Robust Autonomous Structure-Based Color Learning on a Mobile Robot

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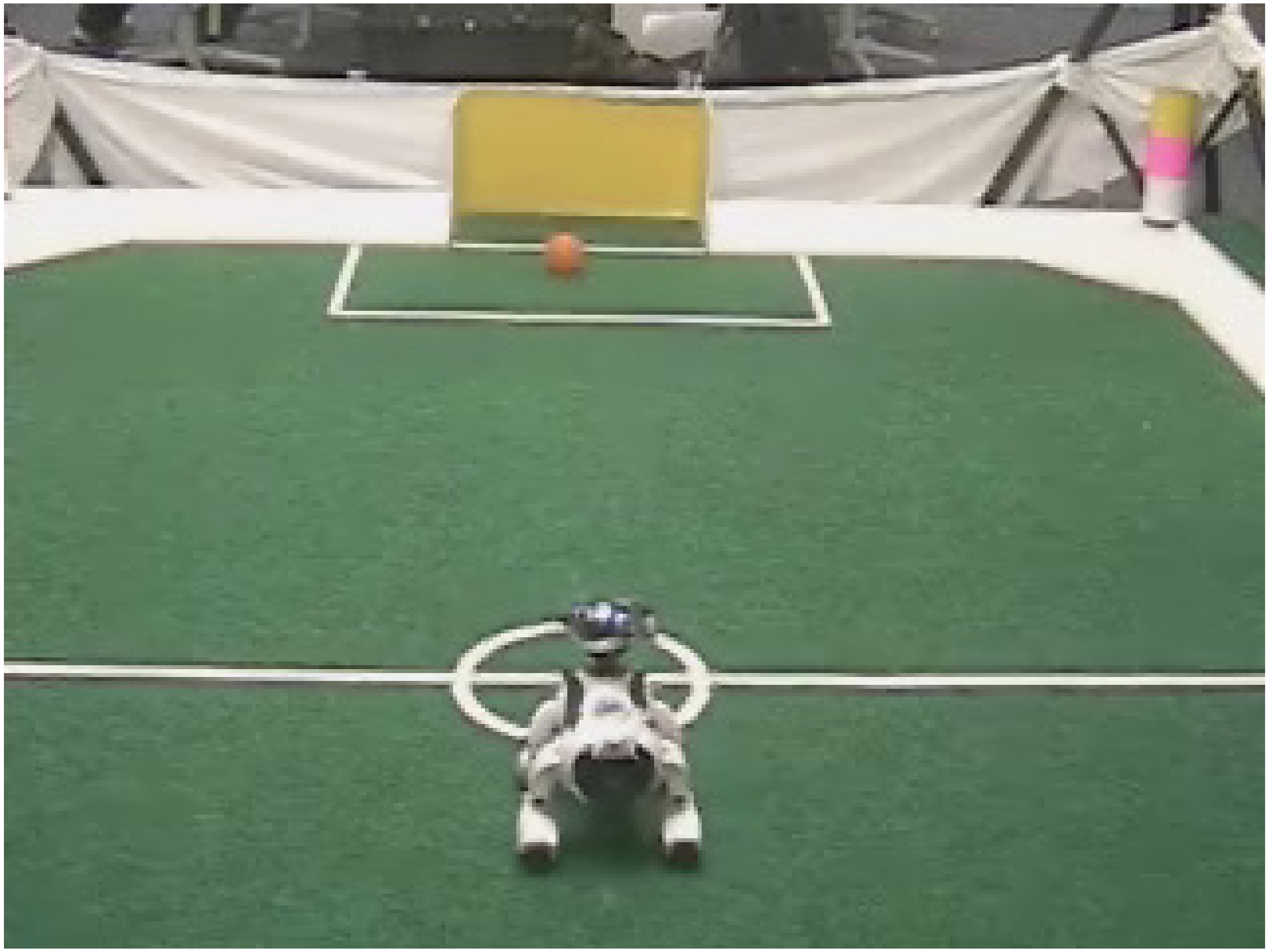
Sample Video - External



Sample Video – Input

Motivation

- Mobile Robot Vision **challenging**.
- Real-time requirement: **computational** and **memory** resources limited.
- **Rapid** camera motion.
- **Changing illumination** conditions.

The Question

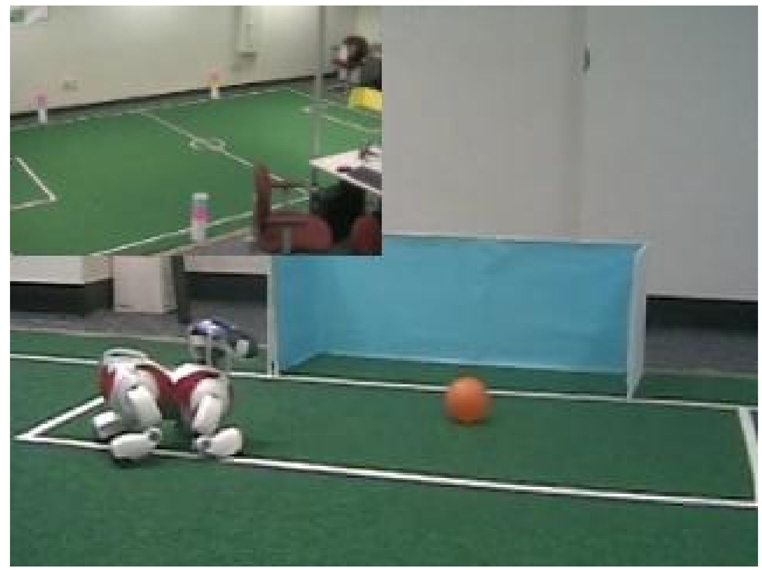
- Can a vision-based mobile robot
- with **limited** computational and memory resources,
- and rapidly varying camera positions,
- operate **autonomously** in a moderately structured environment,
- under **varying illumination** conditions,
- by utilizing the **structure** inherent in its environment ?

Talk Overview

- **Background Information**:
  - Test Platform.
- **Completed Work:**
  - Baseline Vision System.
  - Autonomous Planned Color Learning.
  - Robustness to Illumination Changes.
- **Proposed Work**.

Initial Test Platform – Sony ERS7

- 20 degrees of freedom.
- *Primary sensor* – CMOS camera.
- IR, touch sensors, accelerometers.
- Wireless LAN.
- *576MHz* processor: frame rate – *30Hz*.
- Soccer on 4m x 6m field.



