Graph analysis on uncertain measurements for position estimation

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Abstract: This paper presents a method for multi target detection and localization based on heterogeneous uncertain information produced by multiple agents.

Information association is based on graph analysis which considers georeferences, spatial precision and pre-existing knowledge. The objective of the scoring fusion is to suggest as quickly and as precisely as possible the hypothetic positions of trapped persons by increasing the quality of uncertain information. The overall aim is to ameliorate the search efficiency by increasing the detection capabilities while reducing risks, false alarms and oversight.

1 Introduction

In Urban Search and Rescue (USAR) operations there is a static world of likely multiple and unknown targets. Since rescue is time critical, non-monotonic reasoning should occur after any belief revision. Current state of the art of IT-systems assisting disaster response is the georeferenced presentation of information in order to support the decision-making process [KKHK02, MIH+06], but to our knowledge automatic reasoning for the detection and localization of trapped victims is introduced with this project.

This paper presents a method for information fusion based on graph analysis. Filtering of information can not occur due to ethical considerations. In section 2, we present the crucial process of information association including cut capabilities. The inference machine consisting of classification and localization is explained in section 3.

2 Association

In order to understand association of uncertain information, the source of information i.e. the target has to be distinguished from the uncertain information about the source. Association consists of finding the unknown common information source. Since the link between pieces of uncertain information and the source is often unknown, the least ambiguous link has to be found. This problem is also referred to multisensor multitarget association. During USAR operations the association framework can not necessarily neither rely on exhaustive search results of every search method for all position hypotheses nor on a known number of targets. Several methods exist (see [HM04],[Das08]), but they are mainly designed for static fusion, i.e. dynamic states.

A measurement might not be reproducible if it is based on physical variables which can vanish such as odor, heart beat or respiration. Another challenge is that hypotheses are supported by only a small number of observations which are collected on the fly. Our geographical data association can be divided in four phases illustrated by the dashed boxes in Fig. 1. Input and output of every process are represented by parallelograms. The primary input are reports or measures whereas the final output are regions of interest (ROIs).

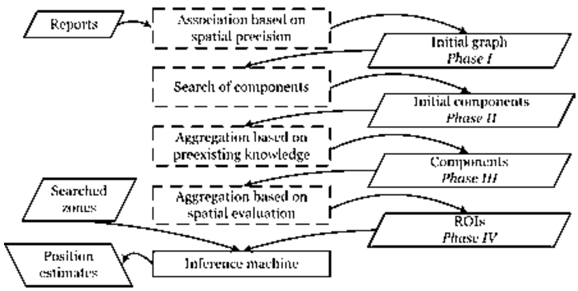


Figure 1: Process of Fusion and Inference

2.1 First phase

An initial graph is created. The spatial precision $\eta(\tilde{\mathbf{r}}_k)$ of a report is used to determine whether there is a link among them or not. An association is given if their surfaces intersect. A report's circular surface is given by its position and its spatial precision which define center and radius, respectively. This condition can be stated as in equation 1. A fulfilled association condition is represented schematically in Figure 2(c).

$$\left\|\tilde{\mathbf{r}}_i - \tilde{\mathbf{r}}_j\right\|_2 \leq \eta(\tilde{\mathbf{r}}_i) + \eta(\tilde{\mathbf{r}}_j) \tag{1}$$

2.2 Second phase

The initial graph represented by an incidence list is searched to identify connected components. A depth first search algorithm is applied to the incidence list to extract N_c components. A report which has no link to another is as well a component. The connected components can not be considered as ROIs per se because they may grow infinitely in surface.

2.3 Third phase

An analysis of the identified components is undergone with respect to preexisting knowledge such as the expected number of trapped persons. If the expected number is bigger than the number of components ($N_c < \hat{N}$), each component is evaluated with respect to its split ability. The split is performed using the k-Means algorithm of Llyod [Llo82] assuming two clusters. The ranking of components is based on the mean distance to the centroid. As higher the mean distance as more probable is that the association hypothesis is based on more than one information sources. However, this does not take into account systematic errors.

