Source Conflicts in Bayesian Identification

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Abstract: In Bayesian identification an ID source is in conflict with the other ID sources, if both provide substantially different, reliable information on a tracked object. After discussing some general aspects of source conflicts and introducing two established conflict-definition approaches, it is denoted that these approaches each show a counterintuitive effect. By applying a conflict definition from the theory of Bayesian networks, the Coherence Approach and as refinement the Extended Coherence Approach are proposed. In an experimental evaluation, all approaches are compared with each other and with the expert's intuitive understanding of source conflicts.

1 Bayesian Identification

Identification of a tracked object is the characterization by assignment of an identity (ID). This identity describes object features, e.g., allegiance or intent, necessary to know in performing military missions. The standard identities *Friend, Assumed Friend, Neutral, Suspect, Hostile,* and *Unknown* are often used in context of military air surveillance and defense. Depending on the application context, different identities might be defined and applied. Bayesian identification facilitates fusion of uncertain information from manifold ID sources, e.g., track behavior, IFF equipment, Electronic Support Measures, and adherence to air traffic regulations. Subsequently, we sketch an exemplary Bayesian identification process. More details can be found in [BP99, pp. 496-497], [HM04, pp. 214-220], and [KK09].

A declaration is the statement of an ID source on a specific attribute or behavior of the considered tracked object, based on emissions measured by sensors. Consider as example the declaration *object follows a civil air route*. We assume that each of N ID sources provides a declaration $d_i \in D_i$ with $i \in \{1, \ldots, N\}$. An object belongs to exactly one of M possible *Operational Object States*. The finite set of all possible states is given by $\mathit{OOS} := \{O_1, \ldots, O_M\}$, e.g., $\mathit{OOS} = \{\mathit{OF}, \mathit{NA}, \mathit{EF}\}$ with own forces (OF), neutral allegiance (NA), and enemy forces (EF).

For each ID source i the *Source Likelihood Vector* $\mathit{SLV}_i = (p(d_i|O_j))_{j=1,\ldots,M}$ is assigned to the declaration d_i. Fusion is performed by element-wise multiplication of the source likelihood vectors of all ID sources, providing the *Combined Likelihood Vector* $\mathit{CLV} = (p(d_1, \ldots, d_N|O_j))_{j=1,\ldots,M}$, whereat conditional independence as a model-given precondition is assumed. Subsequently, by application of the Theorem of Bayes the *Posterior Likelihood Vector* $PLV = (p(O_j|d_1, \dots, d_N))_{j=1,\dots,M}$ is calculated. Finally, the PLV needs to be transformed into a standard identity (*Friend*, *Assumed Friend*, etc.) to be presented to an operational user. A minimax approach can be used to select an appropriate identity based on the PLV, for details see [KK09]. By configuration, a Bayesian identification process can be customized for different operational and technical scenarios, see e.g., [KZ08].

Subsequently, we will define and analyze conflicts based on the sketched exemplary identification process. The treatment can be transferred easily to other Bayesian-based identification processes.

2 Source Conflicts

From the technical perspective, conflicts originate between different ID sources at fusion level but have consequences on the ID result level. A source conflict indicates the situation, that (at least) one ID source provides information to the fusion step, that apparently contradicts the fused information provided by the other ID sources, with both having a high reliability. This source conflict understanding strongly depends on the underlying modeling and fusion approach. E.g., a positive IFF mode 4 reply of an object is only in conflict with the declaration *attack on own forces*, if the problem of fratricide is not modeled.

Applying [JN07, pp. 99, 174-179] and [Las91] to Bayesian identification, a source conflict results from discrepancy between model and source declarations, which can be due to flawed sensor measurements or sensor raw data evaluation, due to facing a rare case, or due to having a situation not covered by the underlying model of identification. For any cause, a source conflict indicates a problem case within the identification process, which needs to be communicated to the operational user. He uses the information on this reliability aspect in order to judge the overall reliability of the assessed ID of an object.

Slightly differing from other approaches, we define source conflicts between a source and all other sources, and not based on source-to-source comparison. Nevertheless, the technical concepts for both approaches are easily exchangeable.

Subsequently, we discuss different approaches of a formal source conflict definition, which measure the discrepancy between the Source Likelihood Vector SLV_i of ID source i and the *Combined Likelihood Vector* $CLV_{-i} = (p(d_1, \dots, d_{i-1}, d_{i+1}, \dots, d_N|O_j))_{j=1,\dots,M}$ of all other sources. For sake of convenient notation in the rest of this section, we denote $X = (x_1, \dots, x_M)$ and $Y = (y_1, \dots, y_M)$ instead of SLV_i and CLV_{-i}, and additionally scale X and Y, such that $x_1 + \dots + x_M = y_1 + \dots + y_M = 1$.

