Uncertainty Minimization in Multi-sensor Localization Systems Using Model Selection Theory

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Abstract

Belief propagation methods are the state-of-the-art with multi-sensor state localization problems. However, when localization applications have to deal with multi-modality sensors whose functionality depends on the environment of operation, we understand the need for an inference framework to identify confident and reliable sensors. Such a framework helps eliminate failed/non-functional sensors from the fusion process minimizing uncertainty while propagating belief. We derive a framework inspired from model selection theory and demonstrate results on real world multi-sensor robot state localization and multi-camera target tracking applications.

1. Introduction

Multi-modality multi-sensor systems are very common today. Some examples are the unmanned robots with global positioning systems (GPS), inertial units, stereo cameras and laser profilers to localize the robot's pose in unknown dynamic environments [1] and sensor networks deployed with seismic, visual and acoustic sensors for target localization. The idea behind using different modalities is to compliment the functionality of one sensor in situations that other sensors may fail. A typical situation could be a GPS failure in downtown areas where vision could act as a dependable back-up. Also, the idea to use several sensors exploits redundancy in the estimated state of the robot by fusing information from different modalities, increasing the confidence in localized state.

However, when each sensor has a different bound on its noise model and the accuracy and confidence of sensors is dictated by the operating environment, one of the three situations illustrated in Figure 1 can occur. The question then that arises is how to identify non-functional sensors online and with no apriori about the dynamics of the environment. How to decide if we should perform sensor fusion or sensor selection from the sensor data based on their apriori noise models?

Our goal with this paper is to provide a solution to these questions and summarize the contributions of this paper as (1) derivation of a generic inference framework inspired by model selection theory for localization applications and (2) applying the framework to decide selection versus fusion guaranteeing state estimation better if not as good as the best sensor in unpredictable environments.

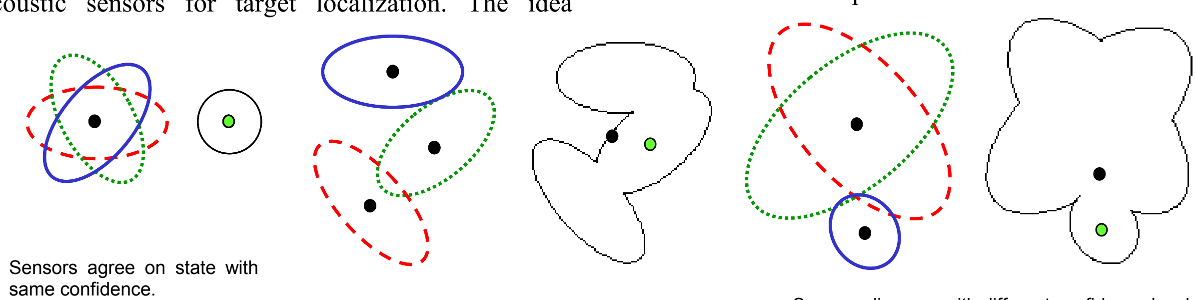

Figure 1: Belief distribution of state in a multi-sensor system operating in dynamic environments. We have shown the sensor state measurement and the uncertainty about that state as an ellipse for three sensors. Right next to each case in color we have shown the covariance-weighted fusion result as a black dot and our result as a green dot in the same probability space of interest. With these figures, we present sensor conflict as an information complexity problem.

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2. Sensor fusion and model selection

Model selection theory [2] is traditionally applied in choosing a statistical model among competing alternatives simultaneously evaluating for the goodness of fit and penalizing for the number of parameters in the fitting model. We perceive the same underlying motivation in multi-sensor belief propagation systems. As shown earlier in Figure 1, our systems generate competing distributions, and we have to infer which distribution(s) individually or after fusion minimizes the uncertainty about the estimated state parameters.

Surveying the literature on data fusion [3, 4], we are encouraged by the results of Joshi and Sanderson [5] and the derivation for geometric fusion using uncertainty ellipsoids [6] towards the application of model selection theory in this domain. Hence, we formulate our multi-sensor integration problem for localization applications from a model selection perspective and present our solution in Section 3.

