A General Information Quality Based Approach for Satisfying Sensor Constraints in Multirobot Tasks

Yu ("Tony") Zhang   Lynne E. Parker

Distributed Intelligence Laboratory
Electrical Engineering and Computer Science Department
University of Tennessee, Knoxville TN, USA

IEEE International Conference on
Robotics and Automation, 2010

Problems we are interested in

Gerkey's taxonomy of robot problems [Gerkey and Mataric, 2004]:

- single-task (ST) or multitask (MT) ROBOT
- single-robot (SR) or multirobot (MR) TASK
- instantaneous (IA) or time-extended (TA) ASSIGNMENT

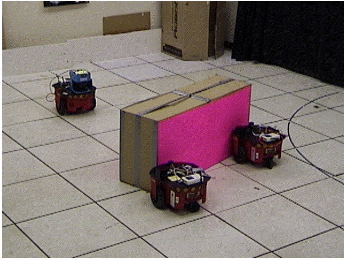
Multirobot (MR) tasks can be:

- loosely coupled
- tightly coupled

An unaddressed issue

Sensor constraints may be established.

For example:



(a) [Gerkey and Mataric, 2001]

(b) [Parker and Tang, 2006]

Questions that need answers

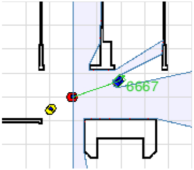
- How to keep these sensor constraints satisfied?
- What if certain sensor constraints are unsatisfiable?

Issues to consider

Issues:

- Non-optimal initial configurations

For example:



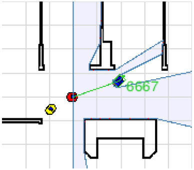
Initial configuration is not optimal for the red robot

Issues to consider

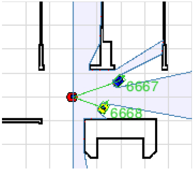
Issues:

- Non-optimal initial configurations
- Environmental influence

For example:



Initial configuration is not optimal for the red robot



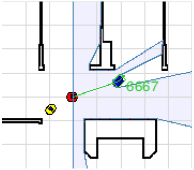
Dynamic environmental factor imposes potential risk

Issues to consider

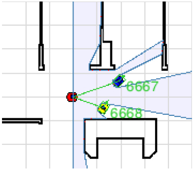
Issues:

- Non-optimal initial configurations
- Environmental influence
- Unsatisfiable sensor constraint

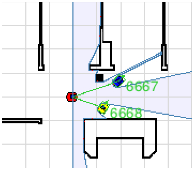
For example:



Initial configuration is not optimal for the red robot



Dynamic environmental factor imposes potential risk



Constraint may potentially become unsatisfiable

No general answer is provided

- Robot deployment task [Howard et al., 2006]
  Fragile to uncertainty and dynamic environmental factors
- Target tracking task [Bandyopadhyay et al., 2006] (ICRA)
  Optimal but application specific
- Robot insertion task [Sujan and Dubowsky, 2005]
  Unscalable and application specific

Contributions – a general approach

- *Local measures of information quality*
  – enables flexible robot control

  Scalable and general

- *Environment and uncertainty sampling*
  – incorporates environmental influence and sensor uncertainty

  General

- *Constraint model*
  – enables dynamic formation control in robot navigation task

  Semi-autonomous

Sensor characterization for constraint satisfaction

The model, $I_s : X \to [0, 1]$.

Sensor characterization for constraint satisfaction

The model, $I_s : X \to [0, 1]$.

- X is the constrainee's sensor's local space.
- A score is assigned to every constrainer's configuration in X.

Sensor characterization for constraint satisfaction

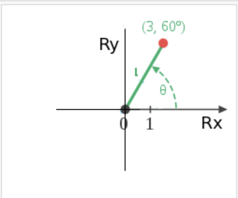
The model, $I_s : X \rightarrow [0, 1]$.

- X is the constrainee's sensor's local space.
- A score is assigned to every constrainer's configuration in X.

For example,

$$I_s(x_{(l,\,\theta)}) = a * \frac{l_{max} - l}{l_{max}} + (1.0 - a) * \frac{\theta_{max} - |\theta|}{\theta_{max}}$$

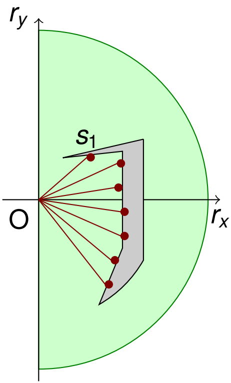
in which a is a weighting factor



To incorporate environmental influence

Environment samples, $S : \{s_1, s_2, ..., s_n\}$.

