# Interactive Online Learning for Obstacle Classification on a Mobile Robot

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## 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

#### Goals

- 1. Realization of a new interactive Learning Scenario on a Mobile Robot
  - Outdoor object recognition in a garden environment
  - Interaction via iPad
  - Recording of a challenging outdoor benchmark dataset for learning

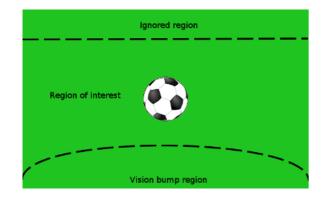
- 2. Improvement of incremental learning for LVQ
  - Analysis of prototype placement strategies
  - Comparison on artificial/real datasets

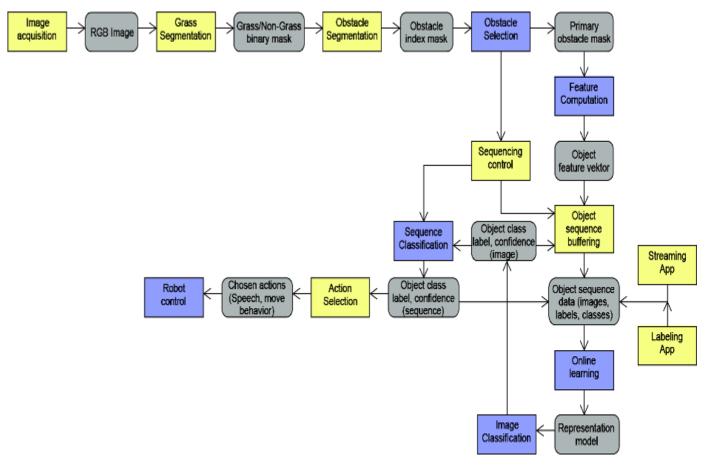
#### Interactive Scenario

- Random exploration
- Grass-segmentation for detection
- Labeling via iPad
- Object specific actions
  - Comment
  - Drive around/over
- Confidence estimation
  - Unknown objects
  - Drive around in case of low confidence



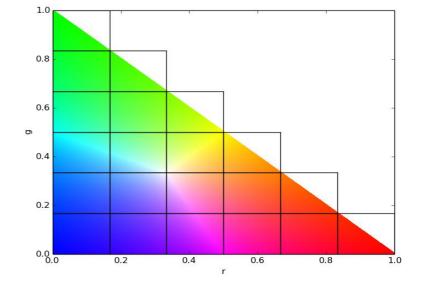
## Perception and Control





## Feature Representation

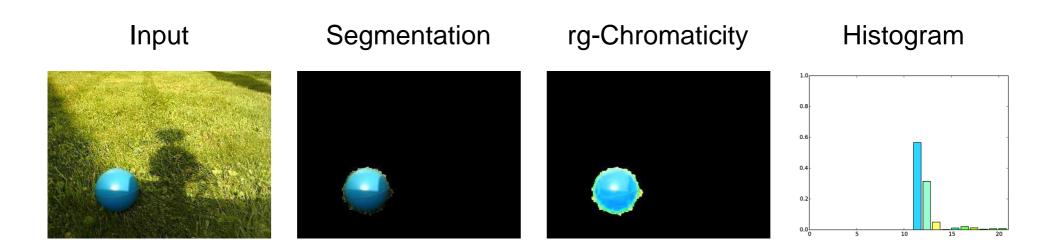
- Color based: simple & robust
- rg-Chromaticity histogram
- Intensity invariant
- ▶ 21 dimensions
- ▶ Hist.-normalization for size invariance







# Processing pipeline



#### Outdoor benchmark dataset

- ▶ 40 objects
- ▶ 5 sequences in cloudy/sunny conditions
- ▶ 10 images per sequence



