

Sensor Selection Using Information Complexity for Multi-sensor Mobile Robot Localization

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Abstract—Our sensor selection algorithm targets the problem of global self-localization of multi-sensor mobile robots. The algorithm builds on the probabilistic reasoning using Bayes filters to estimate *sensor measurement uncertainty* and *sensor validity* in robot localization. For quantifying *measurement uncertainty* we score the Bayesian belief probability density using a model selection criterion, and for *sensor validity*, we evaluate belief on pose estimates from different sensors as a multi-sample clustering problem. The minimization of the combined uncertainty (*measurement uncertainty score* + *sensor validity score*) allows us to intelligently choose a subset of sensors that contribute to accurate localization of the mobile robot. We demonstrate the capability of our sensor selection algorithm in automatically switching pose recovery methods and ignoring non-functional sensors for localization on real-world mobile platforms equipped with laser scanners, vision cameras, and other hardware instrumentation for pose estimation.

I. INTRODUCTION

THERE are two types of sensor problems associated with position and orientation (pose) uncertainty in localizing a mobile robot: (i) the sensor noise and (ii) the validity of sensor measurements [1]. In the robotics literature, the uncertainty due to the sensor noise is well understood and is efficiently handled by using one of several Bayes filters summarized in [2] by representing uncertainty using probability density functions under bounded noise models. However, the second problem of sensor validity attributed to the dynamic nature of environments poses a greater challenge because uncertainty due to sensor validity extends beyond the boundaries of modeling noise. The solution to robot localization by modeling and minimizing both types of uncertainty in dynamic environments through the fusion of multi-sensor information has turned out to be a recent trend [3]. We observe such methods of sensor integration in various applications spanning autonomous ground vehicles operating in deserts [4] to small robots navigating indoor environments [5], carrying a suite of sensors for global localization and navigation in a dynamic environment.

In this paper, we target uncertainty minimization for robot self-localization by presenting a framework that can simultaneously quantify the uncertainty due to noise associated with each sensor measurement and also infer

evidence about sensor validity using belief estimates from multiple sensors. We explain the use of a measure of information complexity in constructing a score for both the sensor validity and the measurement uncertainty from the Bayes filter belief towards choosing a reliable subset of the multi-sensor data for robust self-localization. Towards that end, this paper describes the capability of a sensor selection algorithm with the following contributions to the robot localization literature:

- An information theoretic framework to simultaneously score *sensor measurement uncertainty* and *sensor validation uncertainty* that have thus far been considered as distinct and independent problems in minimizing total uncertainty.
- A new algorithm that can automatically eliminate failed sensors and recover from bad pose recovery due to data association problems in a dynamic environment, also guiding the switch to the next available good sensor.
- A method to minimize instantaneous localization error leading to lesser global error accumulation while considering motion with several degrees of freedom.

In the following section of the paper, we establish the theoretical basis of our sensor selection algorithm, deriving inspiration from related work in mobile robotics and statistical inference using information theory. In Section 3, we use a robot simulation environment to demonstrate our algorithm and then present results on real world systems that use our sensor selection method. We also mention the different pose recovery algorithms implemented on our mobile robots for feeding the sensor selection algorithm with pose estimates. After the discussion of results on real systems with laser scanners, vision cameras and other hardware instrumentation, we conclude with a brief summary in Section 4.

II. SENSOR SELECTION ALGORITHM

Let us consider the general case of a mobile robot with N sensors ($N > 2$) and let S^i refer to the i^{th} sensor or pose recovery instrument providing position and orientation estimates P^i_t of d -state dimensions at time t . By feeding in a priori NM^i noise model associated with the pose measurement using sensor S^i to a Bayes filter [2] (Kalman filters if NM^i can be assumed to be normal), we are able to associate a belief distribution, and hence a likely pose μ^i_t and the uncertainty Σ^i_t about that pose for each sensor S^i . Each one of these estimates μ^i_t contribute to the most likely pose

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of the robot with the Σ_t^i quantifying the doubt in that position. If not using the Kalman filter, both μ_t^i and Σ_t^i can be computed as the first two moments of the belief probability density function. We start with these belief estimates as input to our algorithm as shown in Fig. 1 and then estimate the measurement uncertainty and sensor validity from these estimates using an information theoretic formulation.

