iTaSC concepts and tutorial

Robohow

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problem statement

challenge

programming general sensor-based robot systems for complex tasks

complex tasks:

- combination of subtasks
- sensor feedback
- large variety of robot systems
- uncertain environments

problem statement

current state

- reprogramming for every task
- specialist
- time consuming + expensive

our goal

development of programming support:

- non-specialists
- less time consuming

problem statement

programming support

SYSTEMATIC approach of specification of tasks using constraints
'iTaSC': instantaneous Task Specification using Constraints

our contribution

framework with:

- systematic approach and
- estimation support for uncertain environments

aim of presentation

aim of presentation

- to show, by means of an example application, how framework for 'Constraint-based task specification and Estimation for Sensor-Based Robot Systems in the Presence of Geometric Uncertainty' works and what its advantages are
- explain generic control and estimation scheme
- show application to other example tasks
- give status, extensions, and outlook

laser tracing task

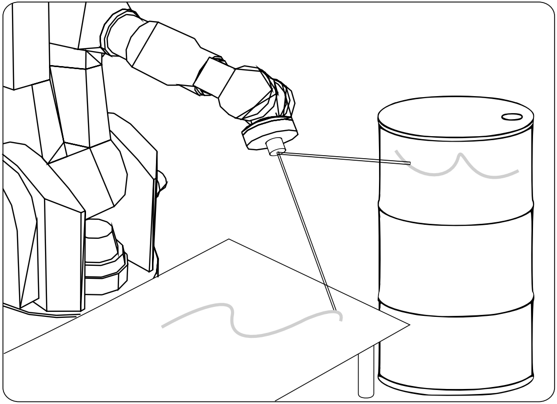

Figure: simultaneous laser tracing on a plane and a barrel

overview

general principle

- robot task: accomplishing relative motion and/or controlled dynamic interaction between objects
- specify task by imposing constraints
  $\Rightarrow$ *task function approach* or *constraint-based task programming*

application independent versus application dependent

- application independent: control and estimation scheme
- application dependent - but systematic: task modeling procedure

control and estimation scheme

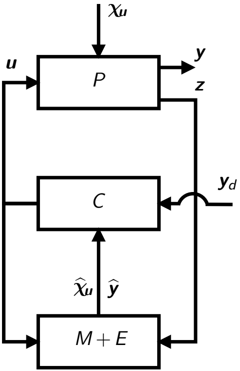

Figure: general control scheme

- plant P:
  - robot system ($\boldsymbol{q}$)
  - environment
- controller C
- model update and estimation $M+E$

control and estimation scheme

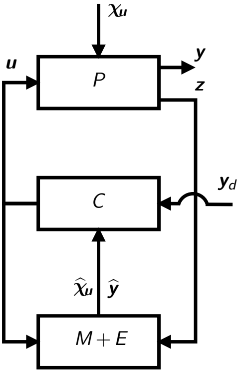

Figure: general control scheme

nomenclature:

- *control input* $\boldsymbol{u}$: desired joint velocities
- *system output* $\boldsymbol{y}$: controlled variables $\Rightarrow$ task specification $=$ imposing constraints $\boldsymbol{y}_d$ on $\boldsymbol{y}$
- *measurements* $\boldsymbol{z}$: observe the plant
- *geometric disturbances*, $\chi_{\boldsymbol{u}}$

control and estimation scheme

conclusion

task independent derivation of
controller block and model update and estimation block
IF
specific *task modeling* procedure is used

task modeling

- task modeling uses TASK COORDINATES:
- two types of task coordinates:
  - *feature coordinates*, χ_f
  - *uncertainty coordinates*, χ_u
- task coordinates defined in user-defined frames

goal

choose frames and task coordinates in a way the task specification becomes intuitive

framework presents procedure to do this

task modeling procedure

four steps:

1. identify objects and features and assign reference frames
2. choose feature coordinates χ_f
3. choose uncertainty coordinates χ_u
4. specify task

task modeling procedure

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1. identify objects and features and assign reference frames
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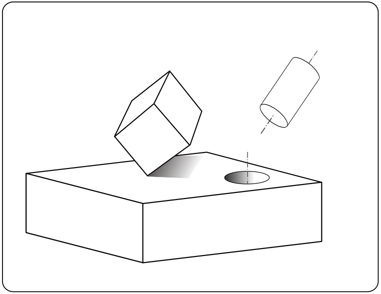
STEP 1: object and feature frames



a feature is linked to an object

- physical entity
  (vertex, edge, face, surface. . .)
- abstract geometric property
  (symmetry axis, reference frame of a sensor,. . .)