- Apply a k-means clustering algorithm on range sensor readings
- Choose a granularity for sample creation



To incorporate environmental influence

Environment samples, $S : \{s_1, s_2, ..., s_n\}$.

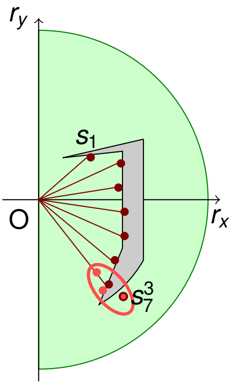
- Apply a k-means clustering algorithm on range sensor readings
- Choose a granularity for sample creation

Uncertainty samples for s_i, $S_i : \{s_i^1, s_i^2, ..., s_i^M\}$.

An example sensor uncertainty model:

$$U_s(x_{(l', \theta')} \mid x_{(l, \theta)}) \sim N((l, \theta), M\Sigma_s M^T)$$

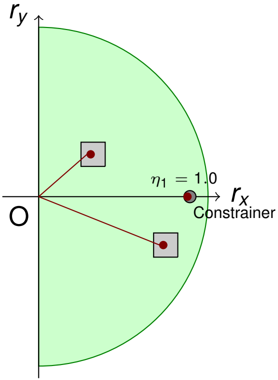
$$M = \begin{bmatrix} |l - l'| & 0 \\ 0 & |\theta - \theta'| \end{bmatrix}$$



The combined measures

Samples from the constrainer. For each s_i,

- if within c from the constrainer, $\eta_i = 1$;
- otherwise, compute $\eta_i = U_s(x_{s_i} \mid x_{cr})/Z$, $(Z = U_s(x_{cr} \pm c \mid x_{cr}))$



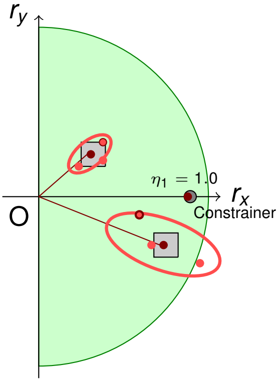
The combined measures

Samples from the constrainer. For each s_i,

- if within c from the constrainer, $\eta_i = 1$;
- otherwise, compute
  $\eta_i = U_s(x_{s_i} \mid x_{cr})/Z$, $(Z = U_s(x_{cr} \pm c \mid x_{cr}))$

Compute weights for sensor quality measures:

- for each s_i^j, compute $h_i^j = H_s(x_{s_i^j} \mid x_{cr})$;
  then compute $r_i = C_{app}(h_i^1, h_i^2, \ldots h_i^M)$



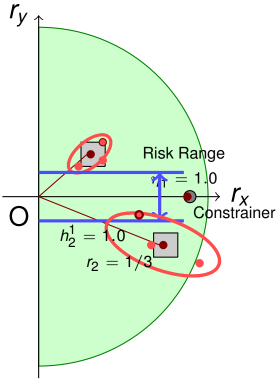
The combined measures

Samples from the constrainer. For each s_i,

- if within c from the constrainer, $\eta_i = 1$;
- otherwise, compute $\eta_i = U_s(x_{s_i} \mid x_{cr})/Z$, $(Z = U_s(x_{cr} \pm c \mid x_{cr}))$

Compute weights for sensor quality measures:

- for each s_i^j, compute $h_i^j = H_s(x_{s_i^j} \mid x_{cr})$; then compute $r_i = C_{app}(h_i^1, h_i^2, \ldots h_i^M)$



The combined measures

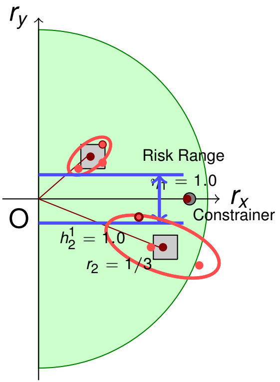
Samples from the constrainer. For each s_i,

- if within c from the constrainer, $\eta_i = 1$;
- otherwise, compute $\eta_i = U_s(x_{s_i} \mid x_{cr})/Z$, $(Z = U_s(x_{cr} \pm c \mid x_{cr}))$

Compute weights for sensor quality measures:

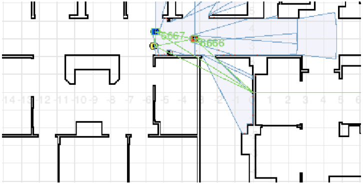
- for each s_i^j, compute $h_i^j = H_s(x_{s_i^j} \mid x_{cr})$; then compute $r_i = C_{app}(h_i^1, h_i^2, \dots h_i^M)$
- compute $w = \prod_i (1.0 - r_i * (1.0 - \eta_i))$

