Using Bayesian Filtering to Simultaneous Parameter and State Estimation in Robot Manipulator Programming by Demonstration

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ABSTRACT

Programming industrial robots is a time consuming and expensive operation to be performed at every change of product in manufacturing industries.

We focus on robotic tasks that involve contact between the objects manipulated by the robot and the environment in which it operates such as assembly. We follow a strategy for robot programming based on human demostration in which an operator shows the robot the task to perform. A human operator manipulates the object to be assembled which is equipped with sensors to measure its positions and the forces arising during the interaction with the enviroment.

Realistic assumptions are that: (a) the position of the manipulated object and (b) the position of the environment are known with uncertainties, while (c) the contacts produced during the demonstration are unknown. They must be estimated using 12 time series of positions and forces measured during the demonstration. We obtain the corresponding posterior distributions of continuous parameters (a, b) and state (c) using a suitable Bayesian filtering.

THE PROBLEM

Manual Task Planning

User specifies all the actions and foresees the sensorial inputs to control de task

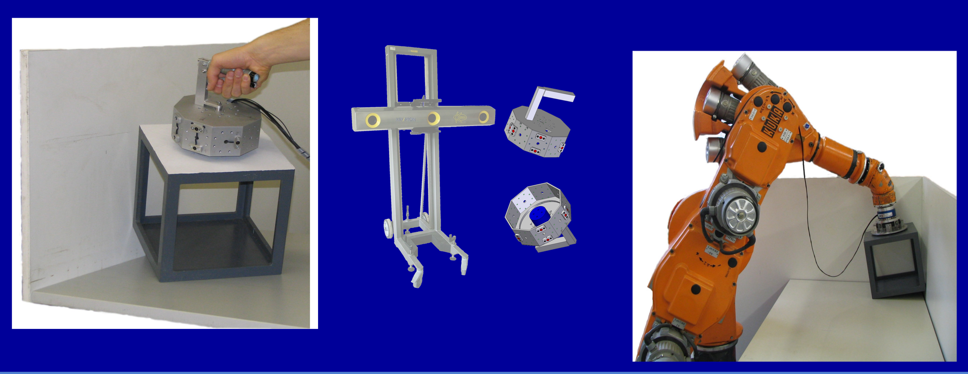
Automatic Task Planning

User specifies start and goal configuration and the trajectory is found automatically

ROBOT PROGRAMMING

Programming by Human Demostration

User shows the robot what to do by demostration



MODEL AND POSTERIOR APROXIMATION

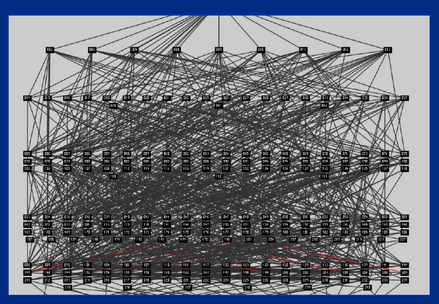
The Data

Sample	Pose						Wrench						Twist					
	Position (m)			Orientation (rad)			Force (N)			Torque (Nm)			Linear Velocity (m/s)			Angular Velocity (rad/s)		
10	-0.01875	0.12486	0.10134	0.253724	0.184328	-0.08001	-0.28945	-0.58902	-0.60959	0.11825	0.05487	0.12956	0.00548	-0.00749	-0.02651	-0.00837	-0.00105	0.03762
30	0.00284	0.09139	0.04733	0.260354	0.184863	-0.04170	-3.67032	6.74443	42.61550	0.41127	-3.44426	0.33102	0.02706	-0.01743	-0.00019	-0.19584	-0.01699	0.03115
50	0.05527	0.05378	0.03810	-0.004852	0.396365	0.05357	1.45988	-1.91942	63.47893	5.39390	-7.95697	0.29669	-0.00912	-0.00119	-0.00807	0.00196	-0.06733	0.00128
70	0.03704	0.07361	0.00404	-0.003448	0.035026	-0.26557	-9.77975	8.09824	57.93021	3.33996	-7.49109	1.56345	-0.00604	0.00149	-0.00846	-0.02137	-0.06165	-0.01509
110	0.02141	-0.02459	-6.31e-05	0.002408	0.000924	-0.17657	3.09468	19.7546	59.83020	-5.25780	-1.08979	0.69758	0.00671	-0.00395	0.00010	0.00659	-0.00066	-0.04389

The System and Measurement Models

Let z_t denote the data at time t and $\mathcal{D}_t = \{z_t, \mathcal{D}_{t-1}\}$, the data until time t. In order to approximate the posterior distribution at time t:

$$P(CF_t = j, \theta | \mathcal{D}_t) \propto P(z_t | CF_t = j, \theta) P(CF_t = j, \theta | \mathcal{D}_{t-1})$$



we use a particle filter with:

- *Prediction step:*

$$P(CF_t = j, \theta | \mathbf{D}_{t-1}) = \sum_{i=1}^{N} P(CF_t = j, \theta | CF_{t-1} = i, z_{t-1}) P(CF_{t-1} = i | \mathbf{D}_{t-1})$$

  where $P(CF_t = j, \theta | CF_{t-1} = i, z_{t-1})$ is given by the CF Graph.