3. Our approach

Our generic approach to multi-sensor systems assumes a set of sensors S_i, measuring state $\hat{x}_i = x + \varepsilon_i$ with error ε_i from an apriori bounded noise model $p_i(\hat{x} \mid x)$. The state x could be the position and orientation of a robot measured using GPS, vision and range sensors or the location of a target tracked in different cameras. We will use belief propagation methods [7] to estimate the belief distribution $\hat{B}_i$ of the state estimate based on the knowledge of $p_i(\hat{x} \mid x)$. For vision based pose recovery and tracking we compute $p_i(\hat{x} \mid x)$ during operation following [8, 9]. For range sensors we use [10] and for the GPS system we use the manufacturers' uncertainty estimate.

During the operation, the distributions $\hat{B}_i$ inherit two kinds of uncertainties, the measurement uncertainty M_i that is caused by the deterioration in the belief due to the noise characteristics of the sensor, and second the errant behavior of the sensor V_i in that environment. Our idea is to approximate M_i as the absolute measure of confidence for a sensor while V_i is the relative confidence inferred from competing sensors. We present the methods to compute M_i in Section 3.1 and V_i in Section 3.2.

3.1. Sensor confidence

Sensor beliefs $\hat{B}_i$ are competing distributions that model the uncertainty about the state vector x and our goal is choosing the sensor/distribution that has the maximum confidence about the state estimate. Having already studied the solution to this problem in model selection theory, we use a criterion popularly called ICOMP [11] to quantify measurement uncertainty.

$$M_i = -2 \log L\left(\hat{x}^t; B_i\right) + 2C_1(F^{-1}(\Sigma_i^t)) \qquad (1)$$

where F^{-1} is the inverse Fisher information matrix and,

$$C_1(F^{-1}(\Sigma_i{}^t)) = \frac{s}{2}\log\left[\frac{tr(F^{-1}(\Sigma_i{}^t))}{s}\right] - \frac{1}{2}\log\left|F^{-1}(\Sigma_i{}^t)\right| \qquad (2)$$

with s being the rank of F^{-1}, |.| refers to the determinant and tr refers to the trace of the matrix. L is the likelihood of the state parameters fitting B_i, F^{-1} of the covariance $\Sigma_i{}^t$ is computed as

$$F^{-1}(\Sigma_i{}^t) = \begin{bmatrix} \Sigma_i{}^t & 0 \\ 0 & D^+{}_p(\Sigma_i{}^t \otimes \Sigma_i{}^t)D^+{}_p{}' \end{bmatrix} \qquad (3)$$

with D^+_p being the Moore-Penrose inverse of vectorized Σ^i_t, $\otimes$ represents the Kronecker product.

Our choice of the model selection criterion was made after several empirical tests considering the flexibility to include uncertainty of the state parameters in the form of the covariance in the criterion.

3.2. Sensor reliability

We extract the information for computing sensor reliability from the same belief distributions $\hat{B}_i$ used in Section 3.1. We define the measure V_i by clustering distributions $\hat{B}_i$ based on information distances. The argument is that, if all sensors agree about the state vector, the fusion of sensory data results in an ellipsoid with minimal parameters (assuming Gaussian models), but with the discrepancy in the state and the confidence, the fused distribution requires more parameters and we now have to deal with mixture of uncertainty ellipsoids. Figure 1 illustrated this observation. Our goal is to quantify sensor reliability via the perturbation in complexity while adding new sensor data.

Suppose, we have three sensors measuring d-dimensional state x at different levels of uncertainty, we evaluate different clustering combinations of three sensors and identify the cases illustrated in Figure 1. The three cases correspond to different hypothesis on the separability of mean and covariance summarized in Table 1. The difference in the number of parameters in the fused combination of a sensor cluster is penalized while appreciating the confidence gained because of the sensor agreement using Equation 4.

$$V_i = -2\log L\left(\hat{x}^t; C\right) + 2C_1(F^{-1}(\Theta)) \qquad (4)$$

where F^{-1} is the inverse Fisher information matrix of the parameter vector Θ, for the cluster combination. The computation of the Fisher information matrix will include the parameter complexity variation while evaluating different hypothesis as shown in [14].

