Information Fusion based on graph analysis during Urban Search and Rescue

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Abstract – *Conventional practices in Urban Search and Rescue (USAR) operations have a great potential for improvement as regards information management. This paper presents a method for automated information processing of uncertain search results produced by multiple agents.*

Information association is based on graph analysis which considers georeferences, spatial precision and preexisting 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.

Keywords: GIS, multi-agent, uncertainty, association, graph, k-means, high-level information fusion.

1 Introduction

Data processing during conventional Urban Search and Rescue (USAR) procedures are mainly based on the cognitive capabilities of the rescue personnel which ensures flexibility. This processing is rapidly however compromised by the quantity and diversity of information collected by various agents during the response of a disaster [1]. These agents can be divided in human, canine and technical ones. This research is carried out under the "I-LOV" project which fosters also the improvement of search technologies for the benefit of civil security and emergency services safety. It goes beyond classical command and control systems such as presented in [2, 3, 4, 5]. Furthermore, the necessary discernment between certain, uncertain, or even erroneous information requires discipline, organization and objectivity. However, any rescuer is under the influence of the traumatic scene of a disaster which may foster psychological stress. This stress impairs his cognitive capabilities.

IT based processing on the contrary has many advantages. For instance, data is stored centrally and permanently which enables to process it objectively. Furthermore, dependencies between different data categories can easily be taken into account by implementing rules.

In this paper a method of automated uncertain data processing is presented to assist the decision making process of decision authorities. The automated data processing aims to suggest and evaluate simultaneously hypothetic positions of multiple victims while also considering the possibility that victims may not exist. This method goes beyond the detection logic presented in [6] because it also considers unsuccessful search activities. Estimated positions are prone to spatial imprecision and hence correspond more to regions which will be denoted: *Regions Of Interest* (ROI). To assume any distribution is often intractable due to the limited observations collected for each ROI.

2 The problem

After the collapse of any structure an unknown number N of people might be trapped. The true position of victim i is given in the Euclidean space by $\mathbf{x}_i = (x, y, z)^\mathrm{T}$ with $i \in \aleph_0^+$. These positions are the targets t of the search process. The orientation of their bodies is neglected because it is of no relevance for finding them. The assumption is made that their position does not evolve i.e. is static and not a function of time since their bodies are often blocked under debris: $\mathbf{x}_i = const.$. Their position $\mathbf{x}_i$ is unknown.

During the USAR activities multiple search methods including sensors are used to find those victims. The result of any search activity concerning the presence of a victim is binary, neglecting additional measurements outcome such as respiration frequency, body temperature which could give additional information such as the health of the victim. Either, the search process resulted in a affirmative statement (f = true) or in a negative one (f = false) about the presence of a victim. Affirmative search results will be called reports. Two cases have to be differentiated. Either this result is certain (c = true) and thus is supported by evidence or it remains uncertain (c = false). We will denote the reports as follows $\mathbf{r}_k = (x, y, z, f, c)^\mathrm{T}$ and k in the bounded set $\mathrm{R} \in \{0, 1, \ldots, \mathrm{K}\}$. For simplicity of notation uncertain, affirmative reports will be denoted with a tilde as $\tilde{\mathbf{r}}_k = \mathbf{r}_k(x, y, z, true, false)^\mathrm{T}$.

In the certain case, an affirmative result of the search process corresponds to the true position $\mathbf{x}_i = \mathbf{r}_k$ of the victim. In the uncertain case, the affirmative search result supports an estimate of the position. An uncertain report is accompanied by a detection probability $P(t|\tilde{\mathbf{r}}_k)$ and spatial precision $\eta(\tilde{\mathbf{r}}_k)$. In the case that a report detected a true target we presume that there is influence of noise on the measured position. If a report is based on a spurious source (clutter) nothing can be said about the relationship between true targets and this false alarm. This distinction allows to model the sensitivity of a search method independently to its spatial precision. These two parameters highly depend on the employed search method and the ambient conditions. Exact assertion of these parameters is practically impossible due to the unknown relevant parameters and always changing conditions.

