Analysis and Synthesis of Effective Human-Robot Collaboration at Varying Levels in Controller Hierarchy

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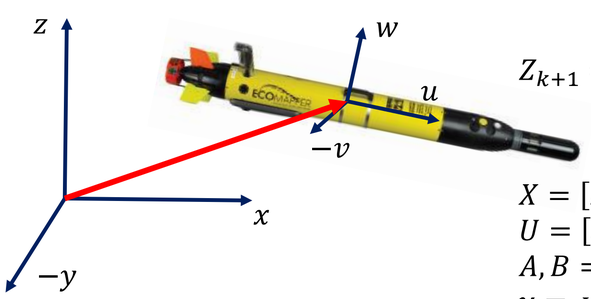
Overview

Autonomy has made great strides over the history of robotics, dramatically decreasing physical and cognitive workload of operators and increasing task performance. However, automation has yet to surpass the adaptability and high-level cognitive reasoning of a human operator. It is therefore desirable to devise novel methods of effective *human-robot collaboration* (HRC) that take into account the strength of both autonomy and human operation by detecting scenarios difficult for autonomy and weighting that difficulty against operator workload.

Robot controller design is usually hierarchical with both high-level task and motion planning and low-level control law design. Presented here are two methods for low-level and high-level control designs, respectively, to guarantee joint performance of HRC systems.

Suboptimal HRC for Guidance and Navigation

In the low-level method, the *switched linear quadratic regulator* (SLQR), an optimal control policy based on a quadratic cost function, is used taking into account system dynamics and operator workload.



$$Z_{k+1} = \begin{bmatrix} A & 0 & 0 \\ 0 & \left(1-\frac{\Delta t}{\tau_\gamma}\right) & \frac{\Delta t}{\tau_\gamma} b_\sigma \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} X_k \\ \gamma_k \\ 1 \end{bmatrix} + \begin{bmatrix} B \\ 0 \\ 0 \end{bmatrix} U_k$$

$X = [\Delta z, \Delta\theta, \Delta\phi, \Delta u, \Delta v, \Delta w, \Delta q, \Delta r]$, error states
$U = [\Delta\alpha, \Delta\beta, \Delta rpm]$, error inputs
$A, B =$ Linearized AUV state and input dynamics
$\gamma =$ workload
$b_\sigma = 1$ (manual) or 0 (autonomy)

Cost Function:

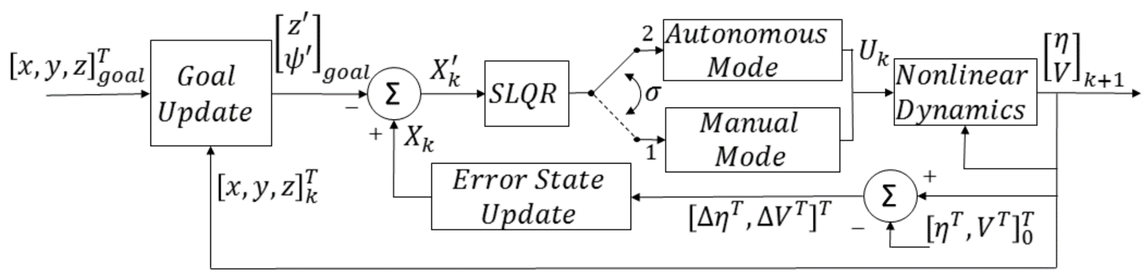
$$J(Z,U,\sigma) = Z_N^T Q_f Z_N + \sum_{k=0}^{N-1} Z_k^T Q_{\sigma(k)} Z_k + U_k^T R_{\sigma(k)} U_k$$

Value Function:

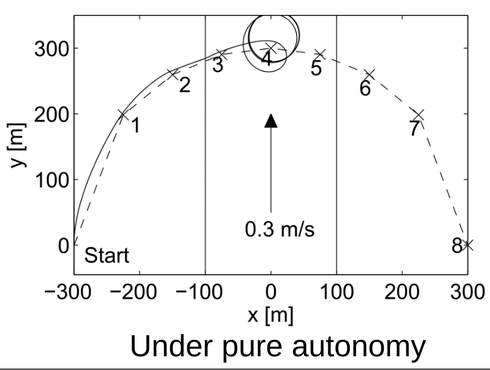
$$V_k(Z_k) = \min_{P \in H_k} Z_k^T P Z_k \qquad H_k = \rho_M(H_{k+1}) = \{\rho_\sigma(P) : for\ \sigma = 1,2\ and\ P \in H_{k+1}\}$$

$$\rho_\sigma(P) = Q_\sigma + A_\sigma^T P A_\sigma - A_\sigma^T P B_\sigma (R_\sigma + B_\sigma^T P B_\sigma)^{-1} B_\sigma^T P A_\sigma$$