Sequences



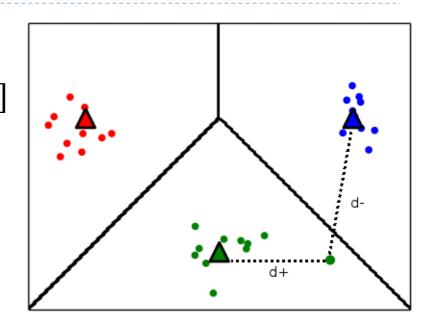
All objects

# Challenges



## GLVQ<sup>1</sup>

- Supervised, prototype—based
- $E(X) = \sum_{i=1}^{n} \Phi[(d_{i}^{+} d_{i}^{-})/(d_{i}^{+} + d_{i}^{-})]$
- Minimized in stochastic gradient descent scheme



## Short term memory

 $\Psi := \langle (x_i, y_i, d_i^+, d_i^-) \mid i \in 1, ..., t \rangle$ , window of recent t samples

Ψ

$$\begin{pmatrix} x_0, y_0 \\ d^+_0, d^-_0 \end{pmatrix}$$

 $x_{n-t+1}, y_{n-t+1}$  $d^{+}_{n-t+1}, d^{-}_{n-t+1}$ 

 $\bullet \bullet \bullet \begin{vmatrix} x_{n-1}, y_{n-1} \\ d^+_{n-1}, d^-_{n-1} \end{vmatrix}$ 

 $\begin{vmatrix} x_n, y_n \\ d^+_n, d^-_n \end{vmatrix}$ 

n

0

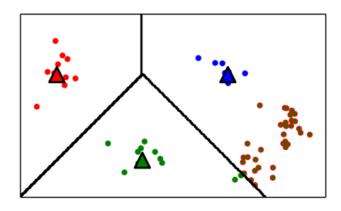
n-t+1

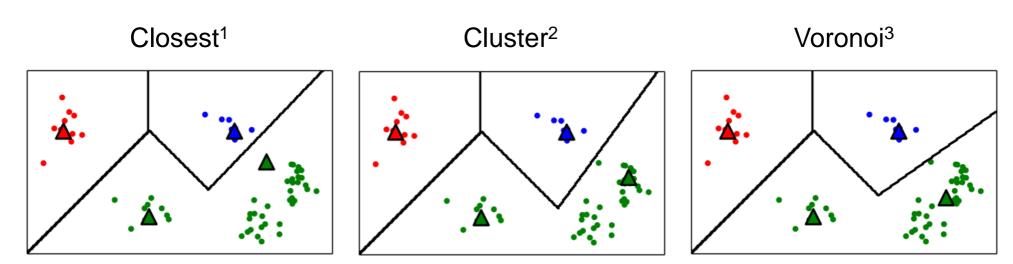
n-1

sample idx.

#### Current Placement Strategies

- Based on class-local heuristics
- Use misclassifications only





<sup>&</sup>lt;sup>1</sup> S.Kirstein, H.Wersing "Rapid Online Learning of objects in a biologically motivated architecture", 2005

<sup>&</sup>lt;sup>2</sup> M.Grbovic, S. Vucetic "Learning Vector Quantization with adaptive prototype addition and removal", 2009

<sup>&</sup>lt;sup>3</sup> S. Bermejo, J. Cabestany "A new dynamic lvq-based classifier and its application to handwritten digits", 1998

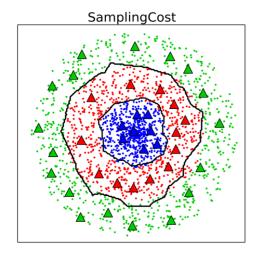
## Proposed Strategy - SamplingCost

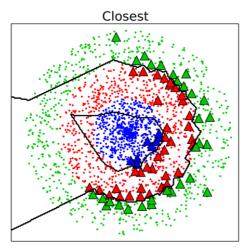
- $-\widehat{\Psi} \subseteq \Psi, |\widehat{\Psi}| = \widehat{t}$
- $\forall (x_i, y_i) \in \widehat{\Psi}$ :
  - $\widehat{W_i} \coloneqq \{W \cup (x_i, y_i)\}$
  - $-\dot{\Psi}_{i} = update \Psi$
  - Calculate cost-function value  $E(\dot{\Psi}_i, \widehat{W}_i)$
- Choose  $\widehat{W}_i$  s.t.  $E(\dot{\Psi}_i, \widehat{W}_i)$  is minimized