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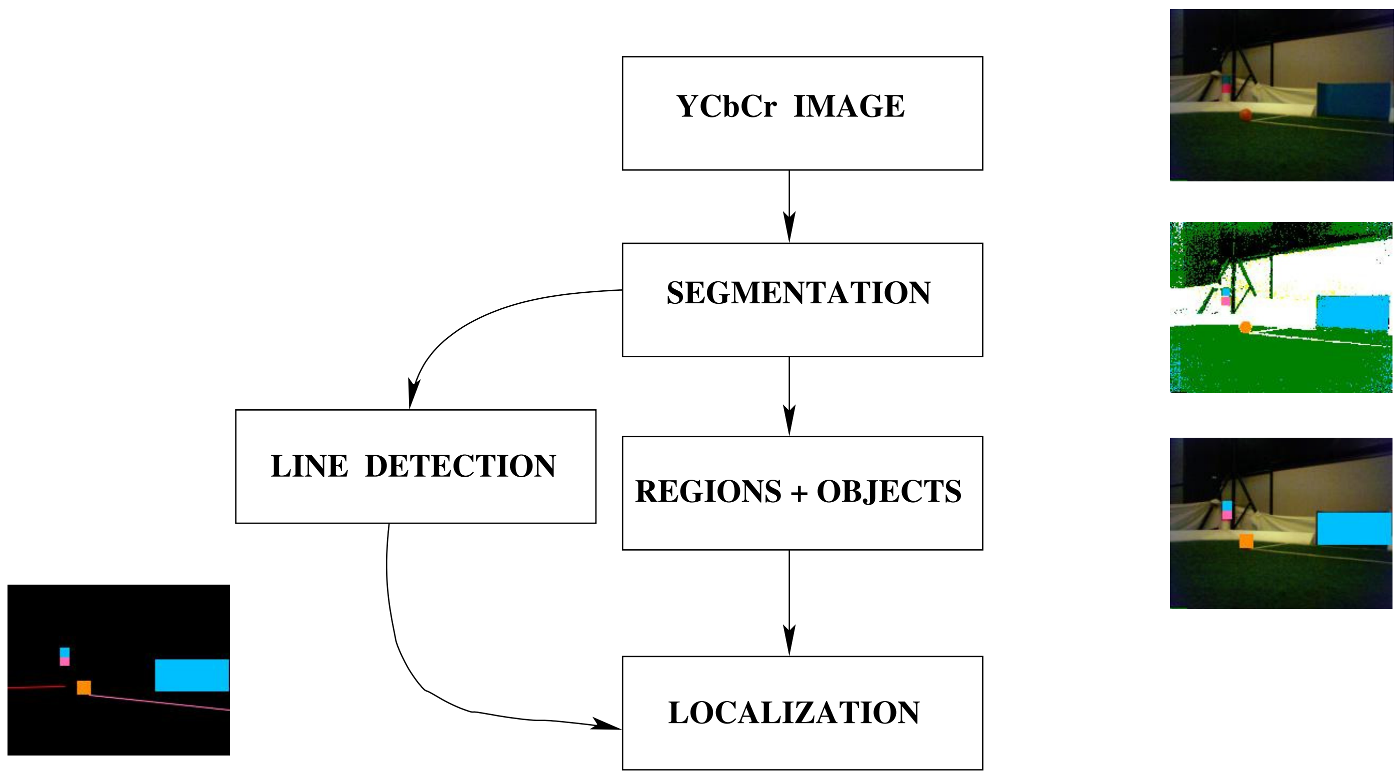
- **Ongoing Work.**

Baseline Vision – I/O

- **Input:** Image pixels in YCbCr Color space.
  - Frame rate: 30 fps.
  - Resolution: 208 x 160.
- **Output:** Distances and angles to objects.
- **Constraints:**
  - On-board processing: 576 MHz.
  - Rapidly varying camera positions.

