Research Notes

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Comparison between Miller et al. problem formulation and an intent recognition problem.

Components of formulation	Miller et. al, Wilson et al.	Intent Recognition Formulation
1. What is being estimated?	$\boldsymbol{\alpha} \in \mathbb{R}^2$, the 2-D position of an object in a workspace.	$g \in \mathcal{G}$, the user's intended goal. The goal is hidden/latent (not revealed directly) and therefore needs to be inferred from observing 'user input'.
2. Sensor used	An electrosense sensor which generates voltages in the presence of objects. The controllable parameters of the sensor is the 1D position $x(t)$. The paper assumes kinematic model (single integrator) for the $x(t)$	The "sensor" can be thought of as the "confidence" measurement.
3. Measurement model	The paper presents a measurement model for the voltage as $$z = \boldsymbol{\Upsilon}(x, \boldsymbol{\alpha}) + \delta$$ where δ is Gaussian noise and $\boldsymbol{\Upsilon}$ is a deterministic relation between the sensor position, object position and voltage (z) recorded and depends on the electric field, conductance et cetera.	What would be an equivalent "noisy sensor model" for intent inference? A possible way would be to consider the confidences conditioned on the mode as the sensor. $$c = \Gamma(m, g) + \delta$$ This is not equivalent to an electrosense model due to various reasons. First of all, m and g are discrete variables.

	Under Gaussian noise assumptions $\delta \sim \mathcal{N}(0, \sigma^2)$, the measurement model $p(z_k(t_j)\|\boldsymbol{\alpha}, x_k(t_j))$ for the k^{th} iteration and timestamp t_j is a Gaussian distribution with mean $\boldsymbol{\Upsilon}(x_k(t_j), \boldsymbol{\alpha})$ and variance σ. (This is similar to the stuff in Probabilistic Robotics book). It also notes that the model has to **differentiable**.	Second of all, m and g do not belong to the same space like x and $\boldsymbol{\alpha}$. This might violate the differentiability requirements of the sensor model. It might be that there is a better measurement model that can be used which is not tied to confidences et cetera. But it is not apparent to me right now.
4. Fisher Information (FI)/Expected Information Matrix (EIM)/Expected Information Density (EID)	With Gaussian noise model, the Fisher Information is given by $$\mathcal{I}_{i,j}(x, \boldsymbol{\alpha}) = \frac{1}{\sigma^2} \frac{\partial^2 \boldsymbol{\Upsilon}(x, \boldsymbol{\alpha})}{\partial \alpha_i \partial \alpha_j}$$ The EIM is simply the expectation of FI with respect to the entire parameter space, 2D in this case, since $\boldsymbol{\alpha}$ is 2D. The EID is the determinant of EIM. (D-optimality). Wilson et al. uses E-optimality and chooses to focus on the minimum eigenvalue of EIM. The EID is the determinant of EIM. (D-optimality).	Fisher information definition requires differentiability of the "measurement model" wrt the "unknown parameter". Since the unknown parameter in the intent inference is the discrete goal, I am not entirely sure how this will work out. I might be thinking along the wrong lines when I am trying to fit the confidence based formulation into a measurement model.
5. Ergodic optimal Control	Once EID is defined, it is used as the objective function in an optimal control problem, the solution of which will generate a $x(t)$ such as that the Fisher Information is maximized along the trajectory thereby resulting in better estimate of the "unknown parameter".	Selecting the "best" mode for information maximization can be framed as an optimal control problem, where the action space might be defined as a discrete, finite set $\mathcal{A} = \{pickM_1, pickM_2, \ldots, pickM_N\}$.