STEP 1: object and feature frames

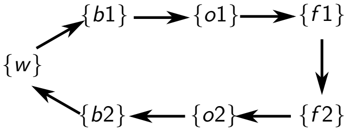


Figure: object and feature frames

each constraint needs four frames:

- two object frames: $o1$ and $o2$
- two feature frames: $f1$ and $f2$

STEP 1: object and feature frames

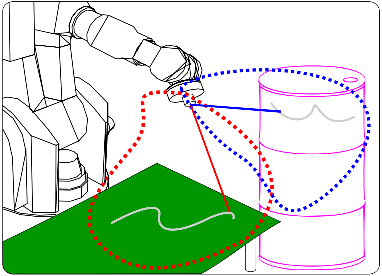
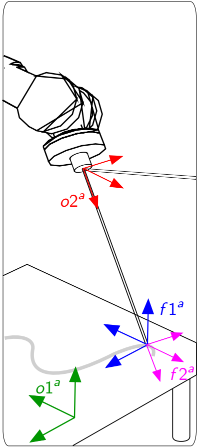


Figure: object and feature frames laser tracing

- natural task description imposes two motion constraints:
  1. trace figure on plane
  2. trace figure on barrel
- ⇒two feature relationships:
  1. feature *a*: for the laser-plane
  2. feature *b*: for the laser-barrel
- the objects are:
  1. laser *a* and laser *b*
  2. the plane
  3. the barrel

STEP 1: object and feature frames



object and feature frames

- for laser-plane feature:
  - frame $o1^a$ fixed to plane
  - frame $o2^a$ fixed to first laser, z-axis along laser beam
  - frame $f1^a$ same orientation as $o1^a$, at intersection of laser with plane
  - frame $f2^a$ same position as $f1^a$ and same orientation as $o2^a$
- for laser-barrel feature:

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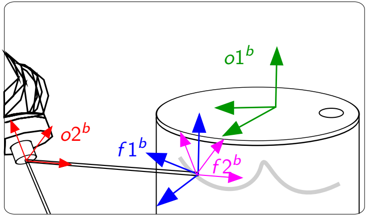
STEP 1: object and feature frames



object and feature frames

- for laser-plane feature:
- for laser-barrel feature:
  - frame $o1^b$ fixed to barrel, x-axis along axis of barrel
  - frame $o2^b$ fixed to second laser, z-axis along the laser beam
  - frame $f1^b$ at intersection of laser with barrel, z-axis perpendicular to barrel surface, x-axis parallel to barrel axis
  - frame $f2^b$ same position as $f1^b$, same orientation as $o2^b$

task modeling procedure

four steps:

1. identify objects and features and assign reference frames
2. choose feature coordinates χ_f
3. choose uncertainty coordinates χ_u
4. specify task

STEP 2: feature coordinates

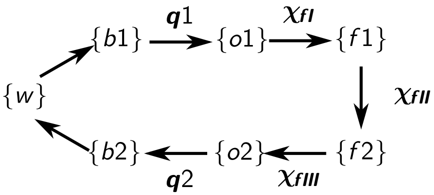
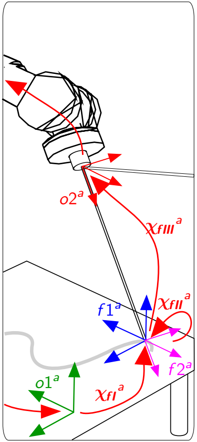


Figure: object and feature frames and feature coordinates

- in general six degrees of freedom between $o1$ and $o2$
- $o1 \rightarrow f1 \rightarrow f2 \rightarrow o2 =$ virtual kinematic chain
- for every feature $\boldsymbol{\chi_f}$ can be partitioned

$$\boldsymbol{\chi_f} = \begin{pmatrix} \boldsymbol{\chi_{fI}}^T & \boldsymbol{\chi_{fII}}^T & \boldsymbol{\chi_{fIII}}^T \end{pmatrix}^T$$

STEP 2: feature coordinates



- laser-plane feature:

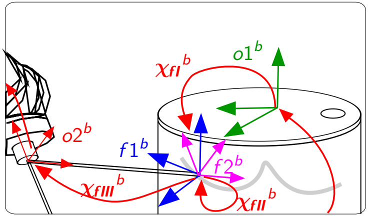
$$\chi_{fI}{}^a = \begin{pmatrix} x^a & y^a \end{pmatrix}^T \quad (1)$$

$$\chi_{fII}{}^a = \begin{pmatrix} \phi^a & \theta^a & \psi^a \end{pmatrix}^T \quad (2)$$

$$\chi_{fIII}{}^a = \begin{pmatrix} z^a \end{pmatrix} \quad (3)$$

- laser-barrel feature

STEP 2: feature coordinates



- laser-plane feature
- laser-barrel feature:

$$\chi_{fI}{}^b = \left(x^b \quad \alpha^b \right)^T \qquad (1)$$

$$\chi_{fII}{}^b = \left(\phi^b \quad \theta^b \quad \psi^b \right)^T \qquad (2)$$

$$\chi_{fIII}{}^b = \left(z^b \right) \qquad (3)$$

task modeling procedure

four steps:

1. identify objects and features and assign reference frames
2. choose feature coordinates χ_f
3. choose uncertainty coordinates χ_u
4. specify task

STEP 3: uncertainty coordinates

focus on two types of geometric uncertainty:

1. uncertainty pose of object, and
2. uncertainty pose of feature wrt corresponding object

uncertainty *coordinates represent* pose uncertainty of real frame wrt modeled frame:

$$\chi_u = \begin{pmatrix} \chi_{uI}{}^T & \chi_{uII}{}^T & \chi_{uIII}{}^T & \chi_{uIV}{}^T \end{pmatrix}^T \qquad (4)$$

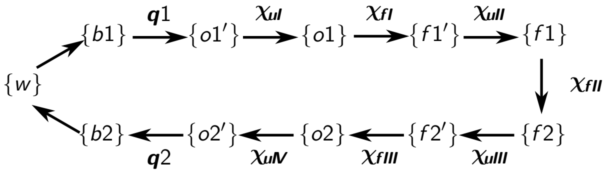
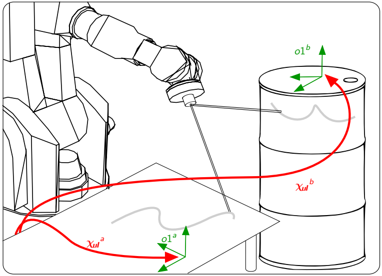


Figure: feature and uncertainty coordinates

STEP 3: uncertainty coordinates



- unknown position and orientation plane :

$$\chi_{ul}{}^{a} = \begin{pmatrix} h^a & \alpha^a & \beta^a \end{pmatrix}^T$$

- unknown position barrel:

$$\chi_{ul}{}^{b} = \begin{pmatrix} x_u^b & y_u^b \end{pmatrix}^T$$

task modeling procedure

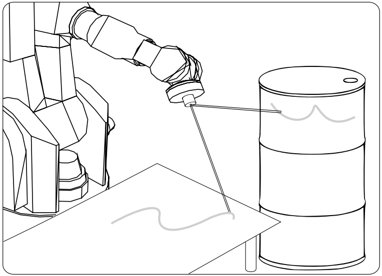
four steps:

1. identify objects and features and assign reference frames
2. choose feature coordinates χ_f
3. choose uncertainty coordinates χ_u
4. specify task

STEP 4: task specification

observation

task is easily specified using task coordinates χ_f and χ_u



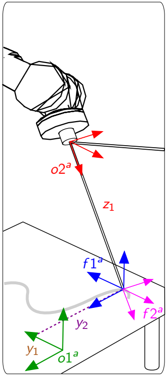
remember: task objective is twofold:

1. trace desired figure on plane
2. trace desired figure on barrel

STEP 4: task specification

observation

task is easily specified using task coordinates χ_f and χ_u



- **output equations:**
  - for the plane:

$$y_1 = x^a \quad \text{and} \quad y_2 = y^a$$

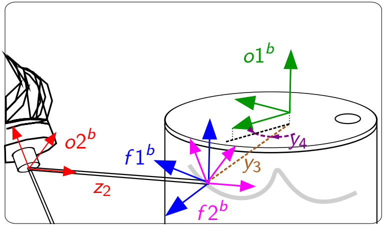
  - for the barrel
- **constraint equations:**
  in this example the desired paths are circles: $y_{id}(t)$, for $i = 1, \ldots, 4$
- **measurement equations:**

$$z_1 = z^a \quad \text{and} \quad z_2 = z^b$$

STEP 4: task specification

observation

task is easily specified using task coordinates χ_f and χ_u



- **output equations:**
  - for the plane
  - for the barrel:

$$y_3 = x^b \quad \text{and} \quad y_4 = \alpha^b$$

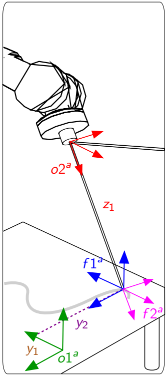
- **constraint equations:**
  in this example the desired paths are circles: $y_{id}(t)$, for $i = 1, \ldots, 4$
- **measurement equations:**

$$z_1 = z^a \quad \text{and} \quad z_2 = z^b$$

STEP 4: task specification

observation

task is easily specified using task coordinates χ_f and χ_u



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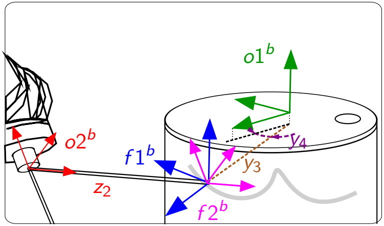
STEP 4: task specification

observation

task is easily specified using task coordinates χ_f and χ_u



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  - for the plane
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  in this example the desired paths are circles: $y_{id}(t)$, for $i = 1, \ldots, 4$
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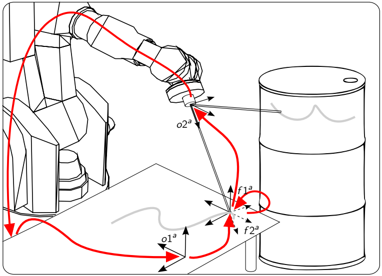
$$z_1 = z^a \quad \text{and} \quad z_2 = z^b$$

STEP 4: task specification

observation

task is easily specified using task coordinates χ_f and χ_u



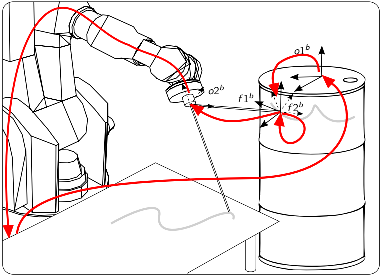
position loop constraints:
two position loop constraints, one for each feature relationship

- laser-plane feature *a*
- laser-barrel feature *b*

STEP 4: task specification

observation

task is easily specified using task coordinates χ_f and χ_u



position loop constraints:
two position loop constraints, one for each feature relationship

- laser-plane feature *a*
- laser-barrel feature *b*

task modeling

conclusion

- application dependent - but systematic modeling procedure provided easy task specification and uncertainty modeling
- application independent controller and model update and estimation block automatically derived

$\Rightarrow$ overall fast and easy task specification

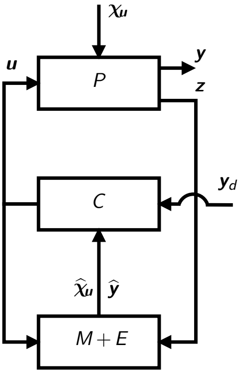


Figure: general control scheme

overview

Equations (1)

- *robot system equation:* relates the control input $\boldsymbol{u}$ to the rate of change of the robot system state:

$$\frac{d}{dt}\begin{pmatrix} \boldsymbol{q} \\ \dot{\boldsymbol{q}} \end{pmatrix} = \boldsymbol{s}(\boldsymbol{q}, \dot{\boldsymbol{q}}, \boldsymbol{u}) \quad (5)$$

- *output equation:* relates the position based outputs $\boldsymbol{y}$ to the joint and feature coordinates:

$$\boldsymbol{f}(\boldsymbol{q}, \chi_{\boldsymbol{f}}) = \boldsymbol{y} \quad (6)$$

Equations (2)

- *measurement equation:* relates the position based measurements $\boldsymbol{z}$ to the joint and feature coordinates:

$$\boldsymbol{h}(\boldsymbol{q}, \chi_{\boldsymbol{f}}) = \boldsymbol{z} \tag{7}$$

- *artificial constraints:* used to specify the task:

$$\boldsymbol{y} = \boldsymbol{y}_d \tag{8}$$

- *natural constraints:* for rigid environments:

$$\boldsymbol{g}(\boldsymbol{q}, \chi_{\boldsymbol{f}}) = \mathbf{0} \tag{9}$$

$\longrightarrow$ special case of the artificial constraints with $\boldsymbol{y}_d = 0$

Equations (3)