Table 1: Sensor clustering and parameter complexity

Sensor clusters (C)	*Parameter agreement* (Θ)	*Parameter complexity*
[(1,2,3)]	$\Theta=\left[\underbrace{\mu,\mu,\mu,......,\mu}_{N\ times},\underbrace{\Sigma,\Sigma,\Sigma,......\Sigma}_{N\ times}\right]$	$d+\frac{d(d+1)}{2}$
[(1)(2)(3)]	$\Theta=\left[\mu_1,\mu_2,\mu_3,......,\mu_N,\underbrace{\Sigma,\Sigma,\Sigma,......\Sigma}_{N\ times}\right]$	$Nd+\frac{d(d+1)}{2}$
[(1)(2)(3)]	$\Theta=[\mu_1,\mu_2.....,\mu_N,\Sigma_1,\Sigma_2,....\Sigma_N]$	$Nd+\frac{Nd(d+1)}{2}$
[(1)(2,3)] [(1,2)(3)] [(1,3)(2)]	$\Theta=\left[\underbrace{\overbrace{(\underbrace{\mu,\mu...\mu}_{\kappa\ times}),(\mu_g,\mu_g)....\mu_N}^{k\ groups}}_{N\ sensors},\Sigma_1,\Sigma_2,\Sigma_3,....\Sigma_N\right]$	$kd+\frac{kd(d+1)}{2}$

We evaluate the first three cases listed in Table 1, to avoid the combinatorial evaluations in the nested form in the fourth case. The minimum value after evaluating the three cases is assigned as V_i to all the sensors. If *min* (V_i) indicates sensor discrepancy as in Case 2 or 3, we evaluate the nested forms to identify the k reliable sensors. The value of V_i for optimal C by evaluating the subset of clusters will be less or equal to the initial three case hypothesis evaluated. We assign the k reliable sensors the lower information score value as their reliability score.

All sensors having the same reliability score implies that the sensors either all agreed or all disagreed. The magnitude of the scores however will measure the confidence gain because of the clustering leading us to an interesting criterion in Section 3.3.

3.3. Fusion vs. selection dilemma

In this paper, we have provided developments by replacing the Akaike information criterion used in our previous implementation in [12] by ICOMP. This newer derivation normalizes M_i and V_i, helping us decide on the dilemma between fusion and selection. Following the rules in building fusers that perform better than the best sensor [13], we are able to derive the following condition.

Condition: If C^* represents the optimal cluster with maximal k reliable sensors identified in Section 3.2, and V_i and M_i the respective reliability and confidence scores of the sensors, find sensor S^* with *min* ($V_i + M_i$). If $M(S^*) < V(S^*)$ decide sensor selection and choose S^*, else decide to fuse 'k' reliable sensors in cluster C^* of which S^* is a member for belief propagation.

We demonstrate how our approach answers the selection versus fusion dilemma avoiding "catastrophic fusion" [4] with a simple example in Figure 2. Figure 2(a) is the case when sensors all agree on the state with different levels of confidence. We use this example to show how our method can eliminate less confident sensors. Our framework selects Sensor 1, keeping sensors with confidence less than 2Σ away from the belief propagation stage. In Figure 2(b), we show 5 sensors, out of which 2 clusters agree on the state, but with the same level of confidence from all the sensors. Our framework is able to identify this situation in the reliability score and decides to fuse sensors 3, 4 and 5.

4. Experiments and results

In this section, we present experimental results in two different localization applications: (1) robot localization using hardware, video and range sensors and (2) target localization using multiple cameras evaluated as successful handoff.

4.1. Robot localization

The experiment was to localize using GPS/INS hardware, vision and range based pose recovery methods. The Kalman filter was used for the belief propagation and fusion. In Figure 3, we compare the