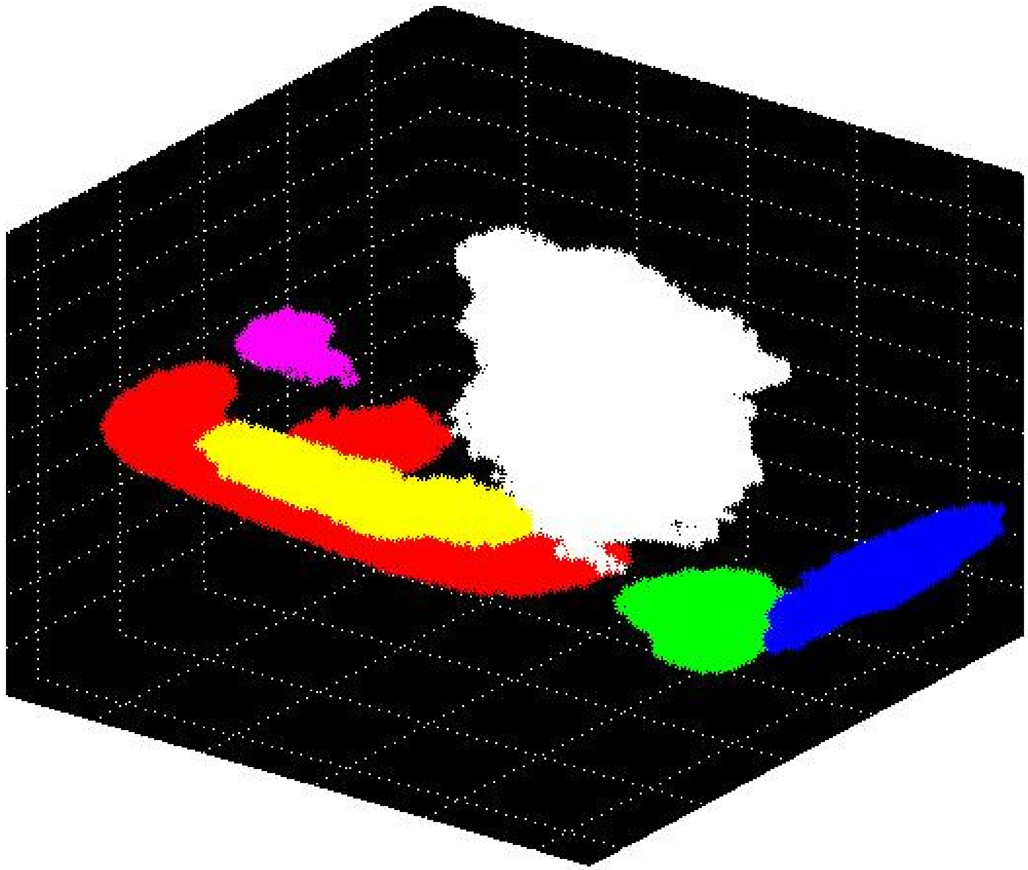
Baseline Vision – Flowchart



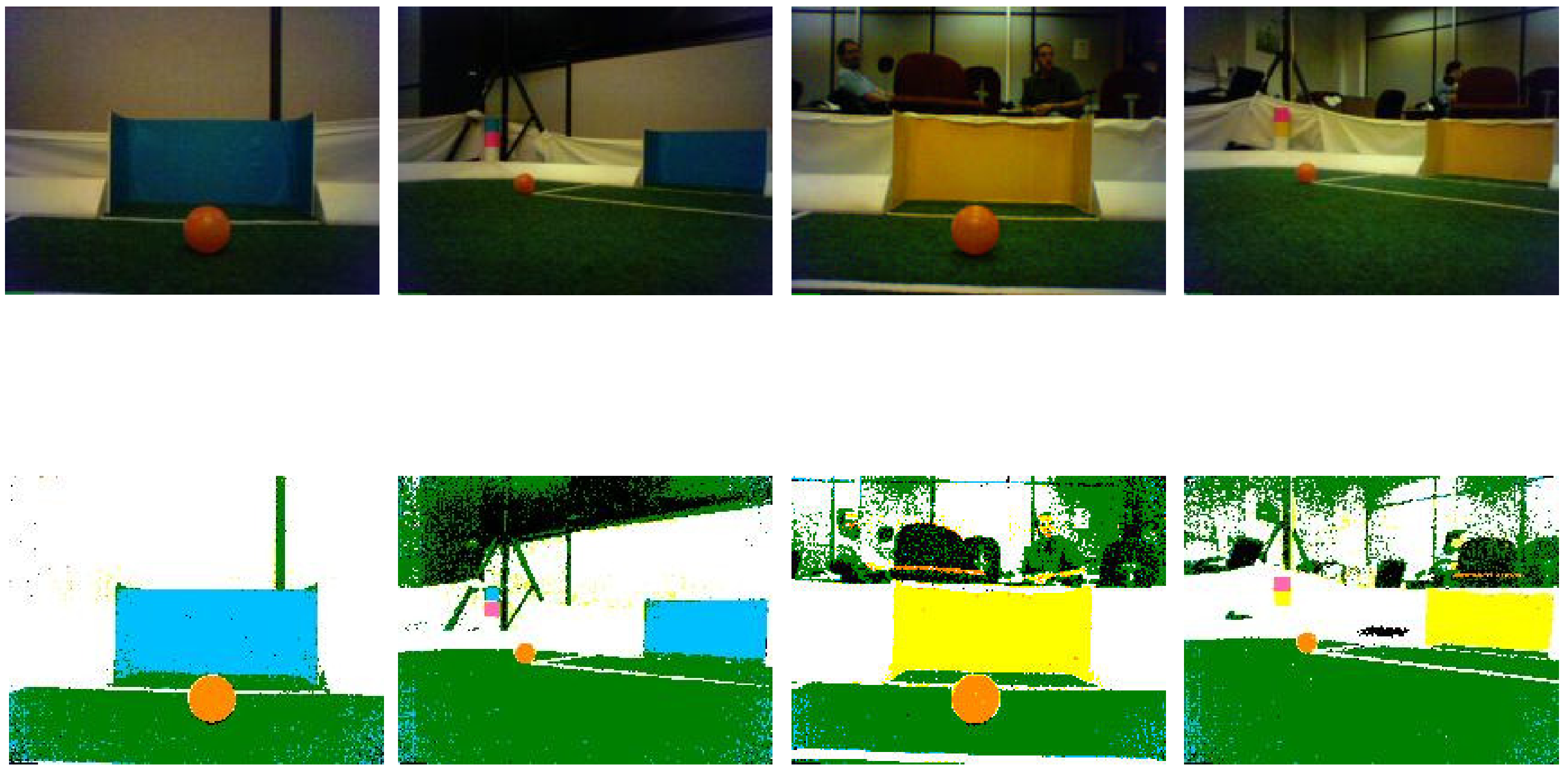
Baseline Vision – Phase 1: Segmentation

- Assign color labels to image pixels.
- Image pixel values 0 – 255 in each of the three channels.
- Sub-sample and assign color labels for 128*128*128 possible combinations: **Color Map**.
- Hand-label discrete colors.
- Locally Weighted average – Color map generalization.

Sample Color Map

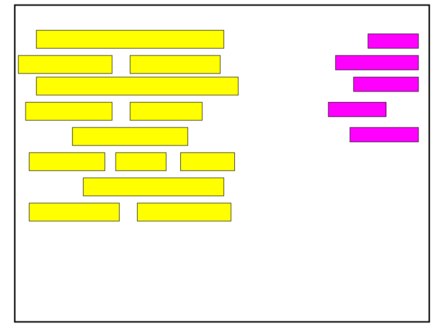


Sample Images – Color Segmentation

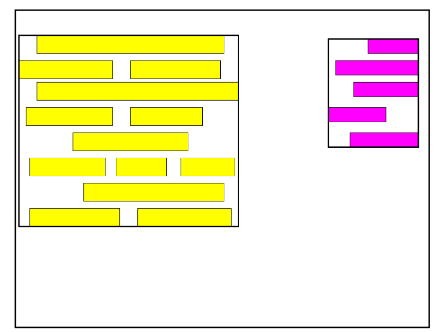


Baseline Vision – Phase 2: Regions

- **Run-Length encoding**.
  - Starting point, length in pixels.

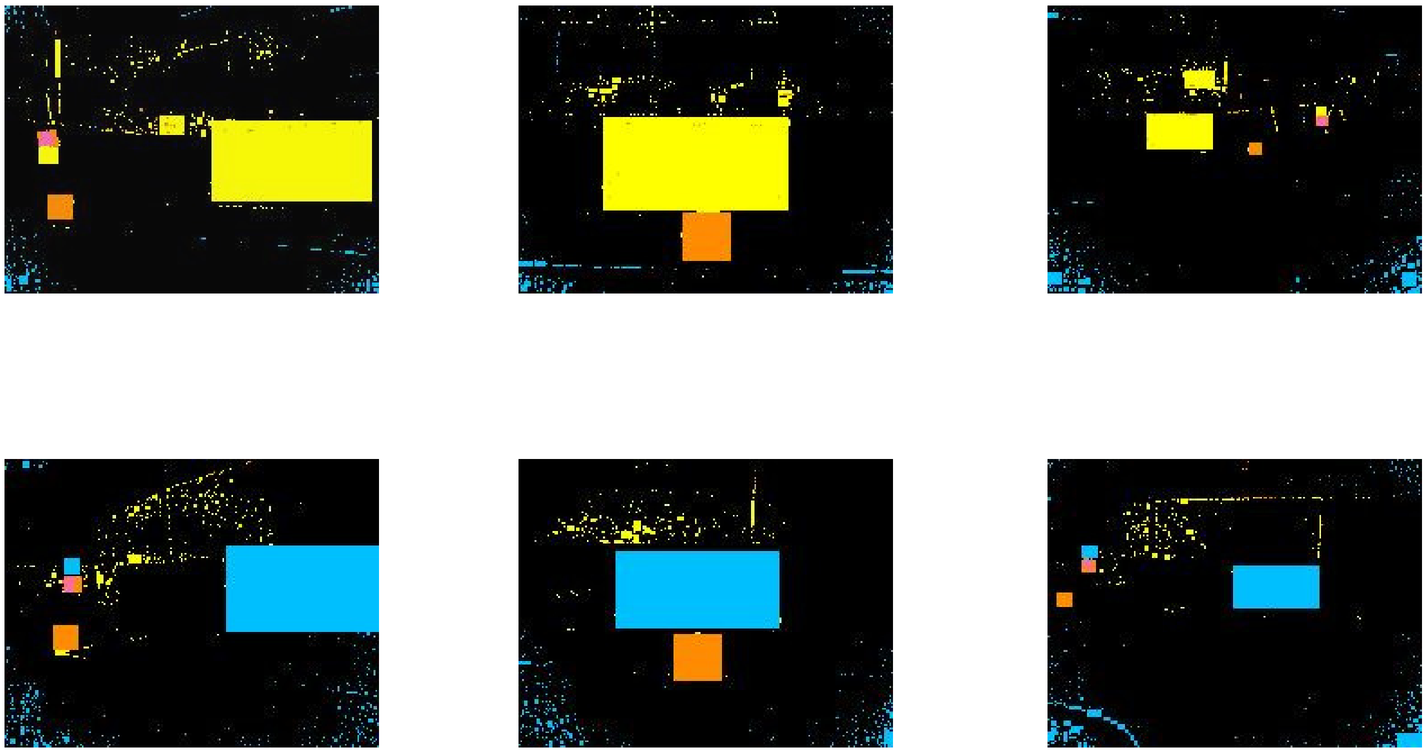


- **Region Merging**.
  - Combine run-lengths of same color.
  - Maintain properties: pixels, runs.



- **Bounding boxes**.
  - Abstract representation – four corners.
  - Maintains properties for further analysis.