Measures of information quality: $\imath = \imath_s * w$

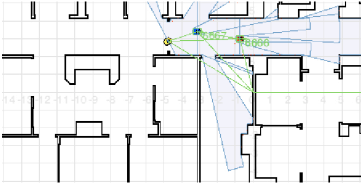


Finding alternative solutions

Constraint relaxation:



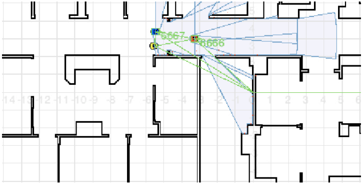
(a) Initial: $R_y \rightarrow R_r$



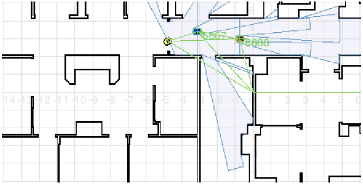
(b) Relaxed: $R_y \rightarrow R_b \rightarrow R_r$

Finding alternative solutions

Constraint relaxation:



(a) Initial: $R_y \rightarrow R_r$



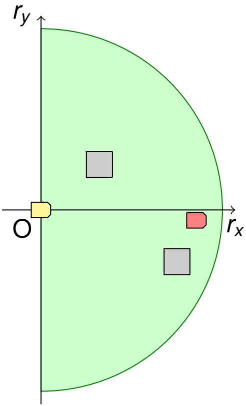
(b) Relaxed: $R_y \rightarrow R_b \rightarrow R_r$

As long as constraints form a connected graph: e.g., $R_y \rightarrow R_b \rightarrow R_r$

- $\imath_{R_y \rightsquigarrow R_r} = L_{app}(\imath_{R_y \rightarrow R_b}, \imath_{R_b \rightarrow R_r})$

The Overall Algorithm

sample the motion vector, $V : \{v_1, v_2, \dots v_D\}$
while true **do**

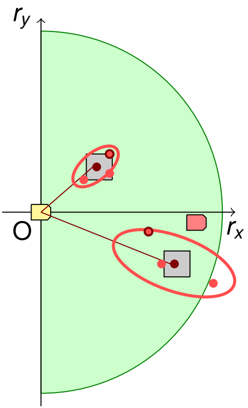


Motion model: $r = v/\omega$

end while

The Overall Algorithm

sample the motion vector, $V : \{v_1, v_2, \ldots v_D\}$
while true **do**
  sample the environment, $S : \{s_1, s_2, \ldots, s_n\}$
  find candidate constrainer configuration x_{cr}
  for all s_i in S **do**
    compute the likelihood $\eta_i = U_s(x_{s_i} \mid x_{cr})/Z$
    sample using the sensor uncertainty model of the
    range sensor, $S_i : \{s_i^1, \ldots s_i^M\}$
  end for



Motion model: $r = v/\omega$

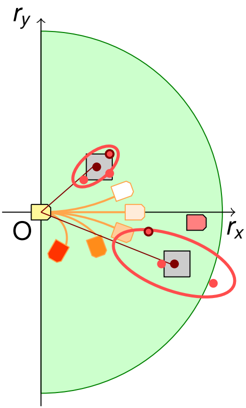
end while

The Overall Algorithm

sample the motion vector, $V : \{v_1, v_2, \ldots v_D\}$
while true **do**
  sample the environment, $S : \{s_1, s_2, \ldots, s_n\}$
  find candidate constrainer configuration x_{cr}
  for all s_i in S **do**
    compute the likelihood $\eta_i = U_s(x_{s_i} \mid x_{cr})/Z$
    sample using the sensor uncertainty model of the range sensor, $S_i : \{s_i^1, \ldots s_i^M\}$
  end for
  for all v_k in V **do**
    predict new configuration $x_{cr}^k = F_m(x_{cr}, v_k)$

