DATA-DRIVEN NEURO-FUZZY MULTI-OBJECTIVE TRAJECTORY PLANNING FOR REDUNDANT MANIPULATORS

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Outline

- Introduction
- Offline Dataset building
  - Robot and Constraints Modelling
  - Non linear Programming Formulation
  - Augmented Lagrangian with Decoupling
- Neuro-Fuzzy Multi-Objective Planner (NeFuMOP)
  - Network Structure Initialization
  - Network Architecture and Learning
- Simulation Results
- Conclusion
Path planning: Geometric path, shortest path, obstacle avoidance
Trajectory planning: Includes velocities, accelerations, dynamic forces, energies, task and workspace requirements
Offline Dataset building

\[ (q) \dot{q}, \]

\[ \dot{q} \quad (q_1, q_2, q_3)^T \]

\[ (q q) q \frac{1}{2} (q_{\text{max}} \quad q_{\text{min}}) \quad \text{diag} (q_{\text{max}} \quad q_{\text{min}}) \]

\[ \dot{q} \quad (D \quad D) \quad 1^T (1^T 1^T 1^T) \]
Offline Dataset building

When the trajectory is being executed, dynamic parameters such as inertia changes and are not completely known, a sensitivity analysis is required.
Offline Dataset building

Discrete dynamic equation rewritten as

\[ x_{k+1} = f_d(x_k, \tau_k, h_k) \] (1)

Kinematic Redundancy Resolution

\[ x_{2k} = D_k(x_{1k}) \] (2)

Torque limits

\[ C \tau_k = \tau_{Min}, \tau_k \tau_{Max}, k = 0, \ldots, N \] (3)

Sampling periods

\[ H \tau_k = \tau_{Min}, \tau_k \tau_{Max} \] (4)

Intermediate pose limits

\[ 1_{\text{Min}}, \tau_k 1_{\text{Max}} \] (5)

Imposed passage points

\[ \begin{bmatrix} 0 & l & 1, \ldots, L \end{bmatrix} \] (6)

where \( L \) is the number of imposed points \( T_{\text{PassTh/p}} \) passage tolerance
Performance index: Travel Time, Electric Energy, and Singularity Avoidance

The discrete multi-objective optimal control problem is:

Find control inputs \( \tau^k \) \( (\begin{array}{c} 1 \\ k \\ \vdots \\ n \end{array})^T \) and \( (h_k) \), \( k = 0, \ldots, N - 1 \),

Solution to

\[
E_d \quad \text{Min} \quad \tau \in \mathcal{C} \quad \sum_{k=0}^{N-1} \left( \tau_k^T U \tau_k \right) \left( \begin{array}{c} x_{1k} \\ \vdots \\ x_{nk} \end{array} \right) \quad h_k
\]

Under associated constraints

\( \tau \),

\( U \),

\[
(x_{1k}) \quad \frac{1}{\sqrt{\det(J(x_{1k})J^T(x_{1k}))}}
\]
The development of the first order necessary optimality conditions allows to find iteratively a solution \((x_0, \tau_0, h_0), \ldots, (x_N, \tau_N, h_{N-1})\) to the problem.

The calculation of the co-states implies the evaluation and differentiation of the right hand member of the dynamic state equation \(f_{d_k}(x_k, \tau_k, h_k)\).

\[
f_{d_k} = D(x_1) - N(x_1, x_2)
\]

\[
u D(q) v - N(q, q) G(q) \]

allows the robot to have a linear and decoupled behavior described as:

\[
\ddot{q} v \quad \text{with} \quad v \quad \text{an auxiliary input}
\]

\[
x_k = \begin{bmatrix}
I_3 & 0 & h_k I_3 & I_3 & x_k & h_k^2 I_3 & v_k
\end{bmatrix}
\]

\[
O_3 \quad I_3 \quad h_k I_3 \quad I_3 \quad x_k \quad h_k I_3 \quad v_k
\]
ALD Flowchart

Offline Dataset building
NeFuMOP is based on a Tsukamoto neuro-fuzzy inference mechanism

NeFuMOP Initialization

Structure parameters through Subtractive Clustering based on the gathered input/output dataset built from offline planning
Neuro-Fuzzy Multi-Objective Trajectory Planning

NeFuMOP Architecture

\[ T_{nm}(x_m) \]

