Evidence Grid Based Information Fusion for Semantic Classifiers in Dynamic Sensor Networks

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Abstract. We propose an anytime fusion setup of anonymous distributed information sources with spatial affiliation. For this approach we use the evidence grid mapping algorithm which allows to fuse sensor information by their inverse sensor model. Furthermore, we apply an online Mixture of Experts training such that faulty voters are detected and suppressed during runtime by a gating function.

Keywords: Evidence grid maps, sensor network, faulty sensor detection

1 Introduction

We are concentrating on a cyber-physical system as a realization of a mobile working vehicle acting on its environment. The main requirements originates from a harvesting application which comprises the exploration and mapping within a dynamic setup of sensors and vehicles. One requirement is the acquisition of exteroceptive conditions like traversability, machinability, and applicability of the crop to be processed. Another belongs to the sensory setup with which the information acquisition is done. It substantially differs from standard vehicle sensor setups like automobiles, due to their changeable operating conditions which is caused by different goods, unstructured or rough environment, or simply the demand of different sensor setups.

In particular our setup is a production system equipped with a distributed set of dynamic heterogeneous intelligent sensors (IS) which comprises but is not limited to cameras, laser range finders, and proximity sensors at position x which are able to map a measurement z to a distinctive location in space m. Every IS can be an own embedded system which is a set of a physical sensor and a processing system consisting of the driver for interfacing the raw data and a set of classifiers which converts the raw data into an evidence grid representing a common source of information (see left fig. 1). We call this information "semantic feature" due to the fact that the semantic meaning, e.g. the representation of

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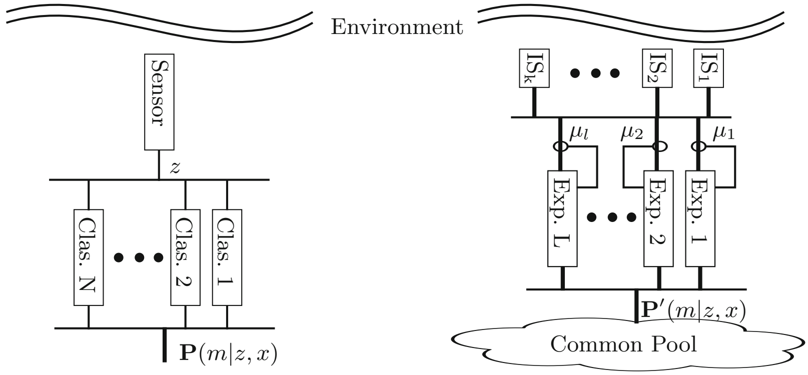

Fig. 1: Left: Intelligent sensor with multiple classifiers. Right: Local expert system.

a stock boundary, is always attached to it. Furthermore, we are not only concentrating on an information fusion system given a single static sensor setup, but a versatile one where sensors can be added or removed even during runtime.

To meet these requirements, our setup is build up as can be seen in the right of fig. 1: Different IS are distributed all over the machinery which may overlap with their detection ranges. All IS can anonymously distribute their evidence grids $\mathbf{P}(m|z,x) = (\mathrm{P}_1(m|z,x), \ldots, \mathrm{P}_N(m|z,x))^{\mathrm{T}}$ into the network where local expert systems listen to their corresponding semantic features. The local expert then fuses a single grid by Elfes [3] occupancy grid map algorithm in a normalized fashion and backpropagates the information such, that faulty classifiers are going to be suppressed using a single parameter μ. The fused information $\mathbf{P}'(m|z,x) = (\mathrm{P}_1(m|z,x), \ldots, \mathrm{P}_L(m|z,x))^{\mathrm{T}}$ is send to the common pool, from which further experts or remote machines get the experts outcome for further reasoning.

The paper is organized as follows: First, we introduce the evidence grid framework in chapter 2. Second, the enhancement of the fusion formulation by the gating network is explained in chapter 3. Finally, we evaluated our approach using a robotic simulation in a standard exploration task in 4 and give a brief summary and discussion in 5.