Components with at least two vertices are split unless their mean distance is smaller than a given threshold μ_{min}. Figure 2(a) illustrates this case where the component's mean distance to the centroid is too small, in contrast to Fig. 2(b) where the component is splittable.

If the number of expected number of trapped persons is smaller than the number of components ($N_c > \hat{N}$) merging of components can not occur since the likelihood of an erroneous estimation can not be excluded.

2.4 Fourth phase

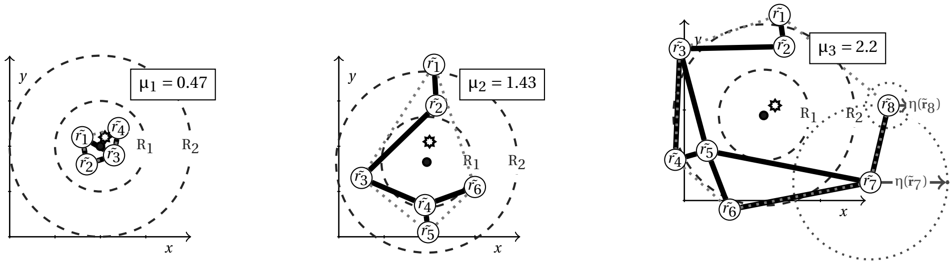
Components are processed with respect to the mean distance to the centroid, which is equivalent to a kind of gating method. If the mean is bigger than a predefined threshold μ_{max} (see Fig. 2(c)), the component is split using the same algorithm as in the third phase no matter how many victims are expected.

The final output (ROIs) correspond to clusters. Spatially a ROI is delimited by the convex hull bounding all vertices of a component.

3 Inference

Performance factors of search methods, ROIs and "*Searched zones*" (i.e. negative search results) are inputs of the inference machine performing the classification and conditionally localization. It is based on a heuristic method for scoring fusion [HM04].

Classification consists of an assessment of all available information within a ROI and after calculation of the *target score* **TS**, outputs whether a position hypothesis is rejected,



(a) $\mu_1 < \mu_{min}$

(b) $\mu_{min} < \mu_2 < \mu_{max}$

(c) $\mu_3 > \mu_{max}$, two dotted circles around $\tilde{r}_7$ and $\tilde{r}_8$ represent the fulfilled association condition

Figure 2: Schematic representation of component splitting cases for $\mu_1 < \mu_2 < \mu_3$ (*reports*: solid circles , *estimated positions* $\hat{\mathbf{x}}$: stars, *edges of component*: solid lines, *convex hulls*: dotted lines, *help circle*s (dashed circles) around *centroids* $\bar{\mathbf{x}}$: filled dots)

confirmed or still unclear. **TS** expresses how likely the presence of a trapped person is at a given position.

If a search-action resulted in a report within the hull, **TS** increases. The number of reports for each search method $N_{r,i}$ is considered. On the contrary, if a search-action was fruitless within the hull and hence, no correlated report is present, **TS** decreases. The counter of searched zones $N_{s,i}$ is also relative to search methods.

The total number of reports is relevant: as more reports are emitted by search teams as higher is the target score. Eqs. 2 are used to assess the scale factor γ_r and γ_s with respect to the total number of reports N_r and negative search results N_s respectively. The denominator in the magnitude of five is empirically determined by the *Federal Agency for Technical Relief.*

$$\gamma_r = \frac{N_r}{5}, \quad \gamma_s = \frac{N_s}{5} \tag{2}$$

Equation 3 calculates the target score **TS** with a weighted average over the detection probabilities and the scale factors γ (see Eqs. 2). Index i iterates through the search methods and N_i is the total number of methods. This equation is based on an exponential recovery function to either increase or decrease **TS** by summing or subtracting from the starting score value of 1/2, respectively. For a schematic representation of **TS** refer to Fig. 3.

$$\mathbf{TS} = \frac{1}{2} + \frac{1}{2}\left[1 - \exp\left(-\frac{\gamma_r}{N_r}\sum_{i=1}^{N_i} N_{r,i} P_i(t|\tilde{\mathbf{r}})\right)\right] - \frac{1}{2}\left[1 - \exp\left(-\frac{\gamma_s}{N_s}\sum_{i=1}^{N_i} N_{s,i} P_i(\neg t|\neg\tilde{\mathbf{r}})\right)\right] \tag{3}$$

A hard limiter function $f(\mathbf{TS})$ (see Eq. 4) gives the output u of the inference machine with $C_{min} \in [0, 0.5]$ and $C_{max} \in]0.5, 1]$ to be defined.