Quantifying sensor measurement uncertainty: Based on the belief estimates alone, if we were to choose the best sensor in the system, we would pick the sensor that is indicative of maximum likelihood with minimum uncertainty. This can be mathematically expressed as the minimizer of the criterion (1) that simultaneously considers the likelihood and also penalizes the uncertainty associated with the likelihood. This model selection criterion in the statistics literature [6] is popularly known as information complexity (ICOMP) and derives from the Kullback-Liebler (KL) distance between estimates and unknown underlying probability density. Quantifying the uncertainty in self-localization from competing belief distributions from different sensors is an analogous selection problem that the ICOMP can be reformulated and applied. We denote the score on the belief density functions of each sensor as the sensor measurement uncertainty M_i .

$$M_i = \text{Lack of fit} + \text{Profusion of uncertainty} \\ = -2 \log(\text{Likelihood of } \mu_t^i) + 2 C_1(F^{-1}(\Sigma_t^i)), \quad (1)$$

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

$$C_1(F^{-1}(\Sigma_t^i)) = \frac{s}{2} \log \left[\frac{\text{tr}(F^{-1}(\Sigma_t^i))}{s} \right] - \frac{1}{2} \log |F^{-1}(\Sigma_t^i)|, \quad (2)$$

with s being the rank of F^{-1} , $|\cdot|$ refers to the determinant and tr refers to the trace of the matrix. F^{-1} is computed as

$$F^{-1}(\Sigma_t^i) = \begin{bmatrix} \Sigma_t^i & 0 \\ 0 & D_p^+(\Sigma_t^i \otimes \Sigma_t^i) D_p^+ \end{bmatrix}, \quad (3)$$

with D_p^+ being the Moore-Penrose inverse of vectorized Σ_t^i , \otimes represents the Kronecker product. The C_1 measure for penalizing uncertainty is obtained by maximizing mutual information in d -dimensions [11, 12].

Though these equations appear complex, a distributional assumption, such as a Gaussian, reduces (1) to a much simpler finite sampling distributional form as shown in (4). We do note that (1) does not make assumptions on the functional form of the density and can be used on belief estimates from extended Kalman or even particle filters.

$$M_i = 2 \left[\frac{f_i d}{2} \log(2\pi) + \frac{f_i}{2} \ln |\Sigma_t^i| + \frac{1}{2} \text{tr}(\Sigma_t^{i-1}) \left(\sum_{j=1}^{f_i} (y_j - \mu_t^i)(y_j - \mu_t^i)^T \right) \right] \\ + 2 \left[\frac{d}{2} \ln \left(\frac{\text{tr}(\Sigma_t^i)}{d} \right) - \frac{1}{2} \ln |\Sigma_t^i| \right] \quad (4)$$

where d is the dimensionality of the state vector and y_j are the f_i measurements of sensor S_i used for estimating belief.