2 Evidence Grid Map Algorithm

In this section we will discuss how a spatial representation of the presence of a property can be learned via an evidence grid map from any sensor data using Bayesian update rules. First introduced by Moravec [8], evidence grids maps are currently the state of the art approach for enabling navigation of mobile robots in real world environments [4–6]. The environment is discretized using an evenly spaced grid, with each cell holding a probabilistic estimate of its property. For the sake of simplicity, we do the derivation for a single expert l ($m \equiv m_l$) as we assume independency between all representations. Given the positions x_{t_n} of IS n at each point in time t is known, where n is drawn from the set of sensors. Suppose $x_{1_n:t_n} = x_{1_n}, \ldots, x_{t_n}$ are the positions of any IS n at the individual steps in time and $z_{1_n:t_n} = z_{1_n}, \ldots, z_{t_n}$ are the perceptions of the environment regarding an IS. Evidence probability grids determine for each cell m of the grid the probability that this cell is occupied by a given representation. Thus, evidence probability grids seek to find the map M that maximizes $\mathrm{P}(m|x_{1_n:t_n}, z_{1_n:t_n})$ for each cell. If we apply Bayes rule using $x_{1_n:t_n}$ and $z_{1_n:t_n}$ as background knowledge, we obtain

$$\mathrm{P}(m|x_{1:t}, z_{1_n:t_n}) = \frac{\mathrm{P}(z_t|m, x_{1_n:t_n}, z_{1_n:t_n-1})\mathrm{P}(m|x_{1_n:t_n}, z_{1_n:t_n-1})}{\mathrm{P}(z_t|x_{1_n:t_n}, z_{1_n:t_n-1})}. \tag{1}$$

We assume that z_{t_n} is independent from $x_{1_n:t_n-1}$ and $z_{1_n:t_n-1}$ given we know m, the right side of this equation can be simplified such that n and $z_{1:t-1}$ can be omitted. This results to the equation for a single sensor as introduced by Moravec [8]:

$$\mathrm{P}(m|x_{1:t}, z_{1:t}) = \frac{\mathrm{P}(z_t|m, x_t)\mathrm{P}(m|x_{1:t}, z_{1:t-1})}{\mathrm{P}(z_t|x_{1:t}, z_{1:t-1})}. \tag{2}$$

Eq. 2 leads us to an update rule to incorporate a new scan into a given map by multiplying its odds ratio $\mathrm{R} = \mathrm{P}/(1-\mathrm{P})$ with the odds ratio of a local map constructed from the most recent scan, divided by the odds ratio of the prior $\mathrm{R}(m)$. Often it is assumed that the prior probability of m is 0.5 (s.t. unknown). In this case the prior can be cancelled out, writing the log odds representation as follows:

$$\log \mathrm{R}(m|x_{1:t}, z_{1:t}) = \log \mathrm{R}(m|x_t, z_t) + \log \mathrm{R}(m|x_{1:t-1}, z_{1:t-1}). \tag{3}$$

Eq. 3 tells us how to update our belief about the occupancy probability of a grid map given the current sensory input z_t with $\log \mathrm{R}(m|x_t, z_t)$ being the log odds representation of the so called inverse sensor model $\mathrm{P}(m|x_t, z_t)$ which can be derived empirically or trained by any gradient descent technique [10].

As a rule of thumb the input probabilities as well as the output probabilities are bounded to $\mathrm{P} \in (0.2, 0.8)$ to avoid over fitting and to retain a good dynamic range when new data arise. A beneficial effect of the bounding is the fact that the log odds ratio becomes a function f which maps P almost linearly into the real numbers. With respect to the task we take a distinctive set of measurements comprising the last time interval T. This technique has first be proposed by Arbuckle [1] to assure that also dynamic and quasi static objects can be mapped by the grid mapping algorithm. Therefore, we concentrate on this particular measurement set of timespan T:

$$\log \mathrm{R}(m|x_T, z_T) \approx \sum_{t \in T} f(\mathrm{P}(m|z_t, x_t)). \tag{4}$$

3 Mixture of Experts

Mixture of Experts (ME) models attempt to solve problems using a divide-and-conquer strategy. They learn to decompose complex problems into simpler subproblems, that is the expert network to partition the input space onto different voters and an intelligent sensors (IS) network which is responsible for the particular region and semantic feature.

Our approach is the application of a gating function which has the property of scaling each inverse sensor model at the particular cell m such that faulty voters are going to be suppressed. Eq. 4 is in a form to fit well in a Mixture of Experts model

$$\log \mathrm{R}(m|x_T, z_T) \approx \sum_{t \in T} g(z_t, x_t) f(\mathrm{P}(m|z_t, x_t)) \tag{5}$$

with $g(z, x)$ being the gating function μ. In eq. 5 the gating function itself is the only one which can be optimized due to the fact, that the inverse sensor models are given. Thrun et. al. [10] proposed the learning of the inverse sensor model by a neuronal network. In that case, the whole system can be trained in a supervised fashion as commonly known for ME models [7].