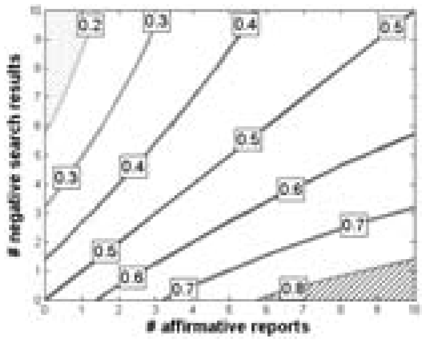


Figure 3: Equipotential plot of **TS** with respect to number of reports and negative search results, for a unique search method with $P(t|\tilde{\mathbf{r}}) = P(\neg t|\neg\tilde{\mathbf{r}}) = 0.8, C_{min} = 0.2, C_{max} = 0.8$; inference for striped area: *confirmed hypothesis*, for dotted one: *rejected hypothesis*

$$u = f(\mathbf{TS}) = \begin{cases} \text{confirmed } H^p & \text{if } \mathbf{TS} > C_{max} \\ \text{unclear } H^p & \text{if } C_{min} \leq \mathbf{TS} \leq C_{max} \\ \text{rejected } H^p & \text{if } \mathbf{TS} < C_{min} \end{cases} \tag{4}$$

If the the target score is bigger than a threshold termed maximal certainty $\mathbf{TS} > C_{max}$, the position hypothesis is confirmed and further actions should be triggered because the existence and the position of a trapped person is credible enough. On the other hand, if the target score is smaller than a threshold called minimal certainty $\mathbf{TS} < C_{min}$, no trapped person is inferred. Between maximal and minimal certainty threshold not enough certainty can be attributed to the hypothesis.

Localization For ROIs with several reports N_r which are provided by a varying number of search methods N_i, the estimated position $\hat{x}$ based on reports under the condition of a confirmed position hypothesis $\{\tilde{\mathbf{r}}(x, y, z)|H^p\}$ is computed with Eq. 6. The aim of this weighted average is to enhance the spatial precision of the position estimate of a confirmed position hypothesis. The confidence c_i is a weighing factor for each search method expressing how reliably the position is estimated. It has to be determined by experience η_i and by assessment of the current situation $\eta(\tilde{\mathbf{r}}_k)$. Eq. 5 expresses this confidence with a weighted sum. Both spatial precisions are normalized and κ expresses how much influence experience has over actual assessment. As represented in Figure 2 the estimated position does not necessarily correspond to the centroid.

$$c_i = \kappa \left\|\eta_i\right\| + (1-\kappa)\left\|\eta(\tilde{\mathbf{r}}_k)\right\|, \ 0 \leq \kappa \leq 1 \tag{5}$$

$$\hat{\mathbf{x}} = \frac{1}{\sum_{i=1}^{N_i} c_i} \sum_{i=1}^{N_i} c_i \left[\frac{1}{N_{r,i}} \sum_{j=1}^{N_{r,i}} \tilde{\mathbf{r}}_{i,j} \right] \tag{6}$$

4 Conclusions

This paper presented a fusion method which is focusing on the association of measures to a common information source. The classification is ternary and accounts for negative search results. The estimated position is calculated with a weighted average considering the spatial precision of heterogeneous search methods. Hence, this method covers the entire fusion process. It is capable of dealing with heterogeneous search results, with multiple targets and with a dynamic fusion process required for static worlds.

Acknowledgment

We gratefully acknowledge financial support from the *German Federal Ministry of Education and Research* (BMBF) (support code: 13N9759). Furthermore, we are most grateful for the support of the *German Federal Agency for Technical Relief* (THW).

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