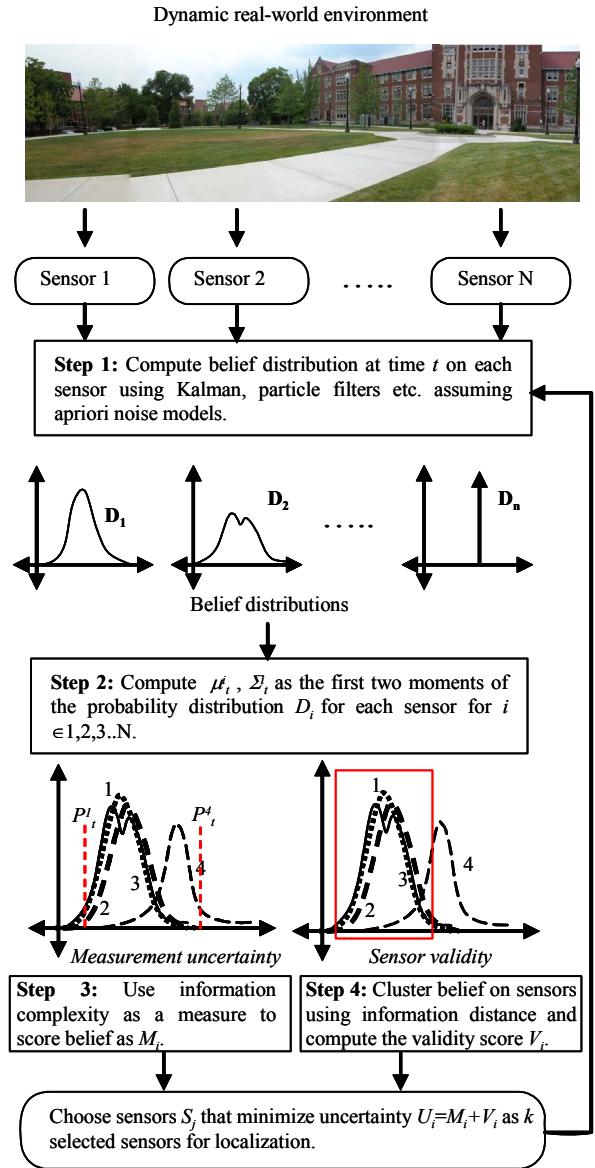


Fig. 1. Flow diagram to illustrate our sensor selection algorithm in the $d=1$ case.

Quantifying sensor validity: Our idea to approximate sensor validity or reliability is based on the argument that the best that we can learn from multi-sensor measurements is by grouping sensors that tell us the same information. The more sensors that provide the same information, the higher the sensor validity we attach to each sensor and its measurements. Though the logical argument sounds very easy, converting it into a mathematical form involves more work. We need a method that can parsimoniously group these distributions associated with the robots pose from different sensors to quantify a measure that indicates optimal clustering in the probability space. For the N -sensor system, this unwinds to a computationally prohibitive hypothesis testing problem and requires a fuzzy estimator as demonstrated in [7]. Our approach is inspired by methods described in the survey in [8] and information theoretic

methods in [9, 10] to formulate sensor validity in a novel information theoretic sense.

For the N -sensor system, we consider combinatorial sensor clusters and evaluate which cluster among the grouping of sensors is parsimonious and believable. We treat the belief distributions D_1, D_2, \dots, D_n in Fig. 1, as random variables and use the information theoretic approach [13] to score each of the hypotheses listed below and choose the one that is minimal in an entropic sense. Following Bozdogan [13] in using Akaike's information criterion (AIC) as shown in (5) to perform the clustering of distributions, we begin by first associating the beliefs with one of the three hypotheses.

1. Case of ' κ sensor' cluster reliability: Not all μ_i^j are equal and not all Σ_i^j are equal with $m = \kappa d + \kappa d(d+1)/2$ parameters to consider.
2. Case of confusion: μ_i^j 's are unequal and Σ_i^j 's are equal with $m = N d + d(d+1)/2$.
3. Case of maximal validity: μ_i^j 's are equal and Σ_i^j 's are equal with $m = d + d(d+1)/2$.

This initial hypothesis verification can avoid the 2^N evaluations when all sensors are accurate and operational. By identifying the sensors not converging on the robot's pose, we immediately infer the possibility that there might be pose recovery problems or non-functional sensors on the robot.

The three competing models of the initial hypothesis is the three cases with the number of parameters m to use in (5). The computation of L for each of these cases involves considering the κ (varying from 1 to N) clusters as one distribution and how this assumption reduces the overall complexity compared to considering all the distributions D_1, D_2, \dots, D_n as individual cases without too much information leakage. We direct the reader to a detailed discussion in [13] for further implementation details on evaluating the likelihood function L .

$$\begin{aligned} AIC(\mu_i^j, \Sigma_i^j, \kappa) &= -(\text{Likelihood of sensor cluster}) + \\ &\text{Parsimony in parameters for clustered model} \\ &= -2 \log L + 2m \end{aligned} \quad (5)$$

We illustrate a simple example with uncertainty ellipses in Fig. 2 for a three sensor system to understand the three cases better. We see that Case 3 refers to the possibility when all sensors are essentially indicating the same localization result. Case 2 points to ambiguity in the localization as sensors are indicating different robot pose with the same belief. In Case 1, when a particular group of sensors are considered, we notice that a particular pose estimate appears more likely. Our interest is to find these group of sensors that are maximising a particular likelihood and use the AIC values that capture this essence as the sensor validity score. In our implementation, as soon as we infer one of the cases to minimize AIC, we assign all the sensors the AIC value of case hypothesis to be the sensor validity score. Then, for

