Human behaviour modelling for teleoperation

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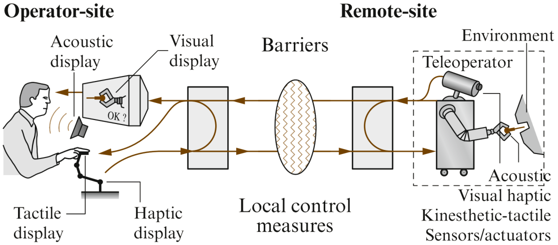
Human modelling aspects in teleoperation

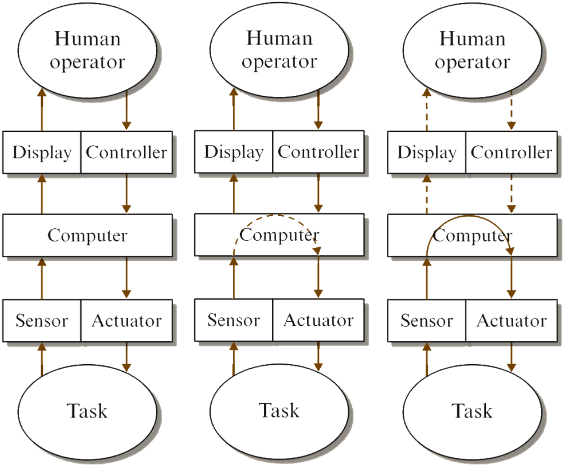
Complex tasks in unstructured/dangerous environments demand teleoperated robots



Aspects of human modelling [She92]

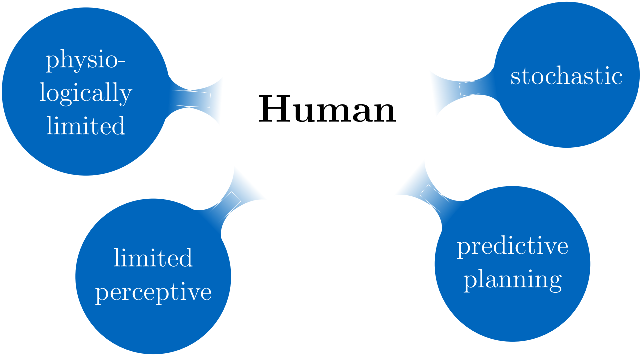
- Sensory perception modelling
  … determines the usefulness of provided information
- Cognitive modelling
  … what a human *will* do in a certain situation
- Response or motor function modelling
  … what a human *can* do, physiological limits apply

Levels of human-in-the-loop involvement [She92]



Direct - Shared - Supervisory Control

Teleoperation-relevant human characteristics



dissipativity-based stability analysis [HB12],[VZ13],[HCF15]

perception-oriented feedback [HB12]

trajectory extrapolation [CDE13]

decision making [PST+15]

motion sequence learning [YXC94]

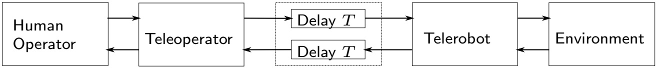
Physiologic limits in bilateral telemanipualtion

- Haptic interface: Human is an impedance
  $m\ddot{x} + d\dot{x} + kx = f$
- Human motion is inherently dissipative [RIM99]
- Delayed communication entails in distorted feedback

A dissipative system is locally stable for a negative semidefinite supply rate $s\left(u(t), y(t)\right)$

$$\dot{V}(x(t)) \leq s(u(t), y(t)),$$

The interconnection of dissipative systems is again a dissipative system with supply rate $s(t) = \sum_i s_i(t)$



A closed-loop dissipative system with a non-passive communication channel has reduced environment distortion [HB12]

Limited human perceptiveness [HB12]

Passivation of delayed communication:

- Hard contacts are displayed softer
- Telerobot seems to be more inert

Just noticeable difference (JND) for inertias: 21%; for stiffness: 8%

Displayed impedances for free motion and hard contact

$$Z_{\mathrm{m}}^{*} = \frac{bT}{2}s \ , \ \ Z_{\mathrm{k}}^{*} = \frac{2k_e b}{2b + k_e T}\frac{1}{s}$$