Sample Images – Region Detection

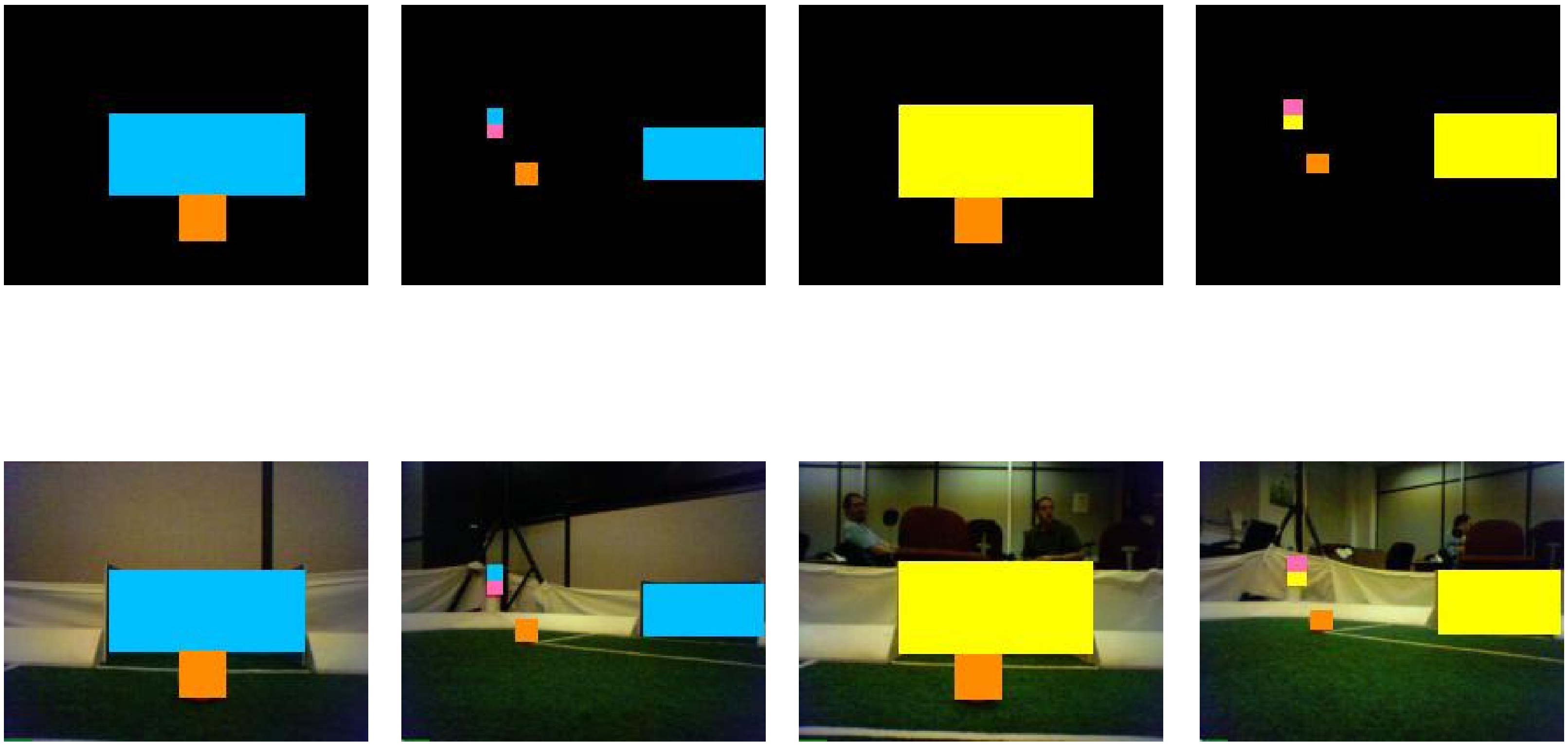


Baseline Vision – Phase 2: Objects

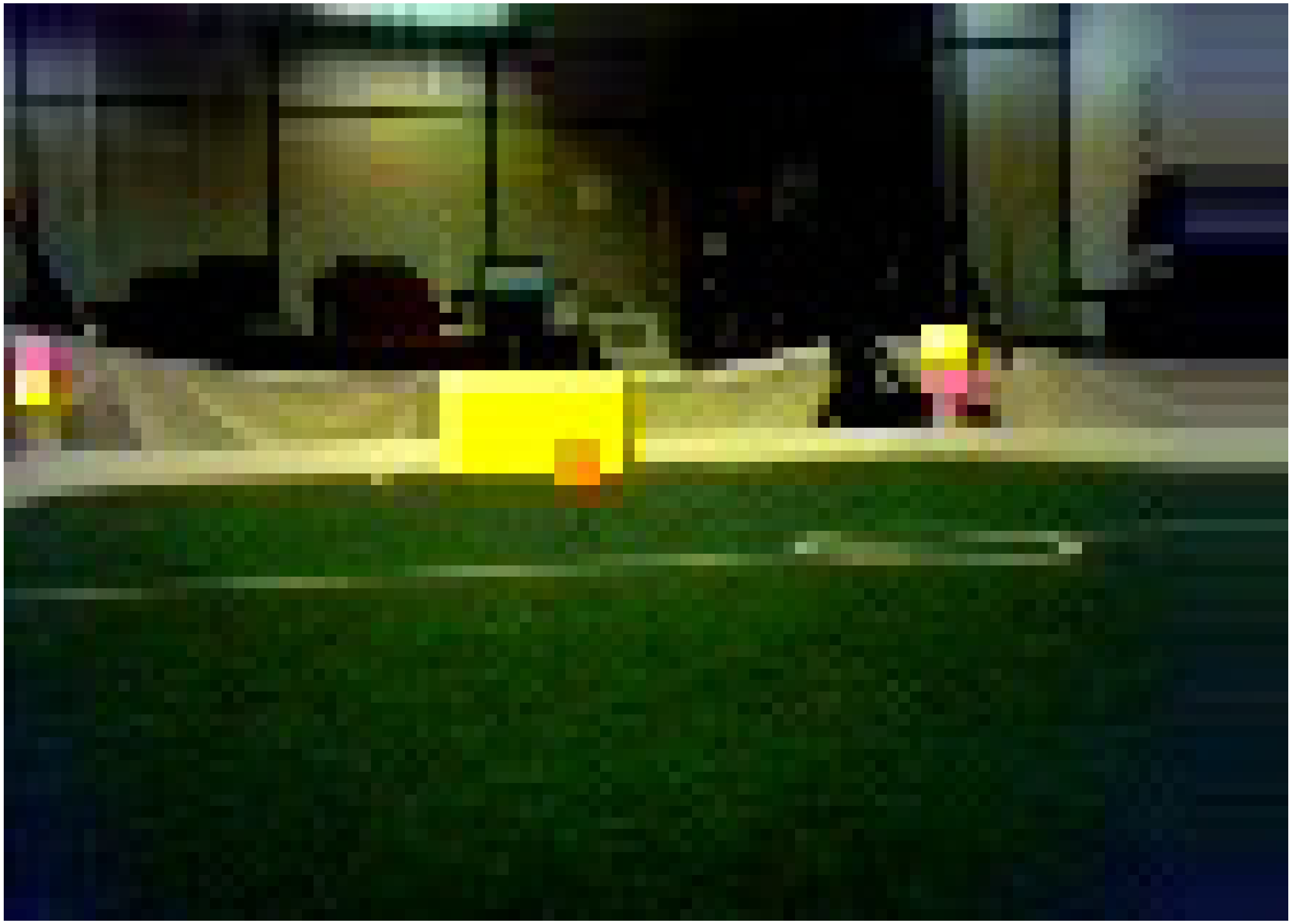
- **Object Recognition.**
  - Heuristics on size, shape and color.
  - Previously stored bounding box properties.
  - Domain knowledge.
  - Remove spurious regions.