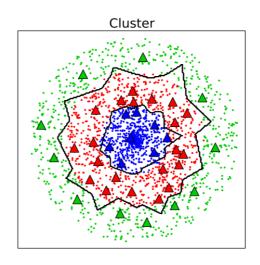
**Cross-class optimization** 

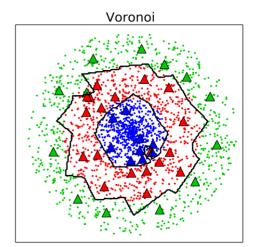
#### Artificial dataset Border

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



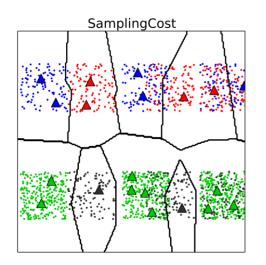


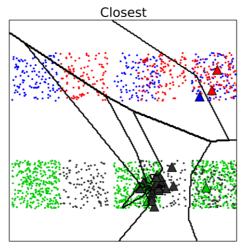


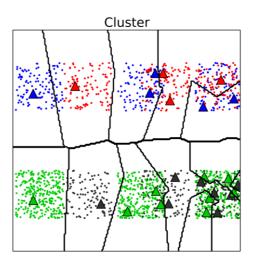


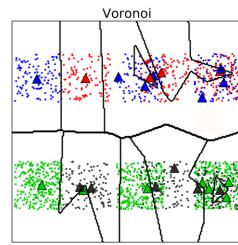
# Artificial Dataset Overlap

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



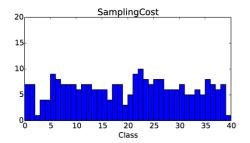


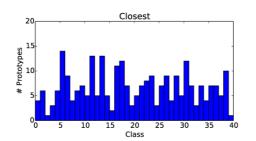


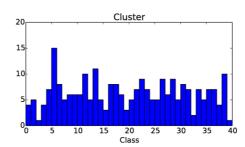


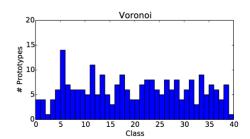
### Outdoor Dataset

Random-order	Test acc.	Train acc.	Nodes	Sequence-order	Test acc.	Train acc.	Nodes
SamplingCost	81.58	85.94	234.8	SamplingCost	61.38	91.04	232.0
Closest	78.03	83.23	253.4	Closest	59.58	88.04	245.8
Cluster	78.55	83.06	247.0	Cluster	59.18	88.96	235.6
Voronoi	81.18	85.62	236.6	Voronoi	58.81	89.22	231.3









Sequence-order	Acc. / Nodes 500 samples	Acc. / Nodes 1500 samples	Acc. / Nodes 2800 samples
SamplingCost-GLVQ SamplingCost-GMLVQ	42.9 / 116.4 <b>44.1</b> / <b>100.4</b>	58.6 / 446.2 <b>59.3</b> / <b>376.6</b>	64.3 / 948.8 <b>67.1</b> / <b>773.5</b>
iSVM	40.6 / 363.3	57.5 / 777.0	65.2 / 1347

# Easy/Difficult Objects

Easy Difficult Object Mostly confused with

### Video

### Summary

- New interactive real-time learning scenario
- Outdoor benchmark dataset for learning
- Proposal of cost-function based placement strategy
- Comparison to current strategies on artificial and real datasets
- SamplingCost performs superior, especially for Overlaps
- Representation not robust enough, could be extended by shape based features

Thank you for your attention!