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Poster Abstract: Entropy-based Sensor Selection for Localization

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ABSTRACT

We propose a novel entropy-based sensor selection heuristic for localization. Given 1) a prior probability distribution of the target location, and 2) the locations and the sensing characteristics of a set of additional sensors, we would like to select an optimal additional sensor such that fusion of its measurements with existing information would yield the greatest entropy reduction of the target location distribution. The heuristic can select a sub-optimal additional sensor without retrieving the measurements of candidate sensors. The heuristic is computationally much simpler than the mutual information based sensor selection approaches for localization and tracking [1, 2]. Just as those existing approaches do, the heuristic greedily selects one sensor in each step.

Categories and Subject Descriptors

H.1.1 [MODELS AND PRINCIPLES]: Systems and Information Theory—*Value of information*

General Terms

Algorithms

Keywords

sensor selection, localization, wireless sensor networks

1. INTRODUCTION

There have been many investigations of information-theoretic approaches to sensor fusion and management. The idea of using information theory in sensor management was first

proposed in [3]. Sensor selection based on expected information gain has been introduced for decentralized sensing systems in [4]. The mutual information between the predicted sensor measurements and the target location distribution has been proposed to evaluate the expected information gain of incorporating a sensor in [1, 2]. The dependency of the localization uncertainty on the sensor locations relative to the target location has been identified during the development of localization algorithms without using information theory [6]. One example is the convex hull heuristic of localization using time-difference-of-arrival (TDOA) sensors. Targets inside the convex hull of TDOA sensors can be much more accurately located than those outside the convex hull. We propose a novel entropy-based heuristic for sensor selection based on our experiences with target localization. It is computationally more efficient than mutual information based methods proposed in [1, 2].

We use the following notations throughout this poster:

- (1) \mathbf{x} is the random variable for the target location, \mathbf{x}_t is the true target location, $\hat{\mathbf{x}}$ is the maximum likelihood estimate of the target location,
- (2) z_i is the random variable for the observation of sensor i , z_i^v is the view of sensor i about the target location,
- (3) \mathbf{x}_i denotes the deterministic location of sensor i .

2. SENSOR SELECTION HEURISTICS

The sensor selection problem discussed in this poster can be formally defined as follows. Given

- (1) the prior target location distribution: $p(\mathbf{x})$,
 - (2) the locations of additional sensors: $\mathbf{x}_i, i \in S$,
 - (3) the sensing models of additional sensors: $p(z_i|\mathbf{x}), i \in S$,
- the objective is to find the additional sensor \hat{i} whose measurements z_i minimizes the conditional entropy of the posterior target location distribution,

$$\hat{i} = \arg \min_{i \in S} H(\mathbf{x}|z_i). \quad (1)$$

Equivalently, sensor \hat{i} maximizes the expected target entropy reduction,

$$\hat{i} = \arg \max_{i \in S} (H(\mathbf{x}) - H(\mathbf{x}|z_i)). \quad (2)$$

$H(\mathbf{x}) - H(\mathbf{x}|z_i)$ is one expression of $I(\mathbf{x}; z_i)$, the mutual

information between the target location \mathbf{x} and the sensor measurements z_i . Thus, using the definition of $I(\mathbf{x}; z_i)$,

$$\hat{i} = \arg \max_{i \in S} \int p(\mathbf{x}, z_i) \log \frac{p(\mathbf{x}, z_i)}{p(\mathbf{x})p(z_i)} d\mathbf{x} dz_i \quad (3)$$

[1, 2] propose to select the sensor with maximum $I(\mathbf{x}; z_i)$. $I(\mathbf{x}; z_i)$ is computed using the predicted $p(z_i)$ based on $p(\mathbf{x})$ and $p(z_i|\mathbf{x})$ without obtaining the actual measurement of z_i . However, $I(\mathbf{x}; z_i)$ could be computationally intensive to low-end micro sensor nodes because $p(\mathbf{x}, z_i)$ could be in a space of up to four dimensions. We propose an efficient sub-optimal solution to the above problem.

During the development of wireless sensor networks for localization, we have noticed that the localization accuracy is greatly effected by two factors, namely, the entropy of the sensor's view of the target and the sensor's sensing uncertainty. From the sensor's perspective, the target is randomly distributed in the measurement space. For example, to a direction-of-arrival (DOA) sensor, there is only a bearing distribution for the target. The probability distribution of sensor's view of the target, $p(z_i^v)$, is the projection of the prior target location distribution $p(\mathbf{x})$ onto the sensor's observation perspective, which solely depends on the target location distribution $p(\mathbf{x})$, the sensor measurement modality (i.e. TDOA, DOA, range), and the sensor location \mathbf{x}_i . The entropy of $p(z_i^v)$ is

$$H_i^v = - \int p(z_i^v) \log p(z_i^v) dz_i^v. \quad (4)$$

The sensing uncertainty is the entropy of the sensor's sensing model $p(z_i|\mathbf{x}_i)$ at the true target location \mathbf{x}_i . For a single-modal $p(\mathbf{x})$, we can use the maximum likelihood estimate $\hat{\mathbf{x}}$ to approximate \mathbf{x}_i , and thus the sensing uncertainty is approximated as

$$H_i^s = - \int p(z_i|\hat{\mathbf{x}}) \log p(z_i|\hat{\mathbf{x}}) dz_i. \quad (5)$$