- **Distances and angles:** known geometry.

Sample Images – Objects

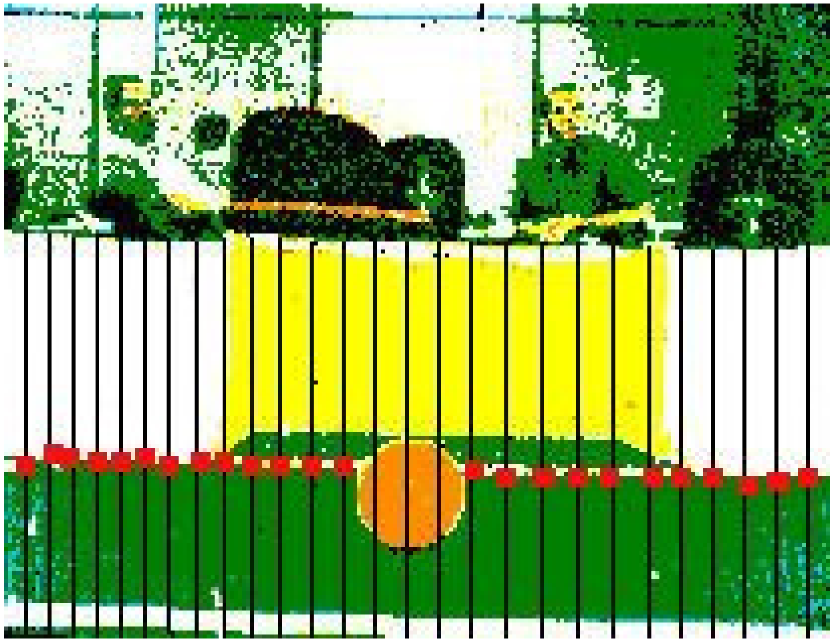


Sample Video – Objects Superimposed



Baseline Vision – Phase 3: Lines

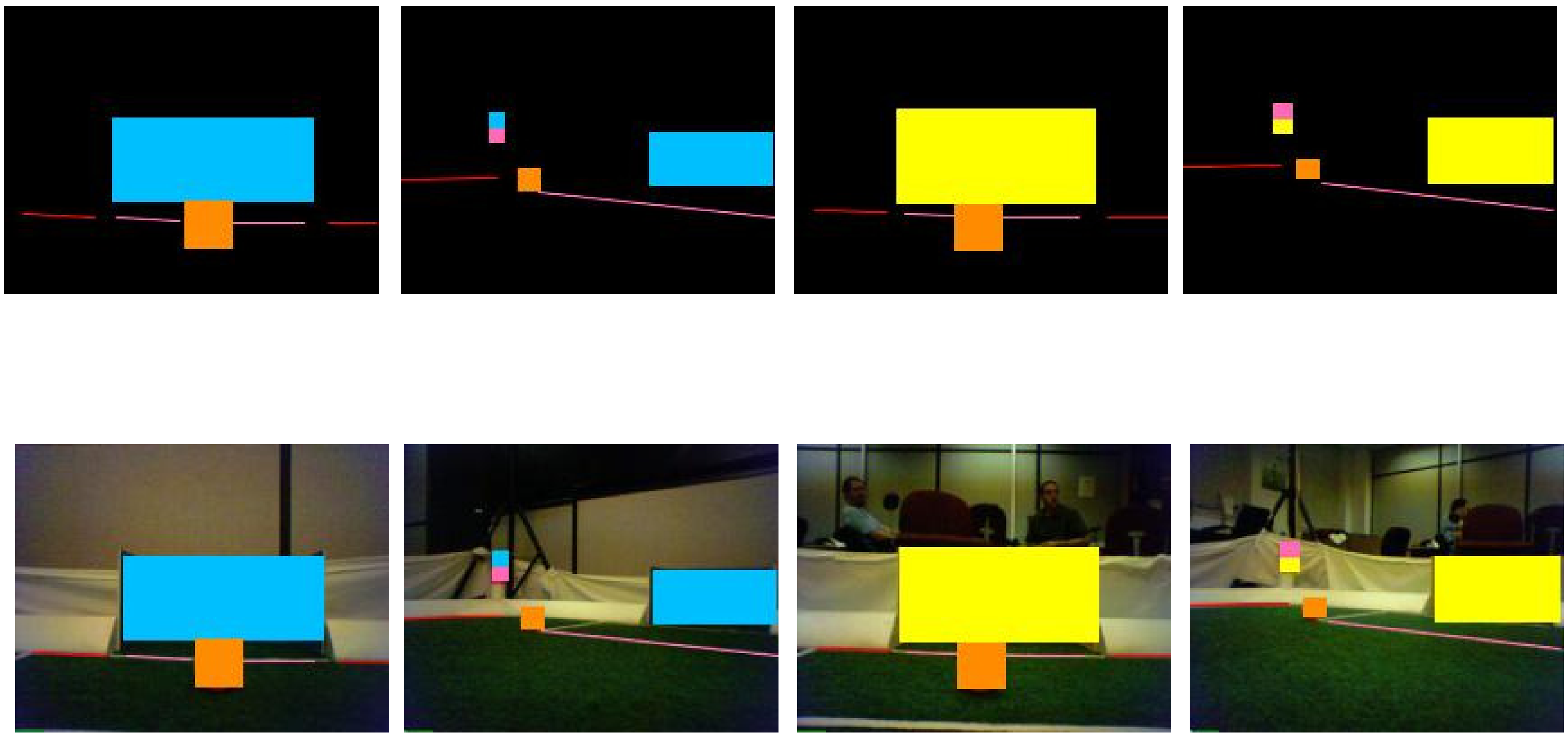
- Popular approaches: Hough transform, Convolution kernels – computationally expensive.
- Domain knowledge.
- Scan lines – green-white transitions – candidate edge pixels.



Baseline Vision – Phase 3: Lines

- **Incremental least square fit** for lines.
  - Efficient and easy to implement.
  - Reasonably robust to noise.
- **Lines**: provide **orientation** information.
- **Line Intersections**: used as markers.

Sample Images – Objects + Lines



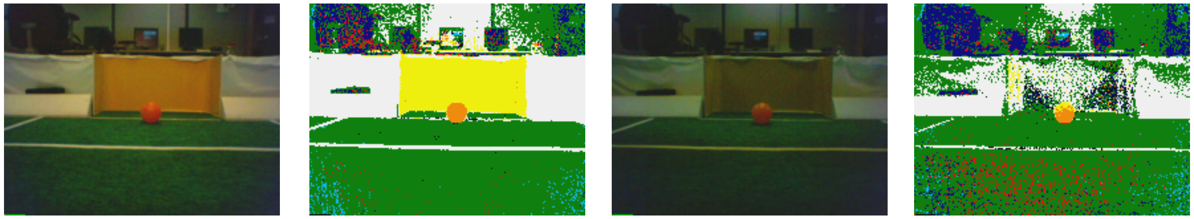
Related Work – Robot Soccer

- CMU vision system: Basic implementation.
  - *J. Bruce, IROS 2000.*

- German Team vision system: Scan Lines.
  - *T. Rofer, RoboCup 2003.*

Some Problems…

- Systems needs to be **re-calibrated**:
  - Illumination changes.
  - Natural light variations: day/night.