Control Scheme:



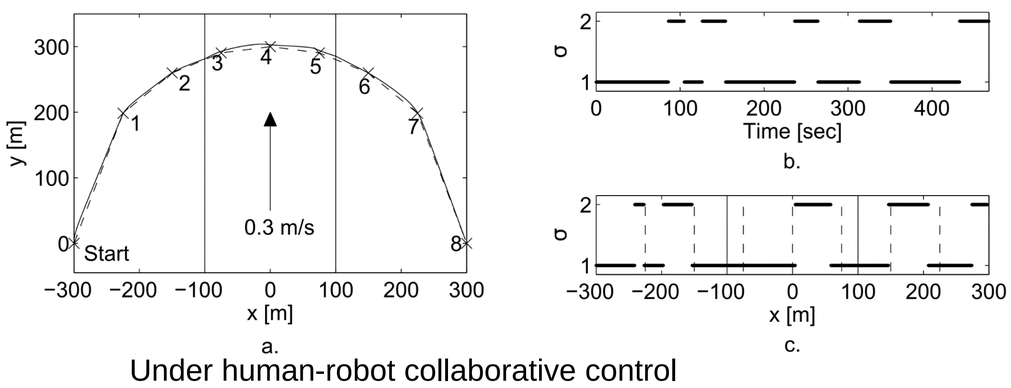
Simulation Results



Under pure autonomy

(Left) Under pure autonomy, the system cannot compensate for the unknown cross current.

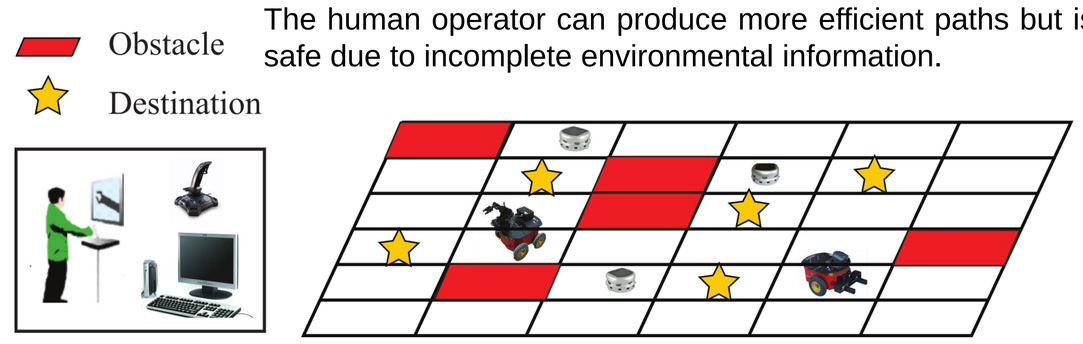
(Below) Using SLQR to choose between manual control ($\sigma = 1$) and autonomy ($\sigma = 2$), system successfully navigates through the environment (a), with switching scheme outlined by time (b) and position (c).



Under human-robot collaborative control

HRC for Safe Symbolic Motion Planning

In the high-level approach, formal methods are applied to a scenario where an operator oversees a group of mobile robots as they navigate an unknown environment. Autonomy uses specifications written in linear temporal logic (LTL) to conduct symbolic motion planning in a guaranteed safe but conservative approach. The human operator can produce more efficient paths but is less safe due to incomplete environmental information.



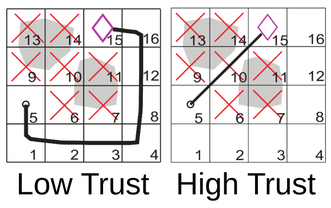
Specification

Safety and reachability specifications are written in linear temporal logic. This *global specification* can be distributed as *subspecifications* and used with model checking to find acceptable paths in the abstracted state.