Crisp Inputs

Crisp Outputs

\[ z \]

\[ x \]

\[ y \]

\[ f_1 \]

\[ f_4 \]

\[ f_9 \]
An input/output dataset is built upon 100 trajectories from different starting to ending points, covering mostly of the robot workspace, each discretized into 20 points. These trajectories are generated by applying the offline planning technique based on Augmented Lagrangian taking into account several constraints. These input/output data are introduced to the network in a sequential order, because the network interpolates through intermediate points of the workspace to build the complete path for given starting and ending points. A subtractive clustering is then used to initialize for NefuMOP parameters and structure.
Simulation Results

Robot parameters and Limits on joint torques and rates

<table>
<thead>
<tr>
<th>Link</th>
<th>Mass (kg)</th>
<th>Inertia $I_i$ (kg m$^2$)</th>
<th>Length $L_i$ (m)</th>
<th>$\tau_{\text{Max}}$ (Nm)</th>
<th>$\tau_{\text{Min}}$ (Nm)</th>
<th>MotorMax (rad/s)</th>
<th>MotorMin (rad/s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>8</td>
<td>9.23</td>
<td>1.0</td>
<td>40</td>
<td>-40</td>
<td>4</td>
<td>-3</td>
</tr>
<tr>
<td>2</td>
<td>4</td>
<td>7.5</td>
<td>0.8</td>
<td>40</td>
<td>-25</td>
<td>4</td>
<td>-3</td>
</tr>
<tr>
<td>3</td>
<td>2</td>
<td>5.21</td>
<td>0.45</td>
<td>30</td>
<td>-30</td>
<td>4</td>
<td>-3</td>
</tr>
</tbody>
</table>

Augmented Lagrangian parameters

$\eta_0 = 0.4$, $\alpha_0 = 0.4$, $\beta_0 = 1 \times 10^{-3}$, $\omega_0 = 0.1$, $\omega_0 = 10^4$

Workspace

$x_{\text{Max}} = 2.5$, $x_{\text{Min}} = 0.4$, $y_{\text{Min}} = 0.2$, $y_{\text{Max}} = 2.5$ (m)

A scenario trajectory

From EE position (1.95, 0.82) (m) to (1.35, 1.3) (m), with zero initial and final linear and angular velocities and sampled trajectory into 20 points

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Simulation Results

- ALD ensures smooth trajectories with monotonous increasing energy.
- Kinematic solution is feasible, but...
- Corresponding torques are outside the admissible domain.
- Minimum Time-Energy Trajectory is 35% faster than only minimum-energy.
- Computational time: quite long, it took about 9 minutes for a 4 inner and 4 outer ALD iterations for the above trajectory.

Simulation Results

- Same trajectory performed with increased third link mass by 0.7 Kg.
- Higher torques & time but converges to the target with acceptable precision.

- Same trajectory with imposed Passages through points (1.7, 0.9), (1.5, 1.0), (1.4, 1.2) (m).
Simulation Results

NeFuMOP Simulation Results

\[ r_a \quad 0.7 \quad 0.2 \quad -1.0 \quad 0.9 \]

Subclustering Parameters

9 rules Tsukamoto model is identified

NeFuMOP Simulation Results

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Simulation Results

RMS-Error (After 15 iterations)

Training data (80%) 0.004571
Testing Data (10%) 0.0013857
Checking Data (10%) 0.000110857

Learning Error RMS
--- Training Data , __ Testing Data, *** Checking Data

Trajectory from $x^T(t_s) (0.2, 2)$ corresponding $(0^0, 15^0, 20^0)$ to $x^i(t_f) (0.7, 1.3)$

The ALD technique was used to achieve the offline planning. The actuator torques and sampling period variations can be obtained from the outcomes of NeFuMOP.
Conclusions

The augmented Lagrangian with projection technique has proven to be efficient in modelling and solving the resulting strong non-linear non-convex multi-objective optimal control problem.

Limitations & Ways for Improvement:

- Achieve experimentation and measurements with a physical robot
- Although optimality cannot be claimed from solutions provided by NeFuMOP, as the network has to interpolate between intermediate points, it does provide sub-optimal solutions as it can be noticed from generalization capabilities of NeFuMOP.

Simulations had shown high learning generalization capabilities of NeFuMOP.