UT Austin Villa 2013

Advances in Vision, Kinematics, and Strategy

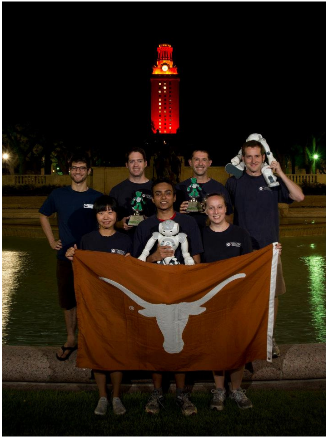
Jacob Menashe, Katie Genter, Samuel Barrett and Peter Stone
{jmenashe,katie,sbarrett,pstone}@cs.utexas.edu

The University of Texas at Austin

October 15, 2013

UT Austin Learning Agents Research Group

UT Austin Villa 2012 - 2013



Introduction

We focus on our improvements to object detection.

- Candidate comparison is a crucial piece of object detection
- Our original method compares attributes sequentially
- Gaussian fitness functions enable parallel evaluation

Introduction

We focus on our improvements to object detection.

- Candidate comparison is a crucial piece of object detection
- Our original method compares attributes sequentially
- Gaussian fitness functions enable parallel evaluation

Introduction

We focus on our improvements to object detection.

- Candidate comparison is a crucial piece of object detection
- Our original method compares attributes sequentially
- Gaussian fitness functions enable parallel evaluation

UT Austin Learning Agents Research Group

Introduction

We focus on our improvements to object detection.

- Candidate comparison is a crucial piece of object detection
- Our original method compares attributes sequentially
- Gaussian fitness functions enable parallel evaluation

Sequential Sanity Checks for Object Detection

1. Retrieve candidates with blob detection

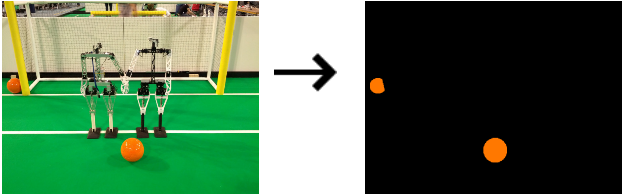


Image from `https://maserati.mi.fu-berlin.de/fub-kit/?tag=robocup-2013`

Sequential Sanity Checks for Object Detection

1. Retrieve candidates with blob detection
2. Sanity check each candidate

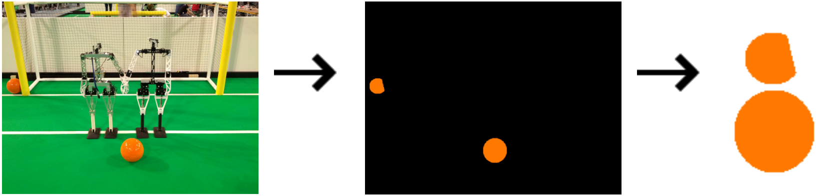


Image from `https://maserati.mi.fu-berlin.de/fub-kit/?tag=robocup-2013`

Sequential Sanity Checks for Object Detection

1. Retrieve candidates with blob detection
2. Sanity check each candidate
3. Accept the first candidate to pass all tests

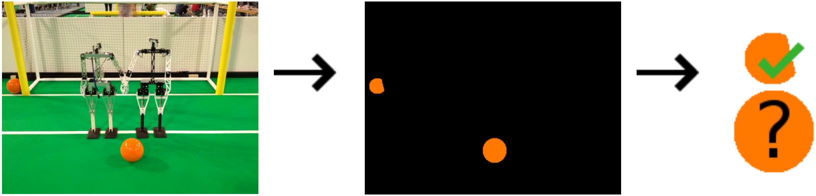


Image from `https://maserati.mi.fu-berlin.de/fub-kit/?tag=robocup-2013`

Problems with the Sequential Approach

- For simple detection problems, the sequential approach works well

Problems with the Sequential Approach

- For simple detection problems, the sequential approach works well
- Simple to code, test and modify