The probability of a report is given by Eq. 1 which takes into account following both cases: a report emitted correctly due to the presence of target t and the false alarm $\alpha = P(\tilde{\mathbf{r}}_k|\neg t)$ with a erroneous report. The same applies to its negation as stated in Eq. 2. In this case, oversight $\beta = P(\neg\tilde{\mathbf{r}}_k|t)$ is included with a missing report given there is a target.

$$P(\tilde{\mathbf{r}}_k) = P(\tilde{\mathbf{r}}_k|t) + P(\tilde{\mathbf{r}}_k|\neg t) \tag{1}$$

$$P(\neg\tilde{\mathbf{r}}_k) = P(\neg\tilde{\mathbf{r}}_k|t) + P(\neg\tilde{\mathbf{r}}_k|\neg t) \tag{2}$$

Once a report is given ($P(\tilde{\mathbf{r}}_k) = 1$) the probability that there is a target given there is a report ($P(t|\tilde{\mathbf{r}}_k)$) can be computed. Using Bayes's inversion formula 3, Eq. 1 can be written as Eq. 4 which expresses this probability.

$$P(\tilde{\mathbf{r}}_k|t) = \frac{P(t|\tilde{\mathbf{r}}_k)P(\tilde{\mathbf{r}}_k)}{P(t)} \tag{3}$$

$$P(t|\tilde{\mathbf{r}}_k) = P(t)(1-\alpha) \tag{4}$$

The same reasoning applies to the probability that there is no target given that there is no report $P(\neg t|\neg\tilde{\mathbf{r}}_k)$. Eq. 5 is the result.

$$P(\neg t|\neg\tilde{\mathbf{r}}_k) = P(\neg t)(1-\beta) \tag{5}$$

Equations 4 and 5 will be referred to as detection probabilities.

To enhance the quality of uncertain information search activities are carried out multiple times either with the same or different search methods. The correct association of reports is crucial. Correct means that all reports related to the same information source i.e. target are associated. Association consists of finding a subset of R supporting the position estimate. The complexity of such association is depicted in Figure 1. In order to determine if a report matches a position estimate the only possible alternative is to use geographical aspects among the reports. The reason is that search methods cannot discriminate between different targets unless there is evidence. Since there is no evidence about correct association several hypothesis exists which will be termed association hypothesis H^a_l. The probability of an association hypothesis being true can be written as $P(H^a_l)$. The number of hypotheses D corresponds ideally to the number of victims, but in practice does not necessarily. Theoretically, D grows factorially as stated in Eq. 6 that considers only feasible associations. Only affirmative uncertain reports have to be taken into account $\tilde{K} \subseteq K \forall \{\mathbf{r}|$ f=true $\wedge$ c=false$\}$ because certain ones are not entering the fusion process.

$$D = \sum_{i=1}^{\tilde{K}} \binom{\tilde{K}}{i} \tag{6}$$

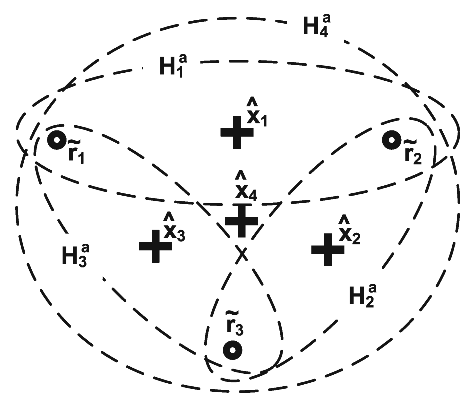


Figure 1: The four association hypothesis H^a of three reports $\tilde{\mathbf{r}}$ represented by ∘ and their consequent position estimate $\hat{\mathbf{x}}$ represented by a +. Not represented are the hypotheses based on only one report.