- Re-calibration very **time consuming**.
  - More than an hour spent each time…

- Cannot achieve *overall goal.*

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Related Work – Color Learning

- Autonomous segmentation: Multiple Color maps.
  - *M. Jungel, RoboCup 2004.*
- Offline Color learning using structure: Edges and objects.
  - *D. Cameroon, RoboCup 2003.*
- Hierarchical Bayesian Approach: Color Priors.
  - *D. Schulz and D. Fox, IROS 2004.*

Autonomous Color Learning – Motivation

- Environment **structured** – use it!

- Inputs:
  - Object positions and descriptions.
  - Robot starting position.
- Autonomously generate suitable motion sequence – *where to move*?
- **Autonomously** learn color map: *no prior knowledge of color distributions*.

- Has to be as **reliable** as the **hand-labeled map**.

Autonomous Color Learning – Approach

- Represent each color as a **3D Gaussian** or **3D Histogram**: goodness-of-fit test.
- Gaussian:
  - Low storage (means, stdevs).
  - Generalizes well with few samples.
  - Not suitable for multi-modal color distributions.
- Histogram:
  - Higher storage.
  - Does not generalize well with few samples.
  - Suitable for multi-modal distributions.
- *Robot selects suitable model*.

Autonomous Color Learning – Approach

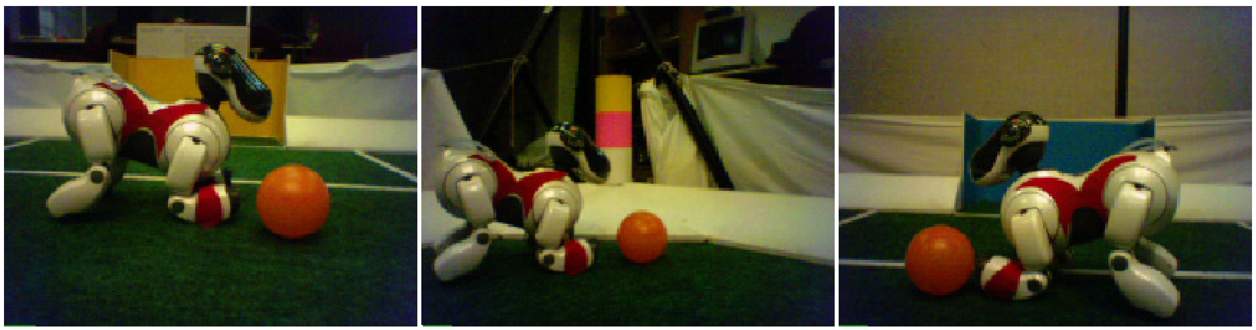
- Start from **known** (**variable**) initial position.
- Motion planning based on object configuration – function minimization.
- Learn colors at each position – *hybrid representation*.
- Use current color knowledge to localize better – *bootstrapping*.
- Works for any robot starting position and environmental configuration.

Autonomous Color Learning – Video

- **Five minutes** instead of **an hour or more**.

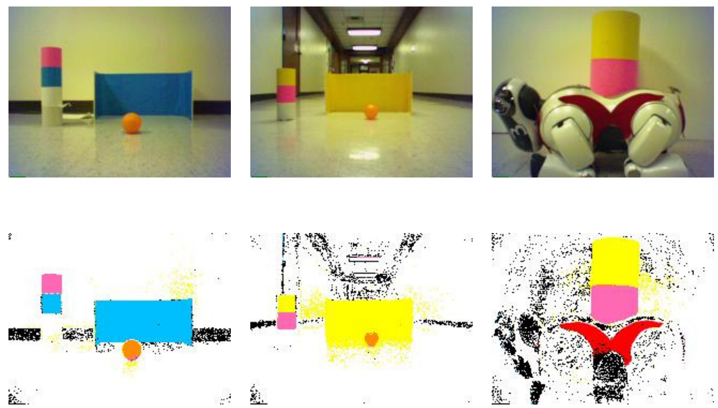
Autonomous Color Learning – Testing

- Inside the lab:

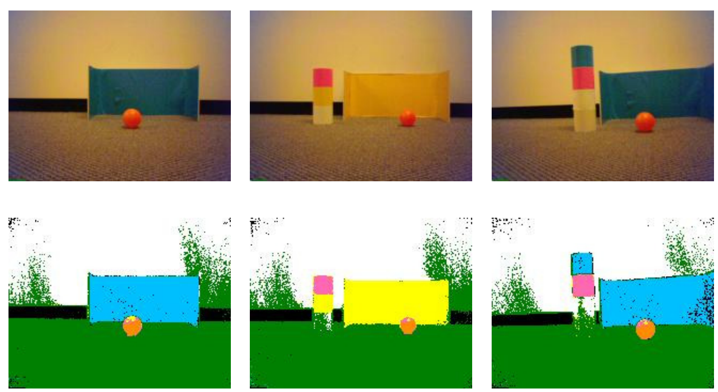


Autonomous Color Learning – Testing

- Outside the lab:
  - Case1



  - Case2



Localization with learned color map - Video

Summary

- Colors learned autonomously.
- 5 mins of robot time instead of an hour or more of human effort.
- Segmentation and localization accuracies comparable to hand-labeled color map.
- Both inside and outside the lab – *hybrid representation*.
- Motion planning for any starting position and object configuration.

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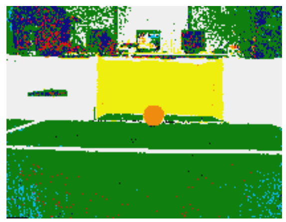
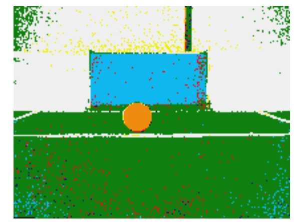
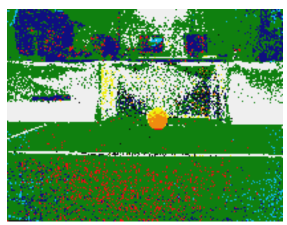
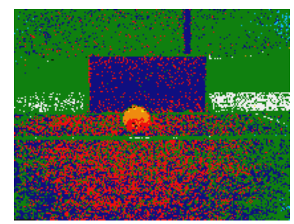
Illumination Sensitivity – Samples