For a $p(\mathbf{x})$ with M modes $\hat{\mathbf{x}}^{(m)}$, $m = 1, \dots, M$, the sensing uncertainty is approximated as a weighted average of the sensing uncertainty for all modes,

$$H_i^s = - \sum_{m=1}^M p(\hat{\mathbf{x}}^{(m)}) \int p(z_i|\hat{\mathbf{x}}^{(m)}) \log p(z_i|\hat{\mathbf{x}}^{(m)}) dz_i. \quad (6)$$

The sensing uncertainty depends on the signal-to-noise ratio (SNR), the sensor hardware, and the sensing algorithms. We have repeatedly observed that the incorporation of the measurements of sensor i with a larger H_i^v and a smaller H_i^s will yield larger uncertainty reduction of the posterior target location distribution. Therefore, we propose to use $H_i^v - H_i^s$ as a suboptimal but efficient alternative to $I(\mathbf{x}; z_i)$ for evaluating the information utility of sensor i . The heuristic is to select sensor \hat{i} such that

$$\hat{i} = \arg \max_{i \in S} (H_i^v - H_i^s). \quad (7)$$

The entropy difference $H_i^v - H_i^s$ can be closely related to $I(\mathbf{x}; z_i)$ under several assumptions. Another expression of $I(\mathbf{x}; z_i)$ is $H(z_i) - H(z_i|\mathbf{x})$. $H(z_i)$ is the entropy of $p(z_i)$,

$$p(z_i) = \int p(z_i|\mathbf{x}) p(\mathbf{x}) d\mathbf{x}. \quad (8)$$

$p(z_i)$ becomes $p(z_i^v)$ when the sensing model $p(z_i|\mathbf{x})$ is deterministic without uncertainty. Thus H_i^v is smaller than

$H(z_i)$. However, the optimal sensor selection does not require an accurate evaluation of sensor information utility. Instead, a correct order of sensors in terms of information utility is needed. Therefore, H_i^v can reasonably replace $H(z_i)$ to sort sensors into the right order of their information utility. We have found a fast algorithm to compute $p(z_i^v)$ given $p(\mathbf{x})$ and \mathbf{x}_i . If the sensing model $p(z_i|\mathbf{x})$ is very complex, H_i^v will be much simpler to compute than $H(z_i)$. $H(z_i|\mathbf{x})$ is actually the expected sensing uncertainty averaged for all possible \mathbf{x} ,

$$H(z_i|\mathbf{x}) = \int p(\mathbf{x}) \{- \int p(z_i|\mathbf{x}) \log p(z_i|\mathbf{x}) dz_i\} d\mathbf{x}. \quad (9)$$

Therefore, H_i^s defined in (5) and (6) are reasonable approximations of $H(z_i|\mathbf{x})$. H_i^s is much simpler to compute than $H(z_i|\mathbf{x})$. Besides, H_i^s could be computed once and re-used multiple times if the sensing uncertainty does not change rapidly with time. On the other hand, $H(z_i|\mathbf{x})$ has to be re-computed each time even if the sensing uncertainty does not change with time. Therefore, the heuristic defined in (7) is much more efficient than the method using mutual information defined in (3).

3. RESULTS, CONCLUSION, AND FUTURE WORK

We have evaluated the above described sensor selection heuristic by using target localization simulations. The heuristic is much simpler to compute than mutual information. More details can be found in [5]. This poster presents the case study of sensor selection for localization using DOA sensors. We plan to implement the method on a real-time wireless sensor network testbed for localization.

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5. REFERENCES

- [1] J. Liu, J. Reich, and F. Zhao. Collaborative in-network processing for target tracking. *EURASIP JASP: Special Issues on Sensor Networks*, 2003(4):378–391, March 2003.
- [2] E. Ertin, J. Fisher, and L. Potter. Maximum mutual information principle for dynamic sensor query problems. In *IPSN*, Palo Alto, April 2003.
- [3] K. Hintz and E. McVey. A measure of the information gain attributable to cueing. *IEEE Transactions on Systems, Man, and Cybernetics*, 21(2):434–442, 1991.
- [4] J. Manyika and H. Durrant-Whyte. *Data fusion and sensor management: a decentralized information-theoretic approach*. Ellis Horwood, New York, 1994.
- [5] H. Wang, K. Yao, G. Pottie, and D. Estrin. Entropy-based sensor selection for localization. Technical Report 0011, NSF CENS, 2003.
- [6] K. Yao, R. Hudson, C. Reed, D. Chen, and F. Lorenzelli. Blind beamforming source localization on a sensor array system. In *AWAIRS project presentation at UCLA*, Los Angeles, CA, USA, December 1997.