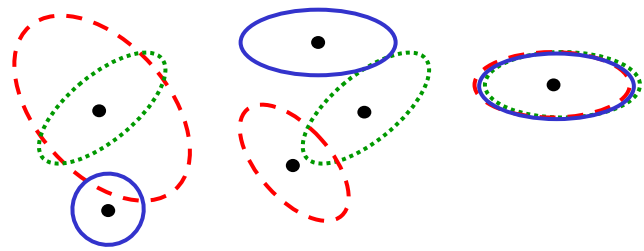


Fig. 2: Uncertainty ellipses to show how sensor clustering can help build sensor validity confidence in localization.

Case 1 and Case 2 alone, we perform the sensor clustering and evaluate all cluster combinations. Table 1 is an example of competing sensor clusters in a 3-sensor system. The minimizer of the AIC points us to the optimal clustering of κ valid sensors. We assign this minimized AIC value for only the sensors within the maximal sensor cluster as their corresponding sensor validity scores V_i . Since AIC is an asymptotic estimate of the KL distance between competing distributions, our sensor clustering is based on information distances between belief distributions.

In other words, sensor validity score is a measure of significant information gain in considering competing sensor data to localize a robot. For example, if s_1 samples of Sensor 1 and s_2 samples from Sensor 2 are considered for construction of D_1 and D_2 , AIC tries to measure the information distance in probability space by considering $s_1 + s_2$ samples to construct another belief distribution D_{12} for localization. The information distance between D_{12} and D_1 or D_2 that we measure using AIC quantifies the significant new information gained after fusing data from both the sensors. Extending this simple example to an N -sensor system, we are able to understand that the minimizer of the AIC after evaluating all the combinatorial clusters of sensors indicates the maximal group of sensors that essentially converge on the state vector. We use this information distance as the sensor validity score to differentiate sensors that agree and the sensors that do not.

TABLE I
COMPETING SENSOR CLUSTERS IN A 3-SENSOR SYSTEM

| κ | Sensor clusters ($N=3$) |
|--------------------------|--|
| Case 1 and 2: $\kappa=1$ | [(1) (2) (3)] |
| Case 1 and 2: $\kappa=2$ | [(1) (2, 3)] [(1, 2) (3)] [(1, 3) (2)] |
| Case 3: $\kappa=3$ | [(1, 2, 3)] |

Both the ICOMP and the AIC values being normalized information measures of complexity in our implementation, we use the sum of the two measures of sensor measurement uncertainty M_i and sensor validity V_i and hence choose the sensors with minimum total uncertainty. We implement a simple weighted scheme [14] based on the total uncertainty values U_j for fusing localization information only from the k selected sensors. In the following section, we demonstrate this implementation of the proposed algorithm on our robot simulator and then discuss results on real systems.

III. EXPERIMENTAL RESULTS

To demonstrate the capability of the algorithm, we start with results from a simulation environment by considering a three sensor system with sensors H , R and V and 2-dimensional state vector in different synthetically generated cases as shown in Fig. 3. The noise models for the simulator being Gaussian, our choice of the noise-variance minimization algorithm was a Kalman filter [15] that takes in Gaussian prior and outputs Gaussian posterior beliefs.

Figure 3 shows three different cases that help understand and appreciate our algorithm. We have plotted the Kalman filter outputs of different sensor measurements. The ellipses seen in these figures are based on the uncertainty estimate from the Kalman filters. In some cases, these ellipses are not visible because of the high degree of certainty they encapsulate. We interpret the output of our sensor selection algorithm in two forms: (i) which sensor to believe (bottom inset) and (ii) the number of sensors contributing to that belief (top inset).