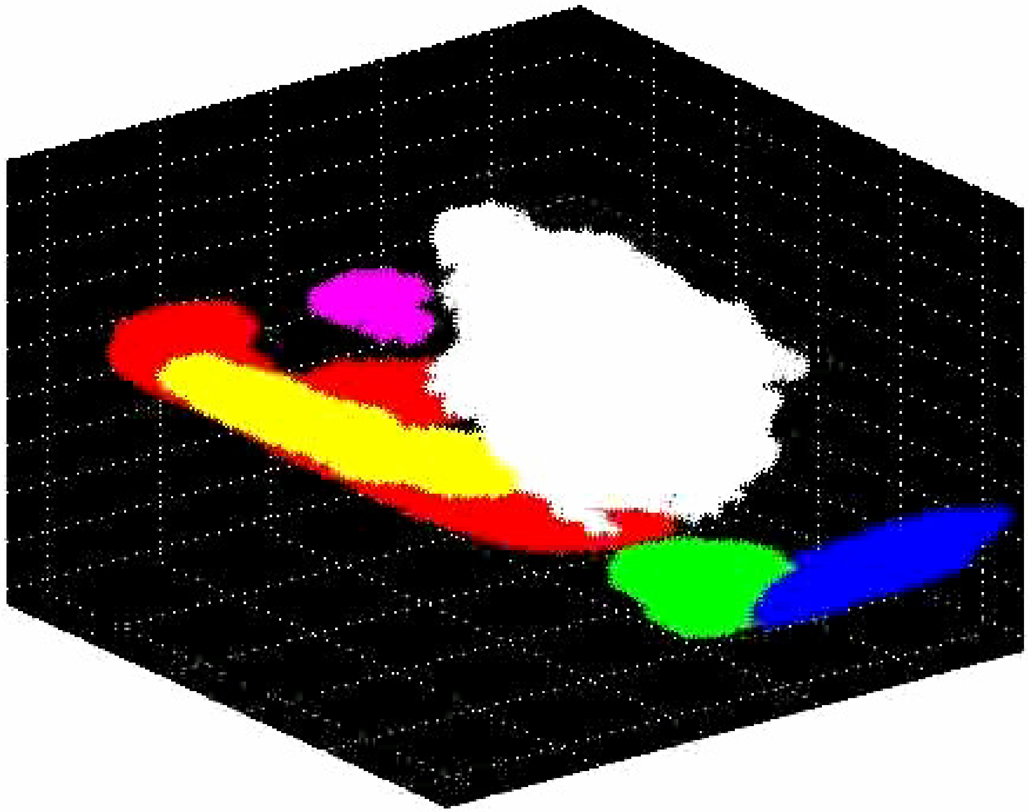
- Trained under one illumination:

- Under different illumination:

Illumination Sensitivity – Movie…



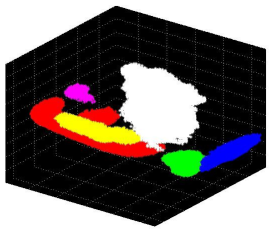
Related Work – Illumination Invariance

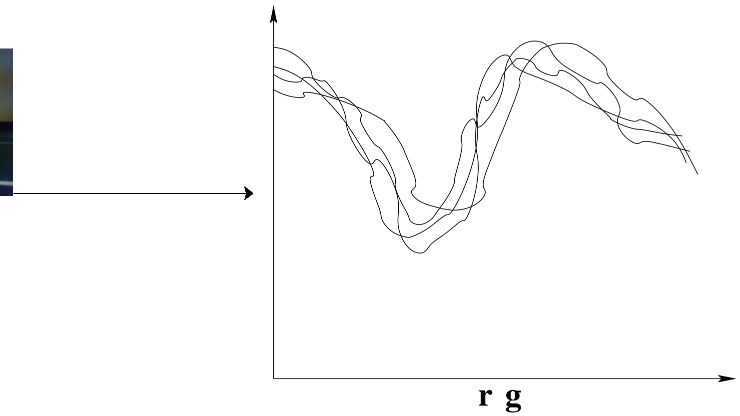
- Sensor and Illuminant models.
  - *C. Rosenberg, ICCV 2001.*
- Time Series Analysis: Aibo.
  - *S. Lenser, ICRA 2003.*
- Mixture of Gaussians: Middle-sized league.
  - *F. Anzani, RoboCup 2005.*

Illumination Invariance - Approach

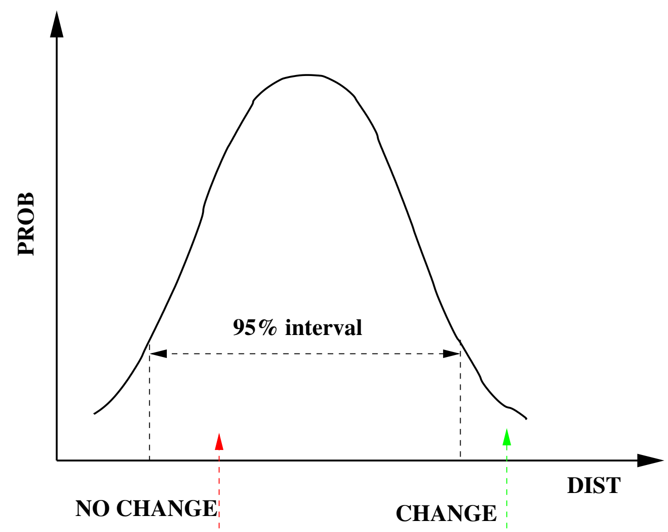
- **Challenges:**
  - Representing Illumination conditions.
  - Detecting a change in illumination condition.
- **Representation:**
  - Distributions in normalized RGB (r, g).
  - Color map for each discrete illumination condition.
- **Detecting change:**
  - Distribution of intra-distribution distances.
  - KLDivergence as distance measure.

Illumination Invariance – Approach



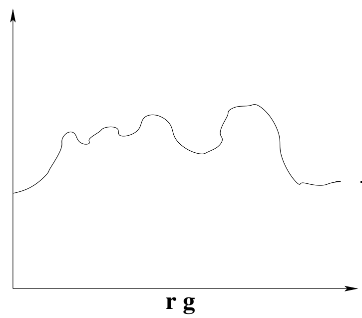


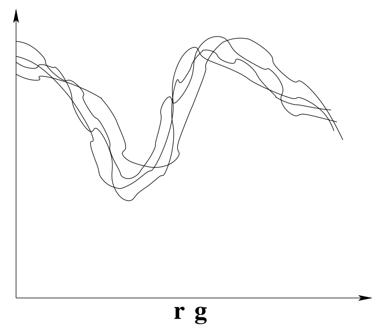
- Learn color map and collect (r, g) image distributions.
- Compute intra-illumination distance distribution and model as Gaussian.



Illumination Invariance - Approach

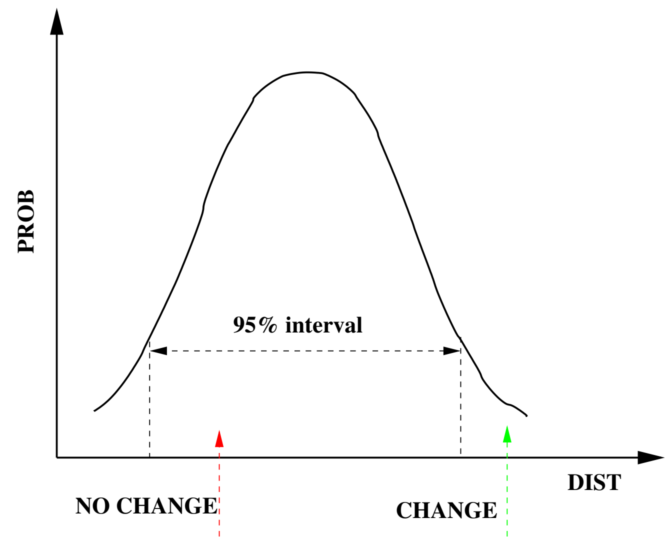
- Compute average distance between test distribution and known distributions **R_avg**.