Tuning the wave impedance b gives conflictive results

Just not noticeable deviation in stiffness

$$b > (1 - \mathsf{JND}_k)\frac{k_e T}{2}$$

Perceived stiffness is not compromised, inertia display becomes more realistic

Human trajectory planning: Extrapolation [CDE13]

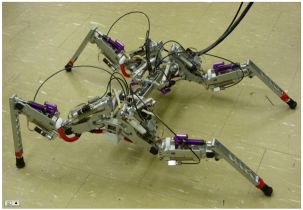
Shared control of quadruped robot: Human controls front legs

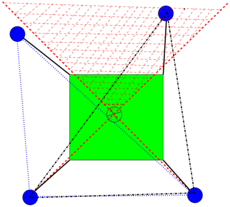
Automatic positioning of rear legs to achieve

- Gait stability during rear leg change
- Gait stability for the next front leg steps

Prediction of the next step allows for a large step size

Human foresight results in a smooth (straight) trajectory





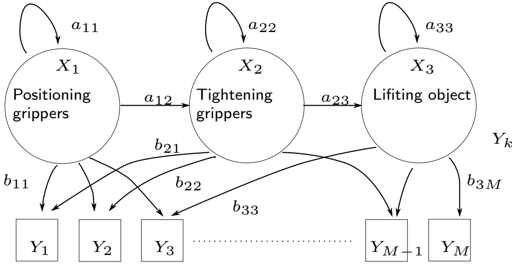
Zero-order hold extrapolation is suitable for a small prediction horizon

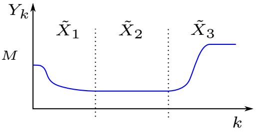
Human motion sequence learning [YXC94]

- Traded control: robot automatically executes repetitive tasks
- Learning "good" motion sequences by demonstration
- Human motion is a doubly stochastic process: Hidden Markov Models
- States (intention) are estimated from the observations (motion)

Selection of the best learned trajectory

$$\max P(\lambda_r \mid O^*) = \frac{P(O^* \mid \lambda_r)P(\lambda_r)}{P(O*)}\ ,\ \forall r = 1 \ldots R$$





Elimination of minor uncertainties, trading of control not perceivable

Neuro-physiological behaviour in pointing

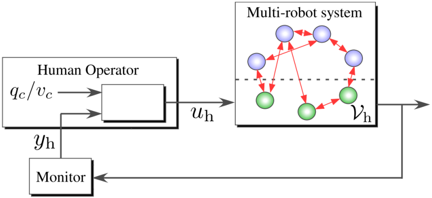
A passive human ensures stability with delayed communication and correct positioning in partially controlled robot-swarms

The *VITE* model generates human arm trajectories

$$\dot{\nu} = \gamma(-\nu + x_{\mathrm{d}} - x)$$
$$\dot{x} = G(t)\max(0, \nu)$$

Target position x_{d}, actual position x, gains γ, G

- Passive for no position overshoot $\nu \geq 0$ [VZ13]
- System identification: passive at low frequencies $f < 1$[rad/s] [HCF15]

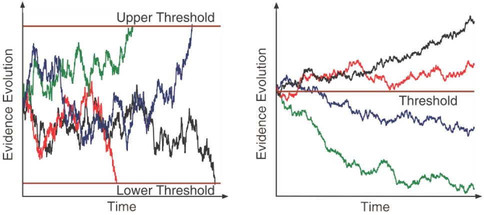


Forced-choice decision making [PST+15]

- Supervision of multiple surveillance agents
- Modelling of human decision making for incident identification and estimation of the evaluation time
- Choice between two alternatives by accumulation of evidence x

$$dx(t) = \mu dt + \sigma dW(t),$$

with the accumulation rate μ, the diffusion rate σ and the Wiener process $W(t)$



Pre-selection and scheduling of tasks reduces human resource allocation

Conclusion

Human modelling in teleoperation can

- ensure stability with a human-in-the-loop
- achieve a more realistic display of the environment
- speed-up motion by prediction of human commands
- improve manipulation skill
- support decision making

Will intelligent control systems "teleoperate" humans?

- Irrigation canal: Human as a mobile sensor and actuator [VSMD15]
- Predictive maintenance in smart factories

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