$$\varphi = \underbrace{\bigwedge_{j \in Goals} \Diamond \pi_j \wedge \bigwedge_{j \in Final\ Goals} \Diamond\Box \pi_j}_{Reachability} \wedge \underbrace{\bigwedge_{j \in Obs} \Box\neg\pi_j}_{Obstacle\ Avoidance} \wedge \underbrace{\bigwedge_{i=1}^{N} (\pi_i^c \wedge \pi_i^o \rightarrow \neg\pi_i^u)}_{Robot\ Collision\ Avoidance}$$

Trust

A *dynamic trust model* is incorporated to aid in task decomposition and real-time switching, with higher trusted robots being allowed to take on more work and traverse riskier human-made paths. Trust is comprised of robot performance (P_R), human performance (P_H), and system faults (F).



$$T_i(k) = AT_i(k-1) + B\Delta P_{R_i}(k) + C\Delta P_H(k) + D\Delta F_i(k)$$

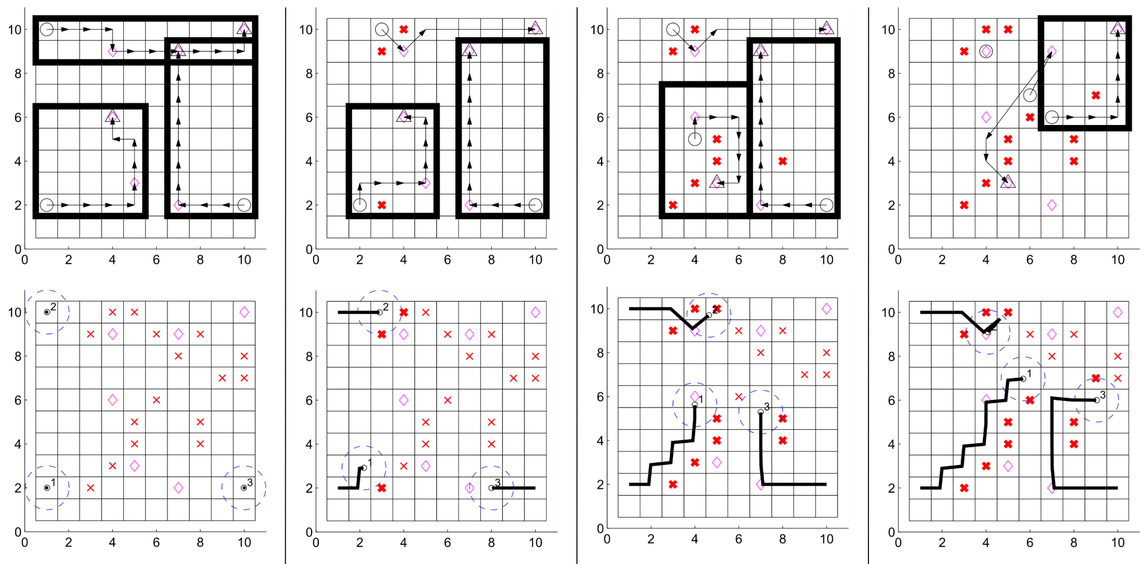
$$P_{R_i}(k) = C_{Obs} N_{Obs_i}(k) + C_{Goals} N_{Goals_i}(k)$$

$$P_H(k) = \begin{cases} 1-\gamma(k)^{S_{Obs_i}(k)+1}, & if\ b_\sigma = 1 \\ 1-\gamma(k), & if\ b_\sigma = 0 \end{cases}$$

$$F_i(k) = C_{Hits} N_{Hits_i}(k)$$

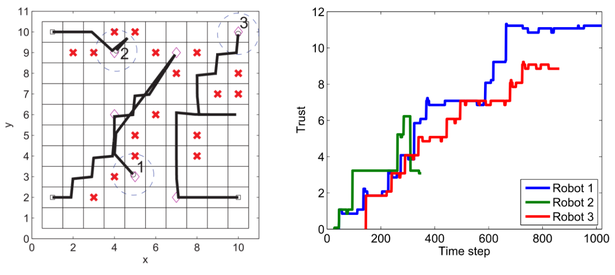
Simulation Results

One operator collaborating with three robots in an unknown environment.



Simulation start Initial plans are generated | Operator paired with Robot 2 and makes a plan | Robot 2 loses trust from near miss | Operator paired with Robot 1 and makes a plan

All agents successfully navigate the unknown environment to achieve each goal (left), with trust progression as shown (right)



Conclusions

Incorporation of HRC into the controller hierarchy takes advantage of the benefits of both human and autonomy. Future works will expand upon this concept to study the advantages of having HRC at multiple control levels simultaneously.

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