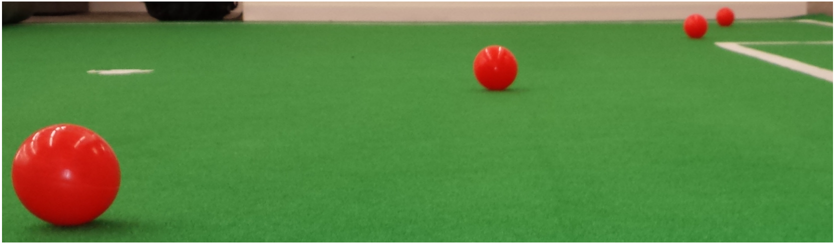
Problems with the Sequential Approach

- For simple detection problems, the sequential approach works well
- Simple to code, test and modify
- More advanced scenarios can be problematic

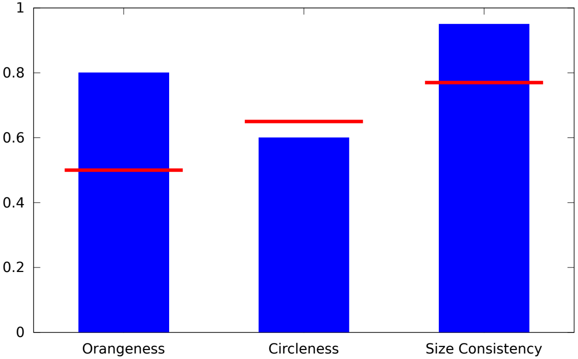
Distinguishing Between Candidates

Image from `http://www.intechopen.com/books/robot-soccer/humanoid-soccer-player-design`

Determining Detection Quality



Parallel Parameter Evaluation



Blue bars are readings, red lines are thresholds.

Solution: Multivariate Gaussian Fitness Functions

- Sanity checks are performed simultaneously

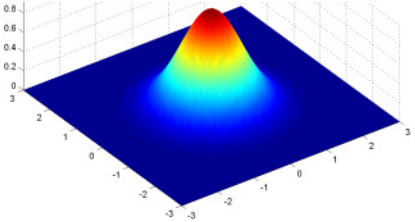


Image from `http://en.wikipedia.org/wiki/Gaussian_function`

Solution: Multivariate Gaussian Fitness Functions

- Sanity checks are performed simultaneously
- Output is a float in [0,1]

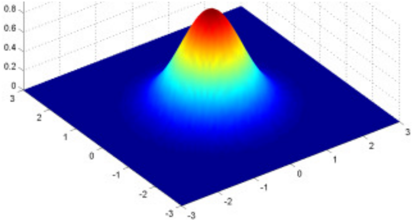


Image from `http://en.wikipedia.org/wiki/Gaussian_function`

Solution: Multivariate Gaussian Fitness Functions

- Sanity checks are performed simultaneously
- Output is a float in [0,1]
- Fitness scores are directly comparable

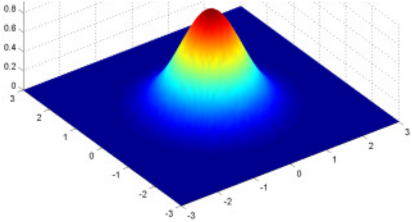


Image from `http://en.wikipedia.org/wiki/Gaussian_function`

Method Overview

1. Select measurements

Method Overview

1. Select measurements
2. Determine the mean μ and covariance matrix Σ

Method Overview

1. Select measurements
2. Determine the mean μ and covariance matrix Σ
3. Use measurements to compute a feature vector v

Method Overview

1. Select measurements
2. Determine the mean μ and covariance matrix Σ
3. Use measurements to compute a feature vector v
4. Compute fitness f using μ, Σ, and the multivariate Gaussian PDF G