An estimate of the true position of a victim is either a consequence of an association hypothesis or may be a position hypothesis which is not supported by any search activity. This position hypothesis will be denoted as H^p_j. In any case, it is represented by a position estimate: $\hat{\mathbf{x}}_j = (\hat{x}, \hat{y}, \hat{z})^T$. Hence, the number of position estimates can be bigger than the number of association hypotheses. A supported position hypothesis is highly dependent of the association hypothesis. A position hypothesis is represented by a position estimate and the probability of the hypothesis being correct $P(H^p_j)$.

The probability of receiving a report $\tilde{\mathbf{r}}_k$ given a unsupported position hypothesis H^p_j is given by Eq. 7. $P(\tilde{\mathbf{r}}_k|t)$ is the probability that a report is emitted and $P(H^p_j|t)$ is the probability that a position hypothesis is present assuming that there is a target t. In other words, the first summand expresses the probability that a target is actually detected given it exists in the world. The second summand however corresponds to the assumption that report and hypothesis exist even though there is no target.

$$P(\tilde{\mathbf{r}}_k|H^p_j) = P(\tilde{\mathbf{r}}_k|t)P(H^p_j|t) + P(\tilde{\mathbf{r}}_k|\neg t)P(H^p_j|\neg t) \tag{7}$$

The association of a new report to the correct component depends on the association rules.

The position estimate may vary over time either due to a modification by a user or by the association of a new report. Anyhow, a supported position estimate ideally converges to the true position of a victim with an infinite number of reports under the condition of a true association hypothesis as stated in Eq. 8. This convergence assumes no systematic error.

$$\lim_{k\to\infty} \hat{\mathbf{x}}(\{\tilde{\mathbf{r}}_k|\mathrm{H}_l^a\}) - x = 0 \tag{8}$$

In conclusion, the goal of this problem consists of identifying the correct hypotheses whereupon *none*, *one* or *multiple* position hypotheses may be correct.

3 Assumptions

Two kinds of position hypotheses exist: either a hypothesis is supported by results of search activities or not. If they are not supported, a person substitutes the search activities by evaluating the disaster site. The information complexity on which this human evaluation is based is not manageable with an IT-system. Therefore, this project restricts its focus on position hypotheses which are based on measurements. The consequence of this simplification is that position hypotheses are equivalent to association hypotheses: $\mathrm{H}^a \sim \mathrm{H}^p$.

The current method only evaluates association hypotheses corresponding to ROIs i.e. connected reports thus does not evaluate multiple theoretically possible associations like in a "soft" association method i.e. probabilistic data association (pda). Due to the hard association the fact that reports might belong to several ROIs is neglected. Implemented is a "hard" association method which can be compared to a "gating" technique which is presumed to be sufficient to provide adequate data association in sparse scenarios [7]. The sparsity of a scenario is defined as the mean distance of the targets to their nearest neighbor (see Eq. 9). We assume that our scenarios are sparse since even if there are not the probability to find all targets is high due to their proximity.

$$\bar{\chi} = \frac{1}{\mathrm{N}} \sum_{i=1}^{\mathrm{N}} argmin \left\| x_i - x_j \right\|_2 \; \forall j \in \{1,\ldots,\mathrm{N}\} \tag{9}$$

Either new association hypothesis are created given certain constraints based on geographical parameters or a priori knowledge is used such as the list of trapped persons to control the association process. This list can be viewed as an estimate of the number of victims $\hat{\mathrm{N}}$. The former alternative has the disadvantage that the number of hypothesis can grow unbound, but does not influence the perception by a suggestive number like the latter. The number of victims can roughly be estimated by the authorities and hence latter alternative is chosen. A framework however has to be set up which allows the handling of hypothesis which number does not correspond to the estimated one.

We assume that all uncertain reports associated to a common unknown target are normally distributed around it.

4 Information processing

It follows, the presentation of the information association and then the inference machine in section 4.2.