Figure 3a shows the case where the robot tries to stay on a sigmoid path with sensor H being more accurate at the first few samples (the red ellipses are not visible because of the high belief), while the other sensors converge on the localization information over time. Our sensor selection algorithm correctly picks up sensor H , switches to the next available sensor R , and also is able to infer that all three sensors are converging after the first few samples. In Fig. 3b, sensors H , R and V are essentially indicating us to the same localization information that our algorithm is able to infer. The third example, in Figure 3c, is the closest to reality where some sensors can fail suddenly forcing the need to switch to a better sensor. We observe the likely pose estimate from the sensor H consistent and believable to begin with but deteriorating over time. Our sensor selection result automatically detects the deteriorating belief on sensor H , guiding the switch to sensor V as a better option.

We compare sensor selection with sensor fusion for localizing the mobile robot in Fig. 4a. We show the sum-squared error of the pose vector from the intended path in each of the three examples considered in Fig. 3. The time required for both these approaches is plotted in Fig. 4b. We observe that the sensor selection performs better by minimizing localization error at each instant. However, the accuracy appears to come at the expense of a few extra computations compared to covariance weighted-fusion [14]. The extra computations that consume a few milliseconds more do not seem to impose a problem for real-time operation. Another interesting aspect to note from the error analysis graph is that sensor selection can only perform as well as the best sensor. This means that our method deals with possibly invalid data not compromising the best case performance, though it does promise improvement as expected out of fusion. On Example 2, when all sensors were essentially telling the same information, we see that sensor selection is not able to perform better than the covariance-weighted fusion while on cases with varying beliefs over time, sensor selection leads to more accurate localization.

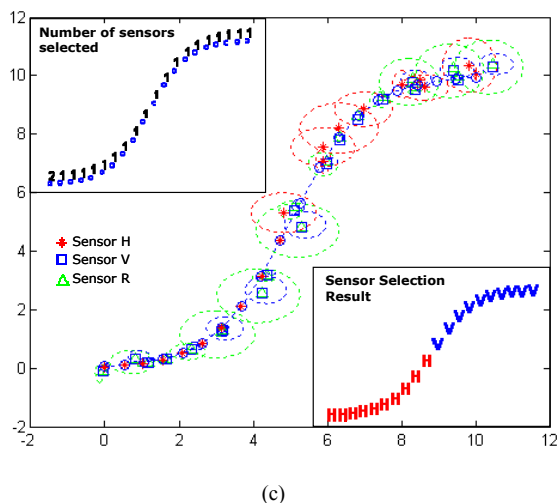
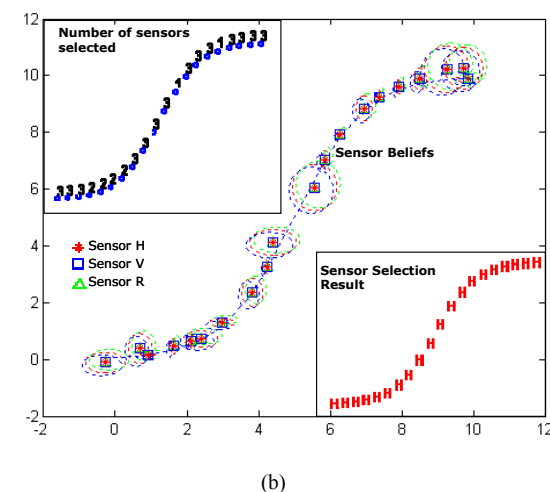
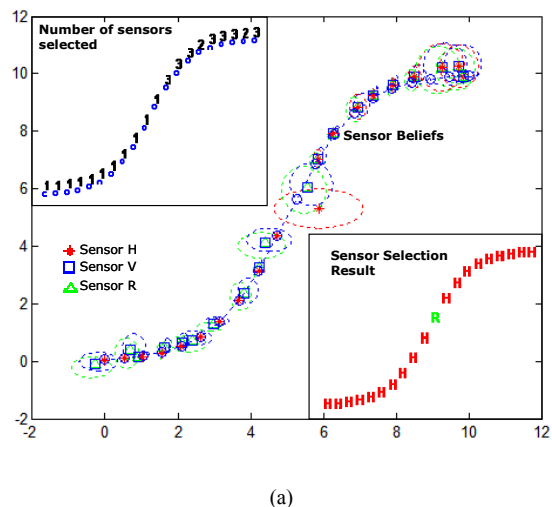


Fig. 3. Localization in a simulation environment. (a) Example 1: Detecting intermediate failure. (b) Example 2: Self-localization when sensors are converging on a believable pose. (c) Example 3: Guiding the sensor switch when the belief in particular sensor pose deteriorates.