  end for

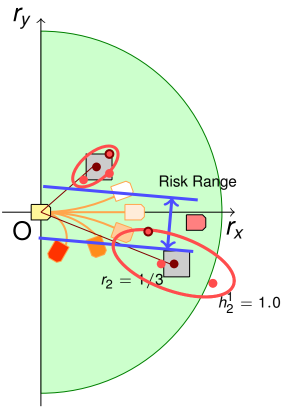
end while



Motion model: $r = v/\omega$

The Overall Algorithm

sample the motion vector, $V : \{v_1, v_2, \dots v_D\}$
while true **do**
    sample the environment, $S : \{s_1, s_2, \dots, s_n\}$
    find candidate constrainer configuration x_{cr}
    for all s_i in S **do**
        compute the likelihood $\eta_i = U_s(x_{s_i} \mid x_{cr})/Z$
        sample using the sensor uncertainty model of the range sensor, $S_i : \{s_i^1, \dots s_i^M\}$
    end for
    for all v_k in V **do**
        predict new configuration $x_{cr}^k = F_m(x_{cr}, v_k)$
        compute $\imath_s^k = I_s(x_{cr})$
        for all s_i in S **do**
            for all s_i^j in S_i **do**
                compute $(h_i^j)^k = H_s(x_{s_i^j} \mid x_{cr})$
            end for
            compute $r_i^k = C_{app}((h_i^1)^k, (h_i^2)^k, \dots (h_i^M)^k)$
        end for
        compute the weight for the sensor quality measure $w^k = \prod_i (1.0 - r_i^k * (1.0 - \eta_i))$
        compute $\imath^k = \imath_s^k * w^k$
    end for

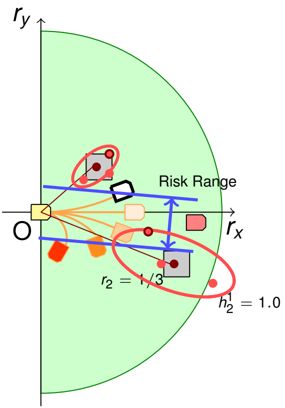


Motion model: $r = v/\omega$

end while

The Overall Algorithm

sample the motion vector, $V : \{v_1, v_2, \ldots v_D\}$
while true **do**
  sample the environment, $S : \{s_1, s_2, \ldots, s_n\}$
  find candidate constrainer configuration x_{cr}
  for all s_i in S **do**
    compute the likelihood $\eta_i = U_s(x_{s_i} \mid x_{cr})/Z$
    sample using the sensor uncertainty model of the range sensor, $S_i : \{s_i^1, \ldots s_i^M\}$
  end for
  for all v_k in V **do**
    predict new configuration $x_{cr}^k = F_m(x_{cr}, v_k)$
    compute $\imath_s^k = I_s(x_{cr})$
    for all s_i in S **do**
      for all s_i^j in S_i **do**
        compute $(h_i^j)^k = H_s(x_{s_i^j} \mid x_{cr})$
      end for
      compute $r_i^k = C_{app}((h_i^1)^k, (h_i^2)^k, \ldots (h_i^M)^k)$
    end for
    compute the weight for the sensor quality measure
    $w^k = \prod_i (1.0 - r_i^k * (1.0 - \eta_i))$
    compute $\imath^k = \imath_s^k * w^k$
  end for
  find $\imath^* = max_{i=1}^D(\imath^i)$
  if indirectly satisfied **then**
    compute $\imath^* = L_{app}(Path_{alt})$
  end if
  if $\imath^* >=$ a threshold **then**
    return v^* (corresponding to $\imath^*$)
  end if
  search for alternative solution using constraint model
  if no alternative solution found **then**
    return failure
  end if
end while



Motion model: $r = v/\omega$

Overview of results

Simulations:

- Robot tracking task
  – behavior and statistical comparison
- Robot navigation task
  – 10 sets of random initial configurations

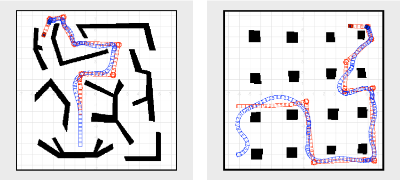
Physical experiments:

- Robot tracking task
  – performance comparison and behavior analysis
- Robot navigation task
  – 2 different environments

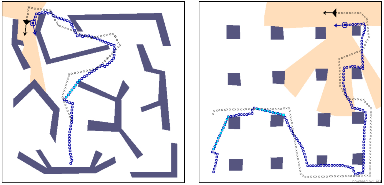
Simulation – tracking task

Robots demonstrate similar behaviors.

Our IQ Based Approach



[Bandyopadhyay et al., 2006]



Simulation – tracking task (cont.)

With comparable performance, our approach is more general.

Env.	Greedy Approach [Bandyopadhyay et al., 2006] (ICRA)		
	Total No. Steps	No. Steps Visible	No. Times Lost (Steps)
Maze	82	74 (90%)	1 (8)
City Blocks	156	131 (84%)	2 (13, 12)

vs.

