

Condensation Tracking

Robert B. Fisher
School of Informatics
University of Edinburgh

CONDENSATION TRACKING

Conditional Density Propagation 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 $t - 1$
 $\mathcal{H}_{t-1} = \{\vec{x}_{1,t-1}, \vec{x}_{2,t-1}, \dots, \vec{x}_{N,t-1}\}$ with associated probabilities $\{p(\vec{x}_{1,t-1}), p(\vec{x}_{2,t-1}), \dots, p(\vec{x}_{N,t-1})\}$

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 $p(\vec{z}_t | \vec{x}_{k,t})$ of observed data \vec{z}_t given state $\vec{x}_{k,t}$
5. Use Bayes rule to get $p(\vec{x}_{k,t} | \vec{z}_t)$ (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