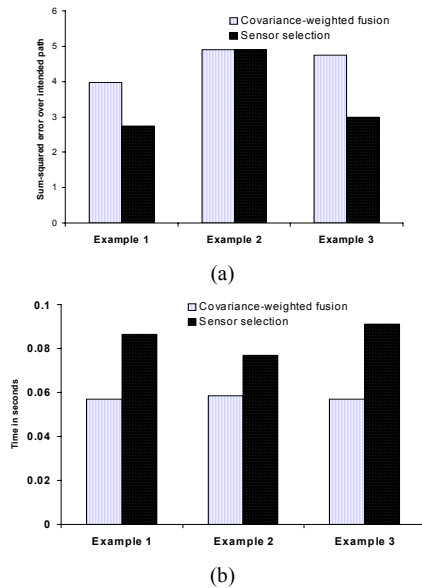


Fig. 4. Error and timing analysis for sensor selection for the three examples presented in Fig. 3. (a) Plot of sum-squared error over the entire intended path localized using the covariance weighted fusion method and our sensor selection method. (b) Timing analysis to compare fusion with selection. Execution time for selection in Example 2 is lesser than the other examples because, most of the time, Case 3 hypothesis was detected avoiding cluster evaluations. The timing analysis was performed on a Pentium IV machine with 1 GB of memory on 20 pose estimates from 3 sensors.

Moving away from simulations, the first real-world application that we discuss is on a mobile platform with laser scanners, video cameras, global positioning systems (GPS) and inertial equipment mounted on a van as shown in Fig. 5a. The noise models for these systems were built through extensive apriori characterization of each of the sensors. With the van, though not completely autonomous in its operation in urban environments, we use the position information from the GPS, orientation from the inertial measurement unit, recover pose from the 3D profile data [16] and video data [17], and use these datasets to automatically detect a GPS outage which is common in urban environments and switch to the next reliable sensor. We show our mobile scanning system along with the intended path overlaid on the aerial map of the city. The test course in Fig. 5 is approximately 400 meters long. Figure 5c shows the result of pose recovery from several sensors indicating areas that have error in the order of a few centimeters that later builds to the order of a few meters. Figure 5d is the result of our sensor selection algorithm indicating reliable pose recovery methods along the total path. We are able to see the areas in which pose from video was not a reliable method compared to pose recovery using hardware and range sensors.

The next set of experiments we conduct uses a small mobile robot navigating a corridor. The robot in the corridor shown in Fig. 6 has five cameras. The idea is that one camera looks ahead in the path and avoids obstacles, while the other four look at different fields of view for

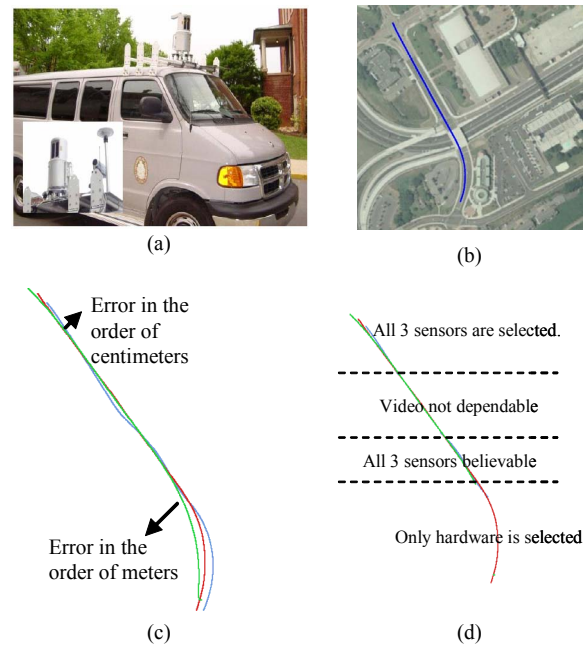


Fig. 5. Localization in urban environments. (a) Our mobile platform with laser range scanners, video cameras, GPS and inertial measurement units. (b) Intended path (blue curve) in the city. (c) Pose recovery from hardware instrumentation (red curve), range scanner (green curve) and the video camera (blue curve). (d) Sensor selection result.