- dependency relation between $\boldsymbol{q}$ and $\chi_{\boldsymbol{f}}$, perturbed by uncertainty coordinates $\chi_{\boldsymbol{u}}$:

$$\boldsymbol{l}(\boldsymbol{q}, \chi_{\boldsymbol{f}}, \chi_{\boldsymbol{u}}) = \boldsymbol{0} \tag{10}$$

$\longrightarrow$ nonholonomic systems: replace $\boldsymbol{q}$ by operational coordinates $\chi_{\boldsymbol{q}}$
$\longrightarrow$ derived using position closure equations $\Rightarrow$ *loop constraints*

auxiliary coordinates

the benefit of introducing feature coordinates $\chi_{\boldsymbol{f}}$ is that they can be chosen according to the specific task at hand, such that equations (6)–(9) can much be simplified. A similar freedom of choice exists for the uncertainty coordinates in equation (10)

control law

goal

1. provide system input $\boldsymbol{u}$ at each time step

- here: assume a velocity-controlled robot ($\boldsymbol{u} = \dot{\boldsymbol{q}}_d$)
- control law is based on system linearization, resulting in an equation of the form (details in appendix):

$$\boldsymbol{A}\dot{\boldsymbol{q}}_d = \dot{\boldsymbol{y}}_d^\circ + \boldsymbol{B}\widehat{\dot{\chi}}_{\boldsymbol{u}}, \tag{11}$$

with

$$\dot{\boldsymbol{y}}_d^\circ = \dot{\boldsymbol{y}}_d + \boldsymbol{K}_p(\boldsymbol{y}_d - \boldsymbol{y}) \tag{12}$$

- *weighted pseudo-inverse solving approach* can handle over- and/or underconstrained cases next to constraint weighting: levels of constraints based on nullspace projections

model update and estimation

goal

1. provide estimate for system outputs $\boldsymbol{y}$ used in feedback terms of constraint equations (12)
2. provide estimate for the uncertainty coordinates $\boldsymbol{\chi_u}$ used in control input (**??**)
3. maintain consistency between joint and feature coordinates $\boldsymbol{q}$ and $\boldsymbol{\chi_f}$ based on the loop constraints

model update and estimation

model update and estimation is based on an extended system model:

$$\frac{d}{dt}\begin{pmatrix} \boldsymbol{q} \\ \boldsymbol{\chi_f} \\ \boldsymbol{\chi_u} \\ \dot{\boldsymbol{\chi}}_u \\ \ddot{\boldsymbol{\chi}}_u \end{pmatrix} = \begin{pmatrix} \boldsymbol{0} & \boldsymbol{0} & \boldsymbol{0} & \boldsymbol{0} & \boldsymbol{0} \\ \boldsymbol{0} & \boldsymbol{0} & \boldsymbol{0} & -\boldsymbol{J_f}^{-1}\boldsymbol{J_u} & \boldsymbol{0} \\ \boldsymbol{0} & \boldsymbol{0} & \boldsymbol{0} & \boldsymbol{1} & \boldsymbol{0} \\ \boldsymbol{0} & \boldsymbol{0} & \boldsymbol{0} & \boldsymbol{0} & \boldsymbol{1} \\ \boldsymbol{0} & \boldsymbol{0} & \boldsymbol{0} & \boldsymbol{0} & \boldsymbol{0} \end{pmatrix} \begin{pmatrix} \boldsymbol{q} \\ \boldsymbol{\chi_f} \\ \boldsymbol{\chi_u} \\ \dot{\boldsymbol{\chi}}_u \\ \ddot{\boldsymbol{\chi}}_u \end{pmatrix} + \begin{pmatrix} \boldsymbol{1} \\ -\boldsymbol{J_f}^{-1}\boldsymbol{J_q} \\ \boldsymbol{0} \\ \boldsymbol{0} \\ \boldsymbol{0} \end{pmatrix} \dot{\boldsymbol{q}}_d \qquad (13)$$

explanation:

1. first row: system equation
2. second row: time-derivative of loop closure $\boldsymbol{l}(\boldsymbol{q}, \boldsymbol{\chi_f}, \boldsymbol{\chi_u}) = \boldsymbol{0}$
3. further rows: 'motion models' for uncertainty coordinates $\boldsymbol{\chi_u}$ (in this example: constant acceleration model)

this model is used in an estimator, e.g. Kalman filter or particle filter

model update and estimation

prediction-correction procedure

- **prediction**
  1. generate prediction based on extended system model
  2. eliminate inconsistencies between predicted estimates
- **correction**
  1. generate updated estimated based on predicted estimates and information from sensor measurements
  2. eliminate inconsistencies between predicted estimates

overview

example applications

rehabilitation robot (LWR)

