence-order	Test acc.	Train acc.	Nodes
SamplingCost	**61.38**	91.04	232.0
Closest	59.58	88.04	245.8
Cluster	59.18	88.96	235.6
Voronoi	58.81	89.22	**231.3**

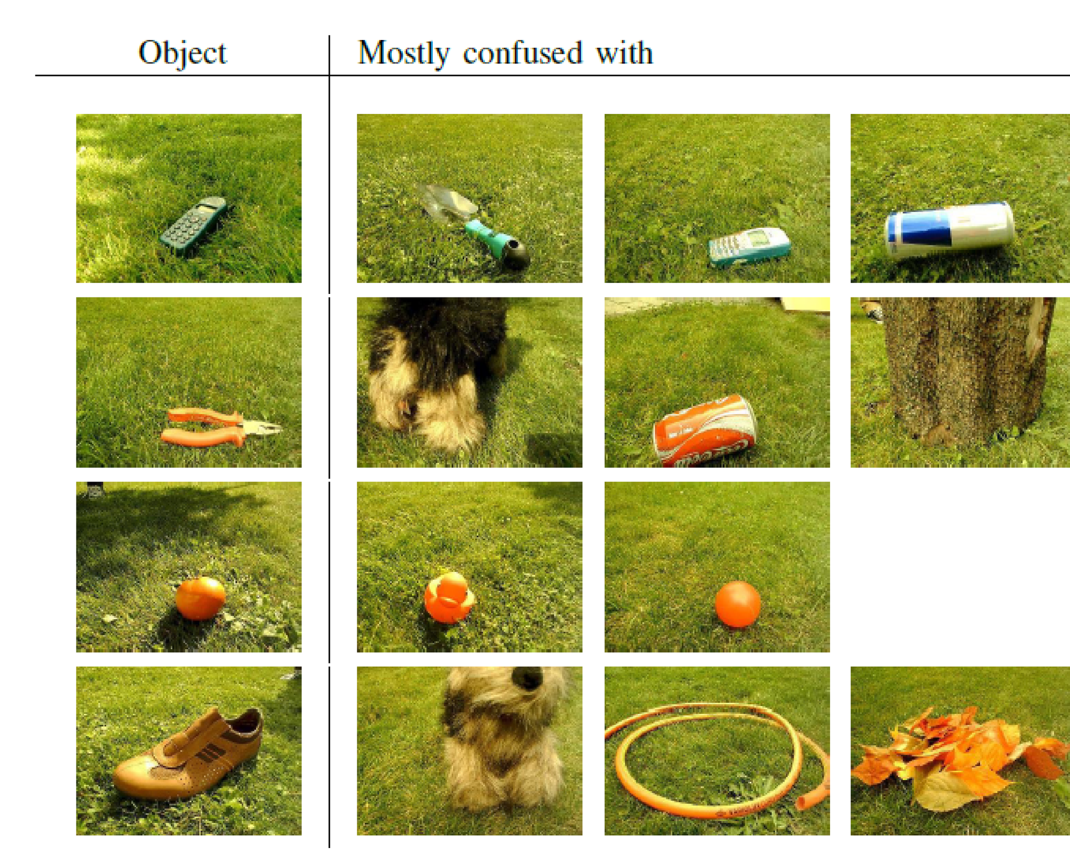

Fig. 12. Objects requiring the highest amount of prototypes.

Fig. 13. The easiest objects.

Comparison with Incremental SVM [6]

Outdoor	Acc. / Nodes 500 samples	Acc. / Nodes 1500 samples	Acc. / Nodes 2800 samples
SC-GLVQ	42.9 / 116.4	58.6 / 446.2	64.3 / 948.8
SC-GMLVQ	**44.1 / 100.4**	**59.3 / 376.6**	**67.1 / 773.5**
iSVM	40.6 / 363.3	57.5 / 777.0	65.2 / 1347

COIL-100	Acc. / Nodes 500 samples	Acc. / Nodes 1000 samples	Acc. / Nodes 1700 samples
SC-GLVQ	83.5 / 337.8	90.4 / 560.0	93.6 / 810.0
SC-GMLVQ	**85.0 / 330.6**	**91.9 / 539.5**	94.7 / 760.0
iSVM	85.6 / 1834	92.7 / 2139	**95.6 / 2501**

References

[1] Fischer L., Hammer B. and Wersing H. Rejection Strategies for Learning Vector Quantization. ESANN (2014)

[2] Sato A. and Yamada, K. Generalized Learning Vector Quantization. NIPS (1995)

[3] Kirstein S., Wersing H. and Körner E. Rapid Online Learning of Objects in a Biologically Motivated Recognition Architecture. 27th Pattern Recognition Symposium DAGM (2005)

[4] Grbovic M. and Slobodan V. Learning Vector Quantization with adaptive prototype addition and removal. IJCNN (2009)

[5] Bermejo S., Cabestany J. and Payeras-Capellà A new dynamic LVQ-based classifier and its application to handwritten character recognition. ESANN (1998)

[6] Diehl C. and Cauwenberghs G. SVM Incremental Learning, Adaptation and Optimization. IJCNN (2013)

Honda Research Institute Europe

Research Institute for Cognition and Robotics