Method Overview

1. Select measurements
2. Determine the mean μ and covariance matrix Σ
3. Use measurements to compute a feature vector v
4. Compute fitness f using μ, Σ, and the multivariate Gaussian PDF G

$$f = G(v; \mu, \Sigma)/G(\mu; \mu, \Sigma)$$

Measurement Selection

- Velocity
- Orange %
- Green/White %
- Circle Deviation
- Field Distance
- Perceived Height
- Distance Discrepancy

Measurement Selection

- Velocity
- Orange %
- Green/White %
- Circle Deviation
- Field Distance
- Perceived Height
- Distance Discrepancy

$$v = (0, \ldots)^\top$$

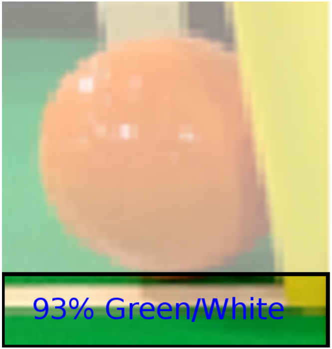
Measurement Selection

- Velocity
- Orange %
- Green/White %
- Circle Deviation
- Field Distance
- Perceived Height
- Distance Discrepancy

$$v = (0, .95, \ldots)^{\top}$$

Measurement Selection

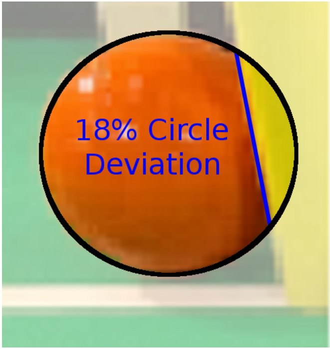
- Velocity
- Orange %
- Green/White %
- Circle Deviation
- Field Distance
- Perceived Height
- Distance Discrepancy



$$v = (0, .95, .93, \ldots)^\top$$

Measurement Selection

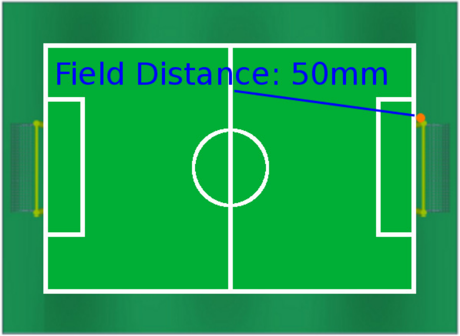
- Velocity
- Orange %
- Green/White %
- **Circle Deviation**
- Field Distance
- Perceived Height
- Distance Discrepancy



$$v = (0, .95, .93, .18, \ldots)^{\top}$$

Measurement Selection

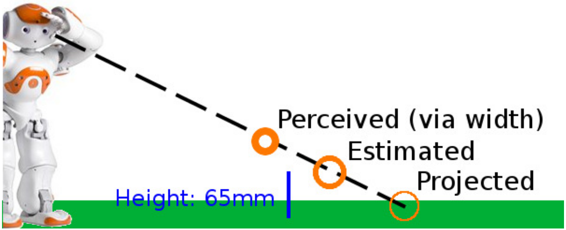
- Velocity
- Orange %
- Green/White %
- Circle Deviation
- **Field Distance**
- Perceived Height
- Distance Discrepancy



$$v = (0, .95, .93, .18, 50, \ldots)^{\top}$$

Measurement Selection

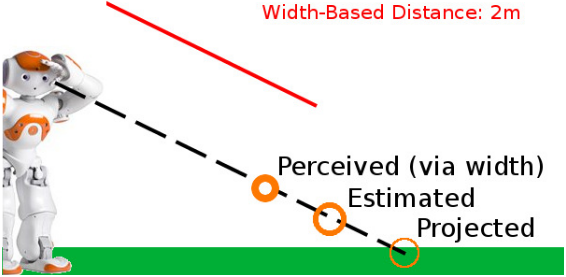
- Velocity
- Orange %
- Green/White %
- Circle Deviation
- Field Distance
- **Perceived Height**
- Distance Discrepancy



