Condensation Tracking

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CONDENSATION TRACKING

Conditional **Den**sity Propog**ation**

AKA Particle Filtering

- Keeps multiple hypotheses
- Updates using new data
- Selects hypotheses probabilistically
- Copes with: very noisy data & process state changes
- Tunable computation load

CONDENSATION TRACKING: THEORY

- Maintains set of multiple hypotheses (eg. state vectors, including different models) with estimated probabilities
- Probabilistically generates new hypotheses from the set
- Update hypotheses with observed data (Kalman filter)
- Update hypothesis probabilities

CONDENSATION TRACKING THEORY

Given set of N hypotheses at time $t-1$
$\mathcal{H}_{t-1} = \{\vec{x}_{1,t-1}, \vec{x}_{2,t-1}, \ldots \vec{x}_{N,t-1}\}$ with associated probabilities $\{p(\vec{x}_{1,t-1}), p(\vec{x}_{2,t-1}), \ldots p(\vec{x}_{N,t-1})\}$

Repeat N times to generate $\mathcal{H}_t$:

1. Randomly select a hypothesis $\vec{x}_{k,t-1}$ from $\mathcal{H}_{t-1}$ with probability $p(\vec{x}_{k,t-1})$
2. Generate a new state vector $\vec{s}_k$ from a distribution centered at $\vec{x}_{k,t-1}$
3. Get new state vector using observation $\vec{z}_t$, dynamic model $\vec{x}_{k,t} = f(\vec{s}_k, \vec{z}_t)$ and Kalman filter

4. Evaluate probability $p(\vec{z}_t \mid \vec{x}_{k,t})$ of observed data $\vec{z}_t$ given state $\vec{x}_{k,t}$

5. Use Bayes rule to get $p(\vec{x}_{k,t} \mid \vec{z}_t)$ (may need to normalize sum over all k to 1)

WHY DOES CONDENSATION TRACKING WORK?

- Many slightly different hypotheses: maybe get one that fits better
- Dynamic model can introduce different effects (eg. state transitions)
- Sampling by probability weeds out bad hypotheses
- Generating by probability introduces corrections

What We Have Learned

1. Method to improve estimation by keeping multiple estimates
2. Method to refresh pool of estimates