Bayesian map fusion for target detection and localization

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Abstract

We introduce a Bayesian fusion scheme for the detection and the localization of targets using multiple sensors. This method could be useful in the field of sea mines detection where different kinds of sensors can be used. From an operational point of view, it is desirable to identify dangerous areas (a mine is present with significant probability), safe areas (high probability that there is no mine) and unknown areas (not enough information to conclude). We illustrate the method by the fusion of two independent fictive sensors and produce two dimensional risk maps for a single target. We extend the method for multiple targets and compare different ROC curves to evaluate its performances.

Bayesian map fusion

- Input: n sensors $S_i, i \in \{1, ..., n\}$ provide $A_i(T_r) = \frac{p(Y_i(T_r))}{p(Y_i)}$
- Hypothesis 1: there is at most one target in the area $V$
- Hypothesis 2: the sensors are independent
- Output: $p(T_r|Y_1, ..., Y_n)$. This joint posterior probability distribution can be calculated as:

$$p(T_r|Y_1, ..., Y_n) = \frac{\prod_{i=1}^{n} A_i(T_r) p(Y_i|T_r)}{\sum_{r} \prod_{i=1}^{n} A_i(T_r) p(Y_i|T_r)}$$

where $A_i(T_r)$ is the prior ratio $\frac{p(T_r)}{p(T_r)}$

Context

Figure 1: In the field of sea mines detection, several sensors can be used, such as sonars, magnetic gradiometers, electromagnetic sensors or electrochemical sensors. We propose a method to fuse the information from the different sensors to achieve better detection performances.

Simple sensor model

- Sensor $S_1$: $R_1 = \{r_1^1, ..., r_1^n\}$, $Y_1 = \{y(r_1^1), ..., y(r_1^n)\}$
- Sensor $S_2$: $R_2 = \{r_2^1, ..., r_2^n\}$, $Y_2 = \{y(r_2^1), ..., y(r_2^n)\}$
- Target parameters: $a_1 \sim p(a_1|T_r)$, $a_2 \sim p(a_2|T_r)$, $\eta \sim \frac{p(T_r)}{p(T_r)}$
- Sensor model

$$y(r_i^j) = \begin{cases} \frac{a_i}{i + \sqrt{\pi \sigma_i}} & \text{if there is a target} \\ \eta & \text{if no target} \end{cases}$$

- Likelihoods:

$$p(Y_i|T_r) = \frac{1}{\sqrt{2\pi\sigma_i}} e^{-\frac{y_i^2}{2\sigma_i^2}}$$

$$p(Y_i|T_r) = \int_{-\infty}^{\infty} p(Y_i|a_i, T_r) p(a_i|T_r) da_i$$

- Multiple targets

- Exclusion radius: $r_0$
- Influence radius: $r_i$
- Measurement subset: $R_i \rightarrow R_i(t) = \{r_i \in R_i : |r_i - r_i| < r_i\}$
- Test : $n_i \in S_i$: Bernoulli trial
- N tests : binomial distribution

Histogram test

- $N_i = 10^4$ simulations
- $p(T_r) = p(T_r) = 1/2$
- $S_i = \{n_i \in S_i : Y_1, Y_2\}$
- Test : $n_i \in S_i$: Bernoulli trial
- N tests : binomial distribution

Simulation results

- Figure 2: Posterior probability distributions (top) and associated risk maps (bottom) for sensor $S_1$, $S_2$ and for the fusion in the absence of a target. The white curves correspond to the trajectories of the sensors. The green and the yellow colors correspond to safe and unknown areas.
- Figure 3: Posterior probability distributions (top) and associated risk maps (bottom) for sensor $S_1$, $S_2$ and for the fusion in the presence of a single target. The cross is the actual position of the target. The red color corresponds to dangerous area.

Figure 4: Frequency of the presence of the target in the region $S_i$ as a function of the quantile $\alpha$ together with the Wilson confidence interval at 95% for the binomial distribution.

Figure 5: ROC curves for sensors $S_i$ and $S_2$ and the output of their Bayesian local fusion [2] and their Bayesian map fusion. ROC curves are obtained by letting vary a threshold on the posterior probabilities $p(T_r|Y_1)$, $p(T_r|Y_2)$ and $p(T_r|Y_1, Y_2)$ on the basis of $10^3$ simulations.

References


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