4.1 Information Aggregation

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. Aggregation consists of finding the unknown common information source among pieces of information which may initially be considered to originate from distinct sources. 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 in the literature. Hence, the association framework can not necessarily neither rely on exhaustive search results of every search method for all position hypotheses, on a fixed sequence of incoming data, nor on a known number of targets. Several methods exist (see [8],[9]), but they are mainly designed for moving targets, i.e. continuous state. Sequential Bayesian filters such as the Kalman filter rely on a continuous process to update the mean and covariance assuming a linear Gaussian process model [10]. This condition seems not to be necessarily fulfilled in this context.

The particularity of a USAR scenario is that targets are quasi static similar to, for instance, landmine detection [11], thus the validity of measurements does not expire. Hence, it is irrelevant whether measurement results arrive out of sequence or not. However, a measurement might not be reproducible if it is based on physical variables which can vanish such as odor, heart beat or respiration. Another fact is that hypotheses are only supported by 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. 2. Input and output of every process are represented by parallelograms.

4.1.1 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 10. A fulfilled association condition is represented schematically in Figure 3(c).

$$\left\| \tilde{\mathbf{r}}_i - \tilde{\mathbf{r}}_j \right\|_2 \leq \eta(\tilde{\mathbf{r}}_i) + \eta(\tilde{\mathbf{r}}_j) \tag{10}$$

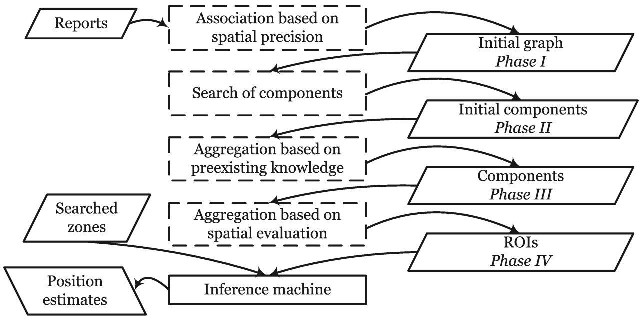


Figure 2: Process of Fusion and Inference

4.1.2 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.

4.1.3 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. For more details refer to section 4.1.5. 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. If there are systematic errors the spatial deviation given in Eq. 15 should be small.

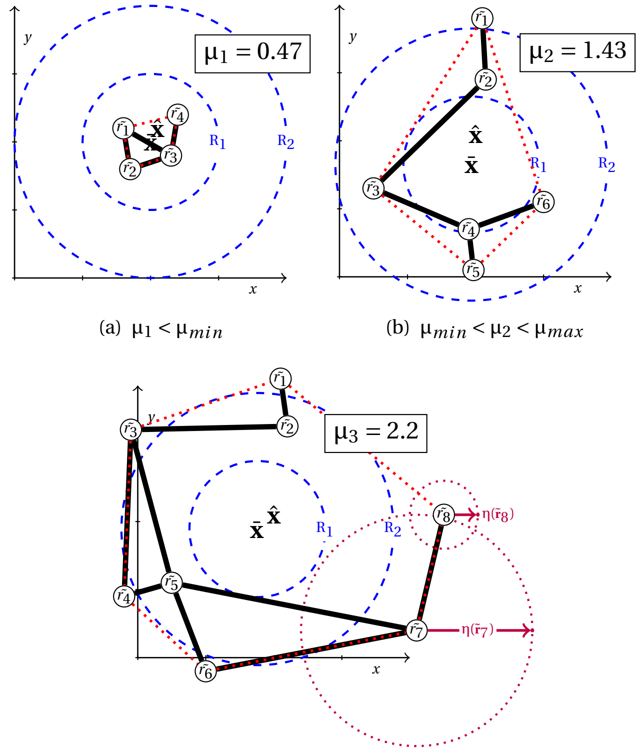
Components with at least two vertices are split unless their mean distance is smaller than a given threshold μ_{min}. Figure 3(a) illustrates this case where the component's mean distance to the centroid is too small, in contrast to Fig. 3(b) where the component is splittable.

Unsolved remains the case where the number of expected number of trapped persons is smaller than the number of components ($N_c > \hat{N}$). Merging of components should occur.