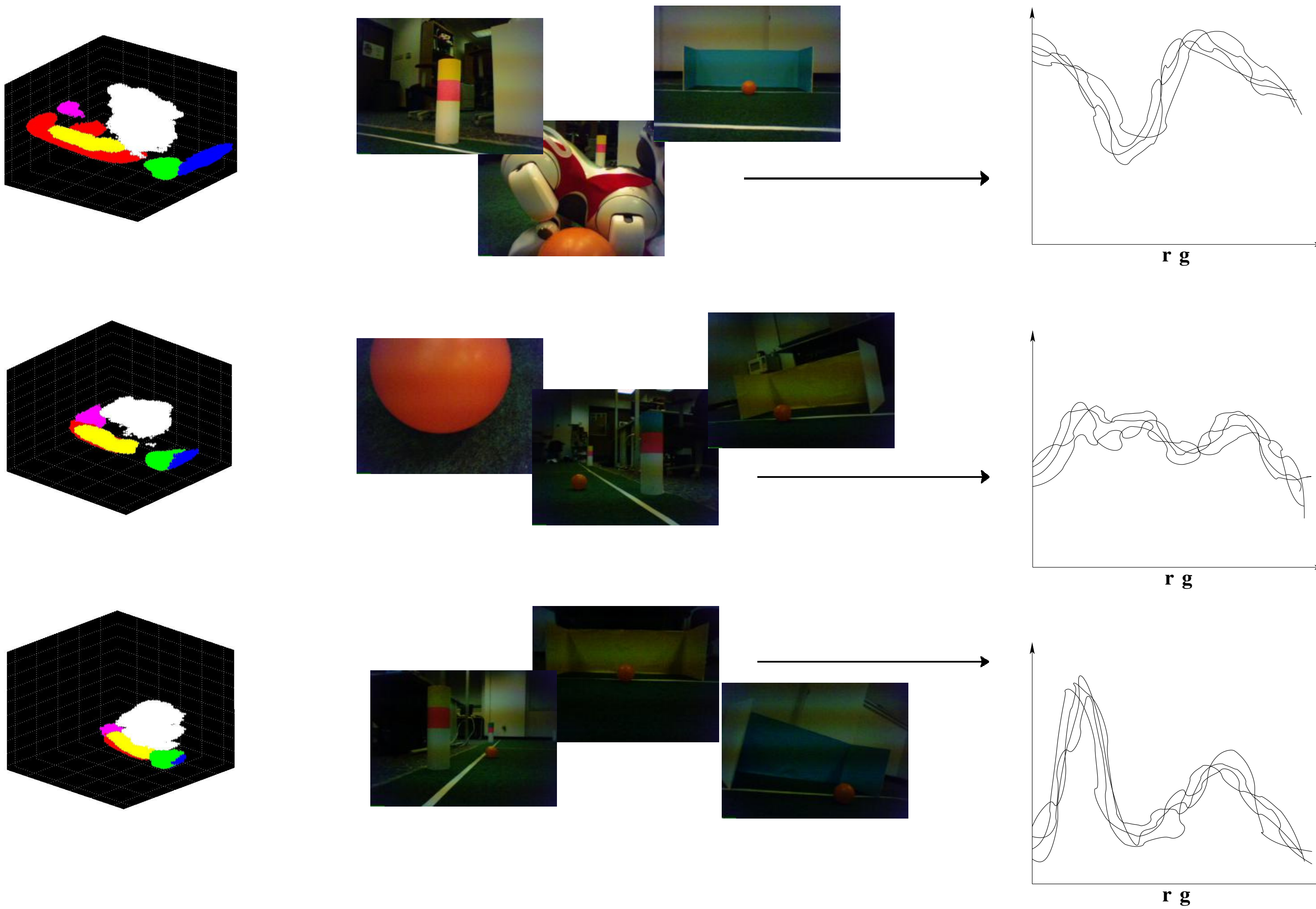


Illumination Invariance – Approach

- If **R_avg** maps outside the threshold range of known intra-illumination distances, accept new illumination condition.
- Else continue with current or other known illumination condition.



Illumination Invariance – Example



Illumination Invariance - Summary

- Robot autonomously trains color map(s).
- Significant changes in illumination detected autonomously.

- With *three* color map(s) robot is able to work under a range of illumination conditions, *even those not explicitly trained for*.

Adapting to Illumination changes – Video

Completed Work – Summary

- **Baseline Vision system**.
  - Works in *real-time*.
  - Works with *rapid camera motion*, noisy images.
- **Autonomous Planned Color Learning**.
  - Colors learned online *autonomously*.
  - Drastic time reduction – 5mins instead of an hour or more.
  - *Accurate* – comparable to hand-labeled map.
  - *Plans* motion sequence based on object configuration.
- **Illumination Invariance**.
  - *Autonomously detects change in illumination*.
  - Adapts by re-learning color map – *no human intervention*.
  - With just three maps works for intermediate illuminations as well.

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- **Ongoing Work.**

Ongoing Work – Overview

- **A** –> Different Robot Platform.
- **B** –> Color learning unknown starting point.
- **C** –> Continuous Illumination adaptation.

Ongoing Work A – Different Robot Platform

- **Initial Position Known**.
- Known colored regions' positions – **world model**.

- **Challenges**:
  - Deal with different *image quality*.
  - Deal with different *processing* and *storage* capabilities.
  - Robot autonomously *plans* efficient motion sequence and incrementally learns colors in a *different setting*.

Different Platform – Approach

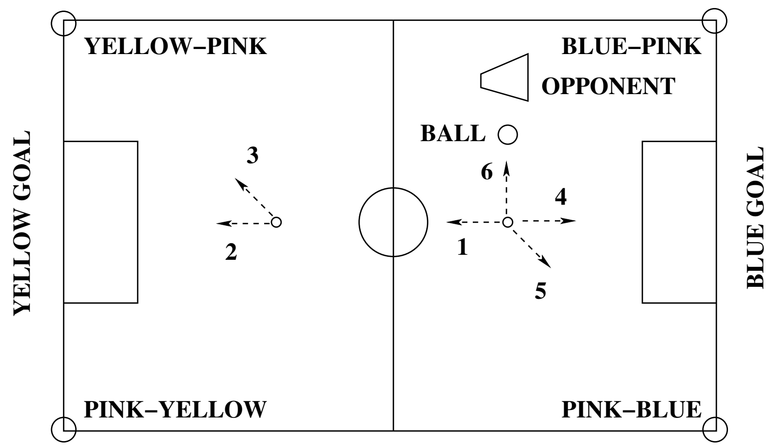
- Segway ? Stereo camera !
- Exploit available machinery: Try existing planned color learning +illumination invariance approach ?
- Exploit available resources: Try adding additional features ? Edges ? Texture ?

Ongoing Work B – Unknown starting point

- **Initial Position unknown**.
- Locations of colored regions known – **world model**.
- **Challenges**:
  - Reason about uncertainty while *planning* efficient motion sequence.
  - Learns colors with good *failure correction*.
  - Severely *disadvantaged initially* – no useful information from the primary sensor.

Unknown Starting Position – Approach

- **Extension** to the planned color learning task: additional sensory input ?
- Better modeling of the **uncertainty**.
- Better **failure detection** and recovery mechanisms.
- **Bayesian** architecture (current approach), **POMDP**s ?



Ongoing Work C – Continuous illumination adaptation

- Current work with discrete illumination conditions *does not handle minor illumination changes*.

- **Challenges:**
  - How to detect minor illumination changes ?
  - Change current representation for illumination conditions ?
  - Cannot have too many color maps – modify them on-the-fly or change representation ?

Where Does this Work Fit in ?

- Robotics ?
- AI ?
- Vision ?
- Nowhere, stop right now ☹

That’s all folks ☺