$$v = (0, .95, .93, .18, 50, 65, \ldots)^\top$$

Measurement Selection

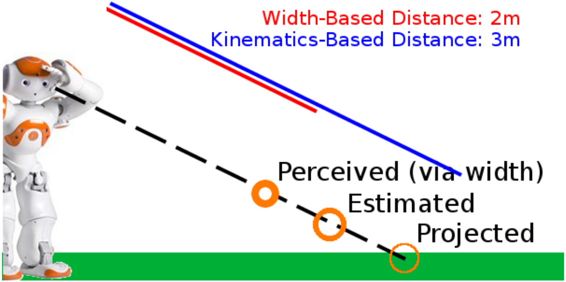
- Velocity
- Orange %
- Green/White %
- Circle Deviation
- Field Distance
- Perceived Height
- Distance Discrepancy



$$v = (0, .95, .93, .18, 50, 65, \ldots)^{\top}$$

Measurement Selection

- Velocity
- Orange %
- Green/White %
- Circle Deviation
- Field Distance
- Perceived Height
- Distance Discrepancy

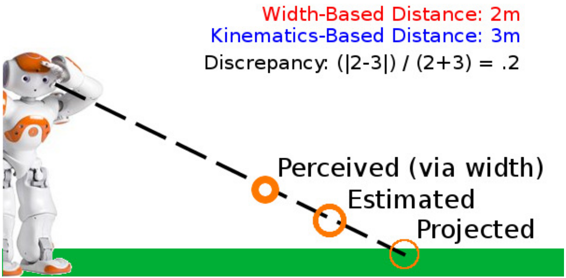


$$v = (0, .95, .93, .18, 50, 65, \ldots)^\top$$

UT Austin Learning Agents Research Group

Measurement Selection

- Velocity
- Orange %
- Green/White %
- Circle Deviation
- Field Distance
- Perceived Height
- Distance Discrepancy



$$v = (0, .95, .93, .18, 50, 65, .2)^\top$$

Gaussian Parameters

Measurement	μ	σ
Velocity	0.0	$\mathtt{max}(100, d/5)$
Orange Percentage	1.0	0.5
Green/White Percentage	1.0	0.4
Circle Deviation	0.0	0.3
Field Distance	0.0	$\mathtt{max}(100, d/10)$
Perceived Height	0.0	150.0
Distance Discrepancy	0.0	0.4

- d is the last known ball distance
- Σ computed as the diagonal matrix with entries σ^2 from each measurement

Computing Fitness

$$
\begin{aligned}
f &= \frac{G(v,\mu,\Sigma)}{G(\mu,\mu,\Sigma)} \\
&= \frac{G\left(\begin{bmatrix} 0 \\ .95 \\ .93 \\ .18 \\ 50 \\ 65 \\ .2 \end{bmatrix}, \begin{bmatrix} 0 \\ 1 \\ 1 \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 500^2 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & .5^2 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & .4^2 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & .3^2 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 250^2 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 150^2 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & .4^2 \end{bmatrix}\right)}{G(\mu,\mu,\Sigma)} \\
&= 0.65
\end{aligned}
$$

Experiment: Baseline

Fitness scores and sequential selections from 500 frames at static positions. The object of interest (left) and decoy (right) are nearly identical.

Left μ, σ	.92, .04
Right μ, σ	.89, .02
Gaussian *P*(success)	.7291
Sequential *P*(success)	.68

Experiment: Velocity

Fitness scores and sequential selections from 500 frames at static positions. The object of interest (left) and decoy (right) differ in their computed velocities.

Left μ, σ	.88, .12
Right μ, σ	.15, .20
Gaussian *P*(success)	.9992
Sequential *P*(success)	0.00

UT Austin Learning Agents Research Group

Experiment: Height

Fitness scores and sequential selections from 500 frames at static positions. The object of interest (left) and decoy (right) differ only in height.

Left μ, σ	.90, .02
Right μ, σ	.78, .04
Gaussian *P*(success)	.9965
Sequential *P*(success)	.87

Experiment: Size

Fitness scores and sequential selections from 500 frames at static positions. The object of interest (left) and decoy (right) differ only in size.