- shared control between robot and human (conflicting constraints)
- constraint weighting (hence impedance) varies during therapy
- trajectory constraints imposed by robot are collected from demonstration by healthy human

example applications

human-robot comanipulation with PR2-robot

- robot head tracks head of human
- grippers are kept parallel and at constant distance
- end effector wrenches are controlled to zero
- joint limits are avoided (inequality constraints)
- obstacle in environment is avoided (inequality constraint)

overview

status, extensions & outlook

lowest level (constraint level)

- both equality and inequality constraints
- control input at velocity, acceleration or torque level
- constraint weighting in constraint space (overconstrained case), joints space (underconstrained case) or constraint priorities based on null-spaces
- constraint values or trajectories can be obtained from (human) demonstrations

status, extensions & outlook

intermediate level (skill level)

- controlled by Finite State Machine
- activates/deactivates constraints
- changes priorities/weights
- changes desired constraint values

status, extensions & outlook

robot systems: holonomic/nonholonomic

- fixed arm
- mobile platforms
- mobile platforms with two arms
- quadrotor helicopter
- multiple robots
- ...

status, extensions & outlook

software support available

- constraint & skill level
- specification & control of constraints
- TODO: estimation of geometric uncertainties

from instantaneous optimal control to globally optimal control

- every robot task is formulated as a global constrained optimization problem (e.g. to plan optimal trajectory)
- fast numerical solver (ACADO) developed at KU Leuven (OPTEC) (OPTEC: Centre of Excellence 'Optimization in Engineering')

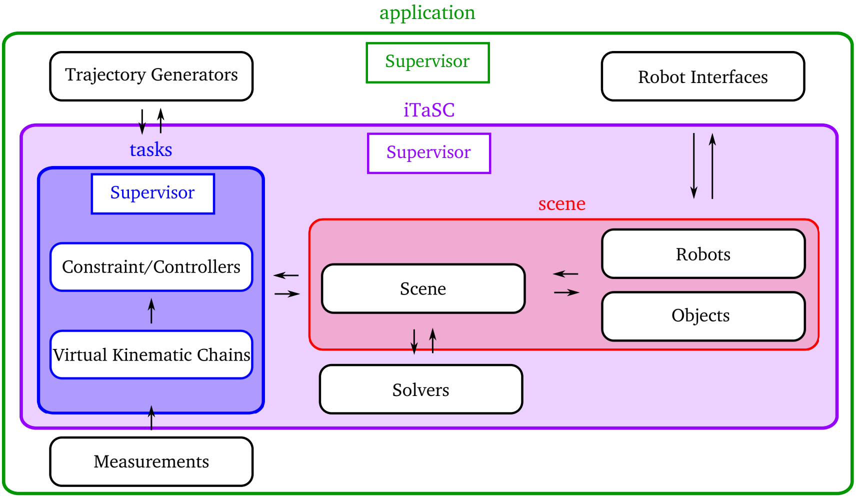
overview

software support

- ✓ modular design
- ✓ flexible user interface: add/remove constraints, change weights...
- ✓ modular task specification: share and reuse tasks
- ✓ separation of concerns: communication, computation, coordination, configuration, and connectivity

- implementation with Orocos
- code available under LGPL/BSD license
- www.orocos.org/itasc

software support



overview

conclusion (1)

conclusion

- motion specification and estimation in unified framework
- automatic application independent derivation of control and model update and estimation
- application dependent - but systematic - task modeling

further reading

framework journal paper

- Constraint-Based Task Specification and Estimation for Sensor-Based Robot Systems in the Presence of Geometric Uncertainty
- Joris De Schutter, Tinne De Laet, Johan Rutgeerts, Wilm Decré, Ruben Smits, Erwin Aertbeliën, Kasper Claes, and Herman Bruyninckx
- Journal of Robotics Research, May 2007, vol. 26, no. 5, pages 433–455

extended framework conference paper

- Extending iTaSC to Support Inequality Constraints and Non-Instantaneous Task Specification
- Wilm Decré, Ruben Smits, Herman Bruyninckx, and Joris De Schutter
- Proceedings of the International Conference on Robotics and Automation, 2009, pages 964–971

THANKS FOR YOUR ATTENTION!