4.1.4 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. 3(c)), the component is split using the same algorithm as in the third phase. In this case, even if there is no corresponding missing person, the probability to find a distinct trapped person is considered to be high.

The output of the association phases are the ROIs which correspond to clusters.



(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 3: Schematic representation of component splitting cases for $\mu_1 < \mu_2 < \mu_3$ (○ reports, $\hat{\mathbf{x}}$ estimated positions, edges of component: solid lines, convex hulls: dotted lines, help circles around centroids $\bar{\mathbf{x}}$: dashed circles)

4.1.5 The spatial cut problem

The undirected weighted graph G=(V,E,w) is defined by edge set E, vertex set V and edge weights $w_e \in \Re$, $e \in E$. The edge weights correspond to the Euclidean distance defined in equation 11 among two vertices $u, v \in V$ which location is defined in the Euclidean space. The assumption is made that in a component all reports $\tilde{r}_k$ are true and that their position is correct. Hence, the fact is neglected that a report might exist given there is no target t, i.e. the second summand of Eq. 7.

$$w_e = \|\vec{u} - \vec{v}\|_2 = \sqrt{(u_x - v_x)^2 + (u_y - v_y)^2 + (u_z - v_z)^2} \tag{11}$$

Given a set of connected reports $(\tilde{r}_1, \tilde{r}_2, \ldots, \tilde{r}_n)$, where each report contains a vector corresponding to a position, the cut problem aims to find a proper partition $(S, V \backslash S)$ with $S \subset V, S \notin \emptyset$ and $T = V \cap S \Leftrightarrow S \cup T = V$, so as to minimize the mean distances to the centroid as stated in Eq. 12:

$$argmin(\mu_S + \mu_T) \tag{12}$$

The determination of the split is non trivial if n>2 since there are more than one separation possibilities. In literature, this is known as k-means clustering. Even for this case where k=2, it is a NP hard problem [12].

Omitting the vector signs for the positions, the arithmetic mean of the position $\bar{x}$ of a set of N vertices is defined with Eq. 13. This is also referred to as the centroid.

$$\bar{\mathbf{x}} = \frac{1}{\mathrm{N}} \sum_{j}^{\mathrm{N}} \tilde{\mathbf{r}}_j \tag{13}$$

The mean distance to the centroid in Eq. 13 is calculated with Eq. 14.

$$\mu = \frac{1}{\mathrm{N}} \sum_{j}^{\mathrm{N}} \left|\tilde{\mathbf{r}}_j - \bar{\mathbf{x}}\right| \tag{14}$$

The sample standard spatial deviation of the distance of the reports to the centroid is given by Eq. 15.

$$s = \sqrt{\frac{\sum_j^{\mathrm{N}} (\left|\tilde{\mathbf{r}}_j - \bar{\mathbf{x}}\right| - \mu)^2}{\mathrm{N}-1}} \tag{15}$$

An exhaustive search over all vertices of a component in order to determine the proper partition which satisfies condition 12 requires a factorial growing number of calculations equivalent to Eq. 6. Lloyd's algorithm [13] for k-means clustering for $k = 2$ is used to split a component into two proper partitions.

4.2 Inference machine

The inference machine performs two steps. First the hypothesis whether a victim is present or not is verified and if confirmed the estimated position is calculated. The next two sections present these two steps.

4.2.1 Verification of presence

Performance factors of search methods, ROIs and "*Searched zones*" (i.e. negative search results) are inputs of the inference machine. It is based on a heuristic method for scoring fusion [8]. Scoring equivalent to summing has been chosen because it outperforms voting fusion assuming Gaussian estimation error distributions [14]. The inference machine assesses available information within the convex hull of each ROI and after calculation of the *target score* **TS**, outputs whether a position hypothesis is rejected, 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 $\mathrm{N}_{r,i}$ is considered. On the contrary, if a search-action was fruitless within the hull and hence, no associated report is present, **TS** of the ROI decreases. The counter of searched zones $\mathrm{N}_{s,i}$ 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. 16 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*.