localization. Our test environment has doors, windows, and objects like chairs, book shelves etc. in the path on either side. We use multiple cameras to accommodate for lack of features on painted walls and also for a larger coverage in the corridor looking for trackable features. A pose from video algorithm similar to [17] provides the robot's pose for localization using apriori calibration information. The uncertainty in pose is determined by estimating the confusion in converging to optimal relative pose as discussed in [18]. Our sensor selection algorithm operated on these values in successfully localizing the robot through the entire intended path that we show in Fig. 6b.

We use this environment as a test bed for localization where we know that there may not be enough trackable features for all sensors over the entire intended path. We expect that when one sensor is tracking features on doors and windows, the others might be struggling to even locate interesting features on plain walls. We plot the number of oriented matches between successive frames in pose recovery using the images from these cameras in Fig. 6c. We are able to see that our sensor selection algorithm automatically switched to the available next best sensor, when the pose recovery was not within acceptable levels minimizing the overall uncertainty in position. This emphasizes the capability of our method in automatically switching to a good sensor while navigating in a dynamic environment where pose recovery methods can fail due to data association problems or lack of features.

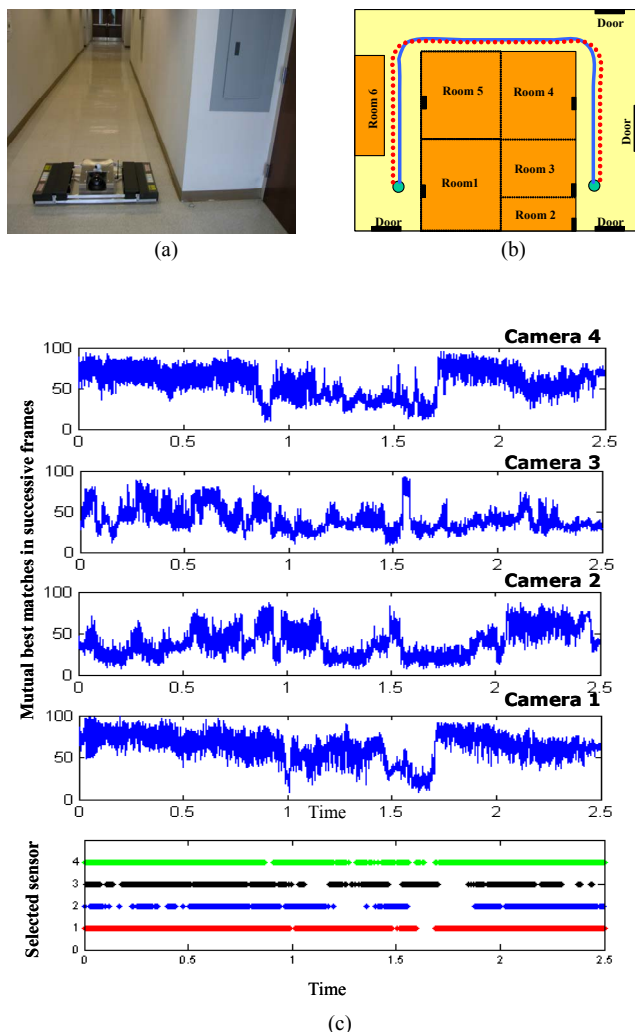


Fig. 6. Localization of a mobile robot with multiple cameras in an indoor environment. (a) Our mobile platform with five cameras (b) Intended path (blue curve) in the corridor and the localized path (red dotted curve). (c) Number of mutual matches between successive frames in the video that can be loosely related to the confidence with pose recovery along with the sensor selection result.

IV. SUMMARY

This paper presented a sensor selection algorithm based on information theoretic model selection criteria for robotic localization. Our approach to bring together measurement uncertainty and reliability using information measures for uncertainty minimization in localization is able to efficiently work on real and synthetic robot environments. Our results further encourage implementation on unmanned ground vehicles in following a well defined path where localization is necessary feedback due to the dynamic nature of the environment. An example of such a scenario is urban traffic, where an unmanned vehicle in addition to maneuvering amidst traffic should be able to switch sensors managing sudden unexpected GPS outage to stay on course towards the intended destination. Our method is particularly suited for such applications involving multi-modality sensors for navigation and localization. However, we also note that our

method can only perform as good as the best sensor in the system and not better than the best sensor as expected in an ideal case of information fusion discussed in [19].

