Title
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Entropy-based Sensor Selection Heuristic for Localization

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Introduction: Each sensor has its own perspective and ability of observation

One sensor could be more informative than another

- **In localization/tracking scenario, each sensor observation updates the probability distribution of the target location estimation. Information about the target location is gained (or uncertainty about it is reduced) by each observation.**
- **Given a prior probability distribution of target location estimation, observation by one sensor could reduce the target location uncertainty more than that by another because sensors have different observation perspectives or sensing uncertainty.**

Select the most informative sensor to use

- **Selective use of informative sensors could reduce the number of sensors involved for a given localization/tracking task, and could reduce the system resource consumption as a result.**
- **The probability distribution of the target location estimation could be gradually but efficiently improved by selecting the most informative unused sensor repeatedly, until the required level of accuracy (or uncertainty) about the target location estimation is met.**

Problem Description: Find the most informative sensor without retrieving actual sensor data

Problem formulation

- **Given 1) a** *prior probability distribution* **of target location estimation, and 2)** *locations and sensing models* **of candidate sensors for selection,**
- **Select the sensor whose data would yield (nearly) the most reduction in uncertainty of the target location estimation.**

Constraints

- **Sensor data could be direction to target, range to target, or signal arrival time difference relative to a reference sensor**
- **Selection decision must be made without retrieving sensor data from all candidate sensors for selection**

Proposed Solution: Entropy-based sensor selection heuristic

Related factors to information gain of a sensor

- **Entropy of sensing model (sensing uncertainty)**
  - Comes from noise corruption to signal, or inaccuracy of signal modeling used by estimation algorithm of a sensor
  - Sensor with *lower sensing uncertainty* yields *more information gain*
- **Entropy of sensor's view to target location distribution**
  - Projection of prior target location distribution to sensing modality, determined by sensor location
  - Sensor with *higher view entropy* yields *more information gain*

Heuristic for suboptimal sensor selection

- **For each candidate sensor**
  - Compute H^v, entropy of view to target location distribution
  - Compute H^s, entropy of sensing model for most likely target location
- **Select sensor with max $H^v – H^s$**

Heuristic Evaluation using simulation

- **Simple Gaussian sensing models, same for all target locations, but with various standard deviations for different sensors**
- **Maximal reduction in uncertainty of target location estimation that a sensor could yield is computed as follows**
  - Optimal sensor data is simulated based on sensing model and actual target location
  - Optimal posterior target location distribution is computed by fusing optimal sensor data with prior target location distribution
  - Maximal uncertainty reduction that a sensor could yield is difference between entropy of prior target location distribution and entropy of optimal posterior target location distribution
- **Maximum uncertainty reduction that a sensor could yield is compared to H^v-H^s of the sensor**

Preliminary results

- **Maximal reduction in uncertainty of target location distribution that a sensor could yield increases as H^v-H^s of the sensor does**
- **Suboptimal sensor can be selected using H^v - H^s without retrieval of actual sensor data**
- **H^v - H^s is simpler to compute than mutual information, which is widely used as sensor selection criteria**

Case study of DOA sensors

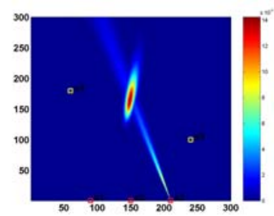

Fig 1. Prior probability distribution of target location and optimal DOA measurement of S_3. Gaussian sensing model has standard deviation of 2 degrees.

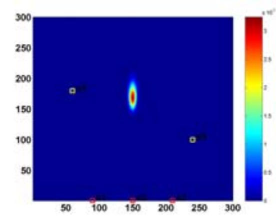

Fig 2. Optimal posterior probability distribution of target location after optimal DOA measure of S_3 is fused with prior target location distribution.

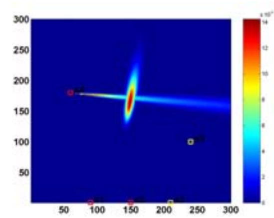

Fig 3. Prior probability distribution of target location and optimal DOA measurement of S_4. Gaussian sensing model has standard deviation of 2 degrees.

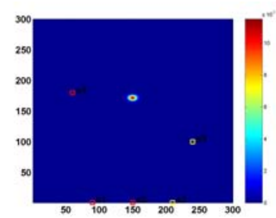

Fig 4. Optimal posterior probability distribution of target location after optimal DOA measurement of S_4 is fused with prior target location distribution.

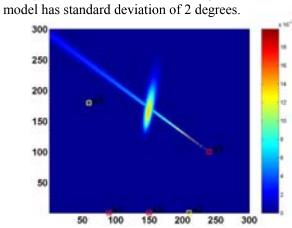

Fig 5. Prior probability distribution of target location and optimal DOA measurement of S_5. Gaussian sensing model has standard deviation of 1 degree.

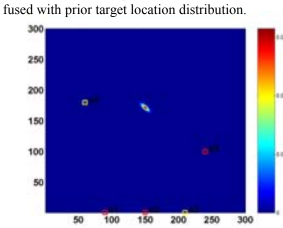

Fig 6. Optimal posterior probability distribution of target location after optimal DOA measurement of S_5 is fused with prior target location distribution.

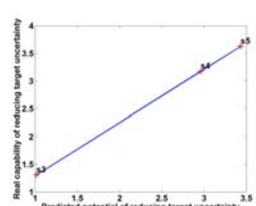

Fig 7. (Left) The vertical axis is the maximal reduction in uncertainty of target location estimation that a sensor could yield. The horizontal axis is $H^v – H^s$ of a sensor. The maximal uncertainty reduction that a sensor could yield monotonically increases as $H^v – H^s$ of the sensor increases. S_5 is selected because it has maximal $H^v – H^s$. Indeed the maximal uncertainty reduction that S_5 could yield is the greatest among those of all candidate sensors.