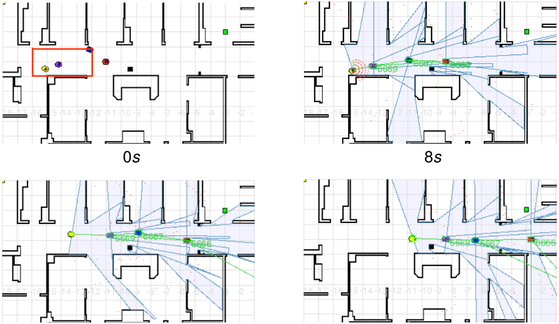
Env.	Our IQ Based Approach		
	Total No. Steps	No. Steps Visible	No. Times Lost (Steps)
Maze	114±3.8	108±4.0 (87±2.1%)	1 (14±2.5)
City Blocks	177±4.3	165±5.5 (91±1.5%)	1 (16±2.5))

Simulation – navigation task

Robust for different initial configurations.

10 sets of random configurations: $x \in [-16.0, -12.0]$, $y \in [2.0, 3.8]$, $\theta \in [-60, 60]$

Snapshots for running with one of the 10 sets:



0s 8s 18s 26s

Physical experiment – tracking task

Performance significantly better than the baseline approach.

Initial Configurations	VFH Approach Total Tracking Time	Time in Track	Track to Goal
Config. 1	29.7	5.3 (18%)	NO
Config. 2	26.5	9.9 (37%)	YES
Config. 3	26.6	2.4 (9%)	NO
Config. 4	18.7	4.1 (22%)	NO
Config. 5	27.2	7.1 (26%)	YES

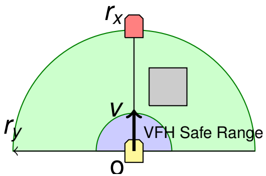
vs.

Initial Configurations	Our IQ Based Approach Total Tracking Time	Time in Track	Track to Goal
Config. 1	30.1	20.2 (67%)	YES
Config. 2	30.4	19.2 (63%)	YES
Config. 3	30.0	17.9 (60%)	YES
Config. 4	26.9	13.4 (50%)	YES
Config. 5	27.5	18.8 (68%)	YES

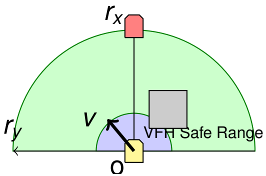
Tracking environment

Physical experiment – tracking task (cont.)

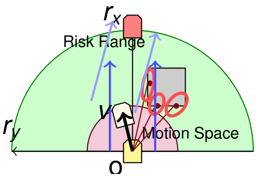
More desirable tracking behaviors.



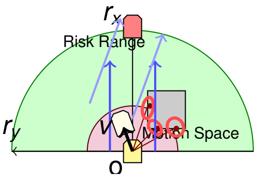
VFH: obstacle is far



VFH: obstacle is near



IQ: obstacle is far



IQ: obstacle is near

Physical experiment – navigation task

Act according to different environmental settings.

Navigation I

Navigation II

Contributions and future work

- *Local measures of information quality*
  – enables flexible robot control

  Scalable and general
- *Environment and uncertainty sampling*
  – incorporates environmental influence and sensor uncertainty

  General
- *Constraint model*
  – enables dynamic formation control in robot navigation task

  Semi-autonomous
- Future Work
  - Implement other multirobot tasks
  - Incorporate information fusion

References

Bandyopadhyay, T., Li, Y., Ang, M., and Hsu, D. (2006).

A greedy strategy for tracking a locally predictable target among obstacles.

In *Proc. of the IEEE Int'l. Conf. on Robotics and Automation*, pages 2342–2347.

Gerkey, B. and Mataric, M. (2001).

Sold!: Auction methods for multi-robot coordination.

IEEE Transactions on Robotics and Automation, Special Issue on Multi-robot Systems.

Gerkey, B. and Mataric, M. (2004).

A formal analysis and taxonomy of task allocation in multi-robot systems.

The International Journal of Robotics Research, 23(9):939–954.

Howard, A., Parker, L., and Sukhatme, G. (2006).
Experiments with a large heterogeneous mobile robot team: Exploration, mapping, deployment and detection.
International Journal of Robotics Research, 25:431–447.

Parker, L. and Tang, F. (2006).
Building multirobot coalitions through automated task solution synthesis.
Proc. of the IEEE, 94(7):1289–1305.

Sujan, V. and Dubowsky, S. (2005).
Visually guided cooperative robot actions based on information quality.
Autonomous Robots, 19(1):89–110.