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REFERENCES

- [1] J. J. Leonard, H. F. Durrant-Whyte, I. J. Cox, "Dynamic map building for an autonomous mobile robot", *International Journal of Robotics Research*, Vol. 11(4), pp. 286-298, 1992.
- [2] S. Thrun, W. Burgard, and D. Fox. "Probabilistic Robotics". MIT Press, Cambridge, MA, 2005.
- [3] F. Matia and A. Jimenez. "Multi-sensor fusion: An autonomous mobile robot", *Journal of Intelligent and robotic systems*, Vol. 22(2):129-142, 1998.
- [4] S. Thrun et al., "Stanley, the robot that won the DARPA Grand Challenge", *Journal of Field Robotics*, Vol. 23(9), pp. 661-692, 2006.
- [5] S. Thrun, "Learning metric-topological maps for indoor mobile robot navigation", *Artificial Intelligence*, Vol. 99(1):21-77, 1998.
- [6] K.P. Burnham and D. R. Anderson, "Model Selection and Multi-model Inference". Springer-Verlag, New York, 2002.
- [7] F. Kobayashi, F. Arai and T. Fukuda, "Sensor selection by reliability based on possibility measure", in the *Proc IEEE Intl. Conference on Robotics and Automation*, Vol. 4, pp. 2614-2619, 1999.
- [8] G. L. Rogova and V. Nimier, "Reliability in information fusion: literature survey", in the *Proc. of the 7th Intl. Conference on Information fusion*, pp. 1158-1165, 2004.
- [9] J. Denzler, C. M Brown, "Information theoretic sensor data selection for active object recognition and state estimation", *IEEE Transactions on Pattern Analysis and Machine Intelligence*, Vol. 24(2), pp.145-157, 2002.
- [10] S. Thrun, Y. Liu, D. Koller, A. Ng, Z. Ghahramani and H. Durrant-Whyte, "Simultaneous localization and mapping with sparse extended information filters", *Intl. Journal of Robotics Research*, 23, pp. 693-716, 2004.
- [11] H. Bozdogan, "Akaike's Information Criterion and Recent Developments in Information Complexity", *Journal of Mathematical Psychology*, Vol. 44, pp. 62-91, 2000.
- [12] Van Emden, "An Analysis of Complexity", *Mathematical Centre Tracts*, Vol. 35, 1971.
- [13] H. Bozdogan, "Multi-sample cluster analysis as an alternative to multiple comparison procedures", *Bulletin of Informatics and Cybernetics*, Vol. 1-2, pp. 95-129, 1986.
- [14] J. K. Hackett and M. Shah, "Multi-sensor fusion: a perspective", *Proc. of Intl. Conf. on Robotics and Automation*, 3, pp. 1324-1330, 1990.
- [15] R.E. Kalman, "A new approach to linear filtering and Prediction problems", *Transactions of the ASME-Journal of Basic Engineering*, Vol. 82, pp. 33-45, 1960.
- [16] J. L. Martínez, J. González, J. Morales, A. Mandow, A.J. García-Cerezo, "Mobile robot motion estimation by 2D scan matching with genetic and iterative closest point algorithms", *Journal of Field Robotics*, Vol.23(1), pp. 21-34, 2006.
- [17] D. Nister, O. Naroditsky, J. Bergen, "Visual odometry", in *Proc. of the Intl. Conf. on Computer Vision and Pattern Recognition*, Vol. 1, pp. 652-659, 2004.
- [18] J. Zhu, Y. Zhu and V. Ramesh, "Error-metrics for Camera Ego-motion Estimation", in the *Proc. of the Intl. Conf. on Computer Vision and Pattern Recognition Workshop*, pp. 67-75, 2005.
- [19] N. S. V. Rao, "On fusers that perform better than best sensor", *IEEE Transactions on Pattern Analysis and Machine Intelligence*, Vol. 23(8), pp. 904-909, 2001.