$$\gamma_r = \frac{\mathrm{N}_r}{5}, \quad \gamma_s = \frac{\mathrm{N}_s}{5} \tag{16}$$

Equation 17 calculates the target score **TS** with a weighted average over the detection probabilities (refer to Eqs. 4, 5) and the scale factors γ (see Eqs. 16). 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. 4.

$$\begin{aligned}\mathbf{TS} = \frac{1}{2} + \frac{1}{2}\left[1 - \exp\left(-\frac{\gamma_r}{\mathrm{N}_r}\sum_{i=1}^{\mathrm{N}_i}\mathrm{N}_{r,i}\mathrm{P}_i(t|\tilde{\mathbf{r}})\right)\right] \\ -\frac{1}{2}\left[1 - \exp\left(-\frac{\gamma_s}{\mathrm{N}_s}\sum_{i=1}^{\mathrm{N}_i}\mathrm{N}_{s,i}\mathrm{P}_i(\neg t|\neg\tilde{\mathbf{r}})\right)\right]\end{aligned} \tag{17}$$

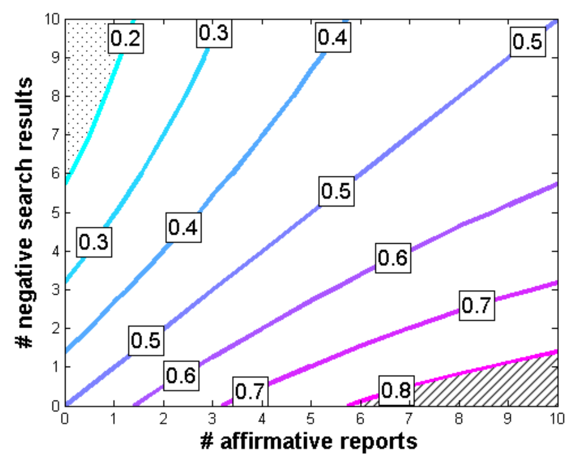


Figure 4: Equipotential plot of **TS** with respect to number of reports and negative search results, for a unique search method with $\mathrm{P}(t|\tilde{\mathbf{r}}) = \mathrm{P}(\neg t|\neg\tilde{\mathbf{r}}) = 0.8, \mathrm{C}_{min} = 0.2, \mathrm{C}_{max} = 0.8$; inference for striped area: *confirmed hypothesis*, for dotted one: *rejected hypothesis*

A hard limiter function $f(\mathbf{TS})$ (see Eq. 18) gives the output u of the inference machine with $\mathrm{C}_{min} \in [0, 0.5]$ and $\mathrm{C}_{max} \in]0.5, 1]$ to be defined.

$$u = f(\mathbf{TS}) = \begin{cases} \text{confirmed } \mathrm{H}^p & \text{if } \mathbf{TS} > \mathrm{C}_{max} \\ \text{unclear } \mathrm{H}^p & \text{if } \mathrm{C}_{min} \leq \mathbf{TS} \leq \mathrm{C}_{max} \\ \text{rejected } \mathrm{H}^p & \text{if } \mathbf{TS} < \mathrm{C}_{min} \end{cases} \tag{18}$$

If the the target score is bigger than a threshold termed maximal certainty $\mathbf{TS} > \mathrm{C}_{max}$, 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.

4.2.2 Calculation of the position

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. 20. 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. 19 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 3 the estimated position does not necessarily correspond to the centroid.

$$c_i = \kappa \left\| \eta_i \right\| + (1-\kappa) \left\| \eta(\tilde{\mathbf{r}}_k) \right\|,\ 0 \le \kappa \le 1 \tag{19}$$

$$\hat{\mathbf{x}} = \frac{1}{\sum_{i=1}^{N_i} c_i} \sum_{i=1}^{N_i} c_i \left[\frac{1}{N_{r,i}} \sum_{j=1}^{N_{r,i}} \tilde{\mathbf{r}}_{i,j} \right] \tag{20}$$