Within this work the gating function is the soft max activation which is trained for each timespan T by the error function

$$E = \sum_{t \in T} \| y(m) - g(z_t, x_t) r(m|z_t, x_t) \| \,. \tag{6}$$

$y(m), r(m|z_t, x_t) \in \{-1, 1\}$ are the overall and currently classified binary classifications of the cell m of being occupied by a feature.

4 Evaluation

We implemented our proposed framework into the AMiRo robot developed by Herbrechtsmeier et. al. [9]. Three different sensors with spatial coverage shown in fig. 2 were used, where each one is attached with a different application creating the inverse sensor model for the semantic feature “obstacle”: A LIDAR was used in combination with Thruns [10] proposed obstacle detection (IS1). Second, a set of eight cocircular arranged proximity sensors were used to detect close obstacles in combination with a detection by Benet et. al. [2] (IS2). At last, we applied a WXGA camera to detect anomalies using the proposed algorithm by Kohlbrecher et. al. [5]. We used the GazeboSim simulator shown in fig. 3 for the robot and created an occupancy map of obstacles in the environment for an exploration task. The coverage of the map compared to the ground truth has been measured over a simulated false-negative rate for a given sensor. Assuming an ideal IS, the false-negative rate is the probability of a feature not being detected by an IS. As long as the false-negative rate of a sensor is below 50%, the evidence grid framework converges to the correct solution anyway due to the fact, that the fusion corrects the measurements over multiple readings. On the other hand, if the rate is going to be above 50% the regions which cannot be correctly classified by the non-faulty voters will be detected wrong, resulting in a massive coverage failure. As can be seen in tab. 1, the gating network detects faulty classifiers

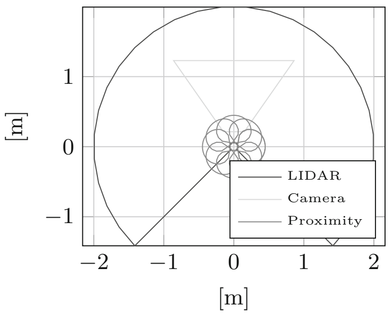

Fig. 2: Full range of sensor cones

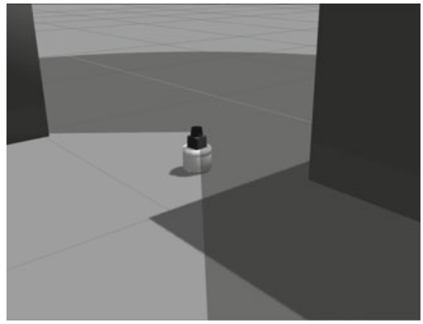

Fig. 3: Simulator view

Fig. 4: Learned spatial gating functions for IS1 (left), IS2 (middle), and IS3 (right). Grayscale represents the gating function value from 0 (white) to 1 (black).

Table 1: Mean coverage until convergence of the mapping process of the obstacle feature (Standard deviation over multiple runs $< .1\%$). Coverage without/with gating and no faulty sensor is both .81.

	Affected Sensor	Coverage				
False-Negative Rate		20%	40%	60%	80%	100%
Without Gating	IS1	.80	.79	.22	.21	.19
	IS2	.80	.81	.30	.22	-
	IS3	.78	.76	.22	.19	.14
With Gating	IS1	.80	.80	.76	.75	.75
	IS2	.80	.80	.79	.79	.79
	IS3	.78	.77	.70	.70	.69

as soon as their majority of measurements is faulty. The gating function for each IS is learned as a spatial representation as shown in fig. 4 for a non-faulty case. The exploration highly rely on the proximity sensors for the near field environment detection. While having a false-negative rate of 100%, meaning that objects are missed constantly, the robot is not able to detect objects for collision avoidance and thus the exploration fails. Equipped with the gating framework, we let the robot move by chance in the beginning which results in the detection and exclusion of the faulty proximity sensors.

5 Summary

To meet the trend of cyber-physical systems applications, where physical processing systems are equipped with sensors attached to communication networks, we enhanced the evidence grid framework to fuse spatial and semantic information of distributed, heterogeneous sensors. First, we designed every sensor system as an IS such, that it emits its information as an inverse sensor model with semantic affiliation attached. Then, we fused the information of a set of IS by applying the computational efficiency log odds update rule. Using our proposed enhanced fusion, the results correctly converge in our simulated robot exploration task even if faulty IS exists due to the application of a gating term to every fusion expert. While every single instance, s.t. IS, expert, or further information processing applications, is independent and not bounded to one physical system, the whole framework suits the demands of cyber-physical systems. In future work we will apply our framework to heterogeneous robot and harvesting scenarios with further cognitive processes acting on the fused information.

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