- *Correction step:* Based on the likelihood $P(z_t | CF_t = j, \theta)$, which is a product of two likelihoods:
  - For the pose measurements, the likelihood is a function of the distance, d_m, for any Elementary Contact ($\equiv$ vertex-plane contact). Any distance is a function of z_t and θ and has a different likelihood for any CF.
    For a CF=k:
    - If the EC is present, $d_m \sim N(0, \sigma_d)$, where σ_d is known and depends on the precision of the pose measurements.
    - If the EC is absent, d_m follows a distribution with a long tail for positive values and with positive mode.
  - For the wrench and twist measurements, the likelihood depends on the residues r_m calculated as the difference between the measured wrench (twist) and the projection in the wrench (twist) space for any CF. $r_m \sim N(0, \Sigma_w)$, $(N(0, \Sigma_t))$, where the variances are known and depend on technical factors.

The Filter

Following Liu and West's Filter, at time t, we have a sample of size N, of current states and parameters:

$$\{CF_t^{(j)}, \theta_t^{(j)} : j = 1, \ldots, N\}$$

with associated weights

$$\{\omega_t^{(j)} : j = 1, \ldots, N\}$$

representing an importance approximation to the time t posterior

For $j = 1$ to N

1.- **Identify** prior point estimates of

$$\widehat{CF}_{t+1}^{(j)} = \text{Mode}[CF_{t+1} \,|\, CF_t^{(j)}, \theta_t^{(j)}]$$
$$\widehat{\theta}_{t+1}^{(j)} = a\theta_t^{(j)} + (1-a)\bar{\theta}_t,$$

where $\bar{\theta}_t = \sum_{j=1}^{N} \omega_t^{(j)} \theta_t^{(j)}$, $a = \sqrt{1-h^2}$ for some smoothing parameter h, here we take $a = 0.95$.

2.- **Sample** k from $\{1, \ldots, N\}$ with probabilities $\{g_{t+1}^{(1)}, \ldots, g_{t+1}^{(N)}\}$ where

$$g_{t+1}^{(j)} \propto \omega_t^{(j)} p(\mathbf{z}_{t+1} \,|\, \widehat{CF}_{t+1}^{(j)}, \widehat{\theta}_{t+1}^{(j)}),$$

and $\mathbf{z}_{t+1}$ denotes the observed data at time $t+1$.

3.- **Sample** a new parameter vector $\theta_{t+1}^{(k)}$ from the k-normal component of the kernel:

$$\theta_{t+1}^{(k)} \sim N(\cdot \,|\, \widehat{\theta}_{t+1}^{(k)}, h^2 \mathbf{V}_t),$$

where $V_t = V_0$, the initial variance calculated from the prior.

4.- **Sample** a value of the current state contact formation

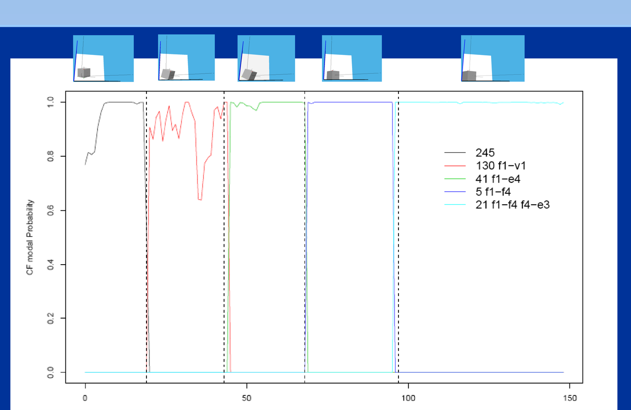
$$CF_{t+1}^{(k)} \sim P(\cdot \,|\, CF_t^{(k)}, \theta_{t+1}^{(k)})$$

5.- **Sample** the corresponding weight

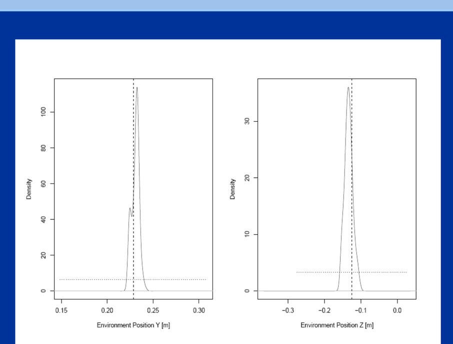
$$\omega_{t+1}^{(k)} \propto \frac{p(\mathbf{z}_{t+1} \,|\, CF_{t+1}^{(k)}, \theta_{t+1}^{(k)})}{p(\mathbf{z}_{t+1} \,|\, \widehat{CF}_{t+1}^{(k)}, \widehat{\theta}_{t+1}^{(k)})}$$

End For

RESULTS AND CONCLUSIONS



Sequence of modal CFs Probabilities



Prior (dotted line) and Posterior (solid line) distributions for parameter positions: y (vertical plane) and z (horizontal plane).

- **We present an application of the West and Liu filter to the problem of simultaneous parameter and state estimation.**
- **The cube+corner system is a highly non linear hybrid system with 245 possible discrete states. In spite of the complex setting, the filter shows a good performance, identifying the contact formations and estimating the geometric parameters used in the demonstration process.**
- **We use uniform prior distributios for enviroment positions with range for X and Y 1.6 cm and Z 30 cm, while for rotations the range is 0.01 rad in all directions. The uncertainty about the manipulated object is practically eliminated.**
- **Here we are making inference about the environment pose wrt to world geometrical parameters. Further work involves making inference about the rest of the parameters (object pose wrt manipulator pose).**
- **Another important issue is the use of statistics on the manifold SE(3), (space of rigid body displacements) in order to avoid inconsistency (e.g. lack of invariance) when using Euclidean Space Statistics.**

REFERENCES

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[2] Meeussen, W., Rutgeerts, J., Gadeyne, K., Bruyninckx, H., De Schutter, J.. 2006. Bayesian Contact State Segmentation for Programming by Human Demonstration in Compliant Motion Tasks. *Submitted to Transactions on Robotics,*