5 Case Study

The first test of this method took place during a disaster simulation in Lanouville near Hartheim, Germany on the 24^{th} of October 2009. The software implementing this method is called FRIEDAA (Functional Remote Information Exchanger with Developing Aggregation Algorithm) Several important lessons were learned from this experience. FRIEDAA can store all search-relevant information. The "2D+1" visualization capabilities of FRIEDAA based on a geographical information system (GIS) are better than traditional methods which are a projected representation of all activities on a white board. Furthermore, the information of completed but fruitless search-actions is not saved with the conventional in contrast to this approach. However, the information representation capabilities of a white board are powerful, versatile and robust.

The strategy prior having evidence about the presence of a trapped person differs substantially to the one afterwards. Before, search activities aim to obtain evidence about the presence of victims. Once achieved, the strategy is modified to enhance the spatial precision of the position estimate as much as possible, because the effort required depends upon the obstacle which has to be overcome to access a trapped person.

6 Discussion

The results of the current approach are dependent on the information fusion and the inference machine. The assessment of the performance of this method is difficult because its parameters such as α, β, μ_{min}, μ_{max}, C_{min} and C_{max} are unknown and have to be determined from experience.

The current position hypothesis logic is based on ROIs, but is obscuring the fact that every position at a disaster site may be a position of a victim.

Furthermore, the association method does neglect the fact that a report might be a false alarm. However, with Eq. 17 several reports are required prior to confirm a position hypothesis of an association. This fact increases the probability to detect correctly, but might decrease the precision of a position estimate if a report based on a spurious source is included.

The implemented fusion algorithm does not explicitly state contradiction of information present within a ROI. "Disfusion" as defined by Myler (see [15]) might help to quantify the ambiguity of information. Function 17 takes however into account disagreement with weighing negative against positive reports within a ROI.

The cognitive and analytical capabilities of humans outperforms these of FRIEDAA, mainly because IT-systems can only process information which has been input. Humans automatically perceive more information. However, the amount of *physical information* may overwhelm the user [1]. Filtering and processing information like implemented in FRIEDAA are solutions, but might blur the human situation assessment. Persistent data storage decreases this risk, on the other hand. Therefore, an IT-system with its centralized data storage is an advantage assuming that it does represent a negligible encumbrance to the users. For instance, to gain a clear picture about a long lasting disaster response is difficult if data is not persistently stored and readily available. This is a major advantage of FRIEDAA.

7 Outlook

Statistic evaluation of the results helps to get experience values. Therefore, the uncertain information that is collected during disaster response will be compared to certain one. Physical information such as the position of reports and processed information such as the estimated positions will be evaluated with respect to the found positions of victims. This evaluation will allow to increase the significance of initially unknown parameters.

The heuristic fusion approach could be replaced by the one chosen by Myler: Dempster's combination rule combined with a Neyman-Pearson test. The question whether or not it is applicable to incomplete datasets must be clarified.

The representation of **TS** with a color coded grid over the whole area of a disaster may be used in combination with a set of unimodal, multivariate distributions [16]. It must however be extended to account for multiple agents. This grid shall indicate the fact that at every position a victim might be trapped. Another opportunity is presented in [17] which has the advantage of a continuous representation instead of a grid, but has to be extended to cope with multiple targets. The advantage of a these representations compared to the current point based one for the estimated position is that regions with low target score can also be represented.

8 Conclusions

This project challenges conventional techniques employed during USAR disaster response. With FRIEDAA more information can be stored more reliably than in conventional methods. Furthermore, the readability due to "2D+1" map representation is enhanced. Filtering of information is possible due the layer's infrastructure. The performance of the information processing can not yet be assessed quantitatively because of insufficient reference datasets. However, we expect that the work currently under progress will result in a quantitative performance assessment. In our opinion, FRIEDAA integrating the here presented data fusion method represents a benefit during disaster response, especially by offering the users opportunities to verify hypothesis by variable assessment of data relevance.

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