Left μ, σ	.89, .04
Right μ, σ	.39, .01
Gaussian *P*(success)	$>$ .9999
Sequential *P*(success)	1.00

Related Work

Samuel Barrett, Katie Genter, Todd Hester, Piyush Khandelwal, Michael Quinlan, Peter Stone, and Mohan Sridharan. Austin Villa 2011: Sharing is caring: Better awareness through information sharing. Technical Report UT-AI-TR-12-01, The University of Texas at Austin, Department of Computer Sciences, AI Laboratory, January 2012.

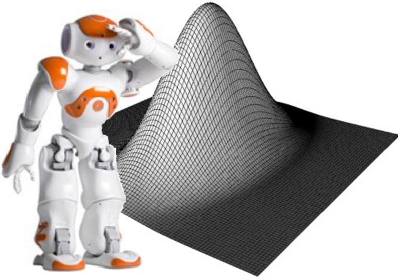
Morgan Quigley, Ken Conley, Brian Gerkey, Josh Faust, Tully B. Foote, Jeremy Leibs, Rob Wheeler, and Andrew Y. Ng. ROS: an open-source robot operating system. In *ICRA Workshop on Open Source Software*, 2009.

Thomas Röfer, Tim Laue, Judith Müller, Alexander Fabisch, Fynn Feldpausch, Katharina Gillmann, Colin Graf, Thijs Jeffry de Haas, Alexander Härtl, Arne Humann, Daniel Honsel, Philipp Kastner, Tobias Kastner, Carsten Könemann, Benjamin Markowsky, Ole Jan Lars Riemann, and Felix Wenk. B-Human team report and code release, 2011. `http://www.b-human.de/downloads/bhuman11_coderelease.pdf`.

Camiel Verschoor, Auke Wiggers, Duncan ten Velthuis, Anna Keune, Michael Cabot, Sander Nugteren, Erik van Egmond, Hessel van der Molen, Robert Iepsma, Maurits van Bellen, Merel de Groot, Eszter Fodor, Richard Rozeboom, and Arnoud Visser. Dutch nao team - technical report, 2011.

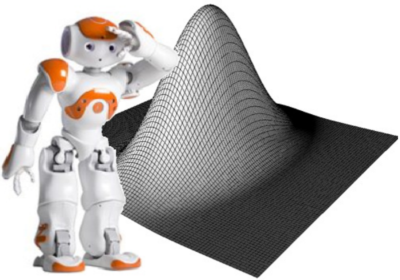
Conclusion

- Improved on the sequential approach with Gaussian fitness functions



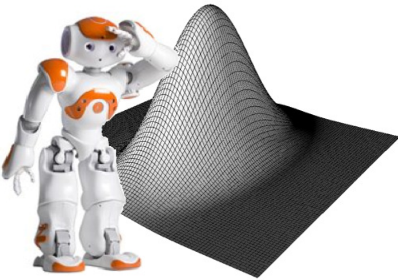
Conclusion

- Improved on the sequential approach with Gaussian fitness functions
- Described the implementation details for the case of ball detection



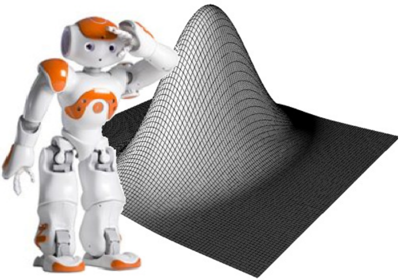
Conclusion

- Improved on the sequential approach with Gaussian fitness functions
- Described the implementation details for the case of ball detection
- This method can be applied for a variety of other field objects



Conclusion

- Improved on the sequential approach with Gaussian fitness functions
- Described the implementation details for the case of ball detection
- This method can be applied for a variety of other field objects
- Improvements to kinematics and strategy included in our work.



UT Austin Learning Agents Research Group