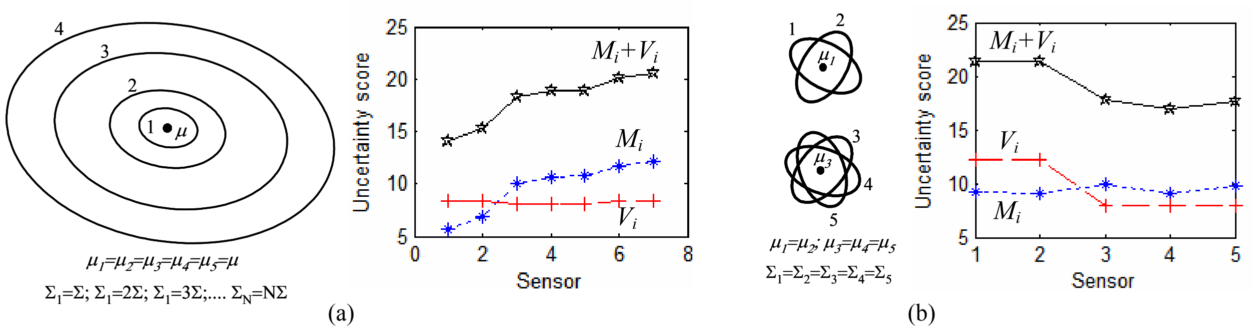

Figure 2: Our formulation of M_i and V_i is able to identify the separability in the mean and the co-variance. (a) V_i being nearly constant identifies sensor agreement on state μ while the M_i monitors the confidence levels. Our framework decides to use only Sensor 1 in the belief propagation. (b) V_i identifies two clusters of sensors agreeing on the same state, while M_i indicates that sensors are operating at the same confidence. We decide to fuse sensors 3, 4 and 5 as $V(S^*) < M(S^*)$ for S^* = Sensor 4.

result of localization in position based on the error in the drift using the Kalman filter-based fusion method with and without and our framework. Over a 300 m path, we observe the reduction in drift by 3m. We note that the deterioration begins when one of the sensors failed in that environment. Our approach was able to eliminate that sensor from the belief propagation.

4.2. Camera target tracking

We monitored the uncertainty about a target's floor plan occupancy in an indoor environment using a multi-camera setup. The target was tracked using the probabilistic method similar to [9] that provides us the belief distribution about the target's position. Our goal was to demonstrate the proposed framework to enable consistent hand-off between cameras while persistently tracking a person. We plot the uncertainty in 80 frames before the complete handoff in Figure 4 and show that our method was able to guide the smooth transition maintaining lower uncertainty levels on the target compared to a hard-coded camera switch.

5. Summary

We have proposed a framework for uncertainty minimization in multi-sensor state-space/localization systems while using data fusion algorithms and belief propagation. By perceiving the fusion process as a model selection problem, we have formulated comparable information-theoretic metrics for sensor confidence and sensor reliability adding to the literature that thus far appears to treat them as independent entities.

Acknowledgements

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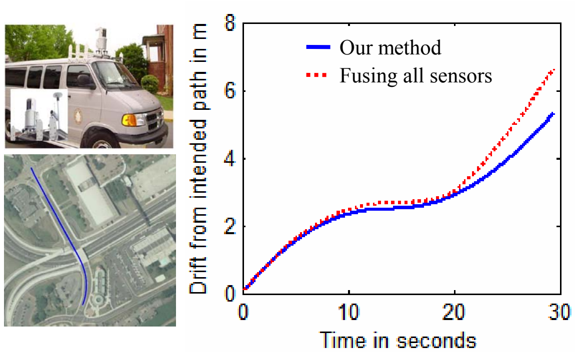

Figure 3: We have shown our system along with the intended path as left insets. The graph plots the drift produced from the intended path if sensor information is fused with and without our framework.

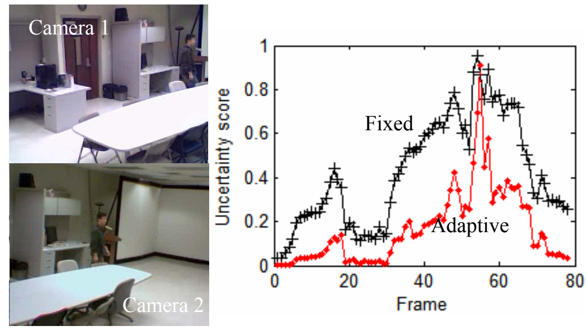

Figure 4: The uncertainty score during the belief propagation of a target monitored in two cameras using the hard handoff approach compared with our adaptive framework.

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