The *Threshold Approach* is an established, very intuitive approach for source-conflict definition in Bayesian identification: Given an appropriate upper and lower threshold ε_{up} and ε_{low}, the vectors X and Y are in conflict, iff there exist i, j with $i \neq j$ such that $x_i > \varepsilon_{up}$ and $y_j > \varepsilon_{up}$, or $x_i > \varepsilon_{up}$ and $y_i < \varepsilon_{low}$, or $y_i > \varepsilon_{up}$ and $x_i < \varepsilon_{low}$.

Next to the Threshold Approach, another established approach to define conflicts is based on metrics. The *Distance Approach* for source-conflict definition uses the taxicab distance: X and Y are in conflict, iff $\sum_{i=1}^{M} |x_i - y_i| > \varepsilon_{dist}$ with a given threshold ε_{dist}.

In search of an effective and efficient definition of source conflicts, we have noticed, that both approaches each show an counterintuitive effect. According to the definition of the Threshold Approach, the vectors $X = Y = (0.5, 0.5, 0, 0, 0, 0)$ with $\varepsilon_{up} < 0.5$ are in conflict, although they are equal. This is an undesired effect of the Threshold Approach, since two equal vectors carry the same information, and therefore can not be in conflict. Note that 0.5 is a high value for an upper threshold. In an implementation of the Threshold Approach, such cases should be handled separately.

In Bayesian Identification, the uniform distribution reflects parts of *no information*. Therefore, for any approach no conflict should be present if X or Y is the uniform distribution. For the Distance Approach, only unrealistic high values of ε_{dist} avoid such cases. Concerning this point, the Distance Approach to define conflicts has room for improvement.

3 Coherence and Extended Coherence Approach

Looking for alternatives, the theory of Bayesian networks provides a definition of conflicts according to [JN07, pp. 99, 175-176] and [Las91]. For definition of the *Coherence Approach*, we applied several minor adaptations but kept the basic idea: Correct declarations from a coherent situation covered by the model support each other, and are expected to be positively correlated. Therefore, a conflict between ID source i and all other ID sources can be defined by $\frac{p(d_i)\cdot p(d_1,\ldots,d_{i-1},d_{i+1},\ldots,d_N)}{p(d_1,\ldots,d_N)} > 1 + \varepsilon_{coh}$, i.e.,

$$\frac{\left(\sum_{j=1}^{M} p(d_i|O_j)\cdot\frac{1}{M}\right)\cdot\left(\sum_{j=1}^{M} p(d_1,\ldots,d_{i-1},d_{i+1},\ldots,d_N|O_j)\cdot\frac{1}{M}\right)}{\sum_{j=1}^{M} p(d_1,\ldots,d_N|O_j)\cdot\frac{1}{M}} > 1 + \varepsilon_{coh} \quad (1)$$

for a given threshold $\varepsilon_{coh} > 0$. Note that scaling of likelihood vectors in this approach does not change the defining criterion. Slightly differing from [JN07] we omitted the application of $\log_2$ in formula (1) and introduced the threshold ε_{coh} to suppress small fluctuations. Additionally, we used the uniform distribution $\left(\frac{1}{M}\right)_{j=1,\ldots,M}$ instead of the a priori probabilities $(p(O_j))_{j=1,\ldots,M}$, because we do not want a conflict definition biased by operational a priori expectations.

The Coherence Approach adequately copes with Likelihood vectors SLV_i or CLV_{-i} being the uniform distribution or equal to each other, by correctly assigning no conflict. But bringing M to the other side in line (1) shows a problem of this approach, which to our knowledge has not been addressed in literature on Bayesian networks: The conflict definition crucially depends on M. Therefore, stretching the vectors by adding additional vector components with value 0 to the likelihood vectors lets the source conflict disappear, if M becomes sufficiently large. This property makes the Coherence Approach insufficient for long likelihood vectors, because conflicts need to be more distinctive in order to be recognized.

Next, we are going to refine the Coherence Approach into the *Extended Coherence Approach* in order to correct its problem with large M:
Let us denote $d_{-i} := d_1, \ldots, d_{i-1}, d_{i+1}, \ldots, d_N$. W.l.o.g. we assume

$$\max\left\{\frac{p(d_i|O_{k+1})}{\sum_{j=1}^{M} p(d_i|O_j)}, \frac{p(d_{-i}|O_{k+1})}{\sum_{j=1}^{M} p(d_{-i}|O_j)}\right\} \leq \max\left\{\frac{p(d_i|O_k)}{\sum_{j=1}^{M} p(d_i|O_j)}, \frac{p(d_{-i}|O_k)}{\sum_{j=1}^{M} p(d_{-i}|O_j)}\right\} \quad (2)$$

for all $k = 1, \ldots, M-1$. Then a conflict is given iff there exists $\tilde{M}$ with $2 \leq \tilde{M} \leq M$ and

$$\frac{\left(\sum_{j=1}^{\tilde{M}} p(d_i|O_j)\right) \cdot \left(\sum_{j=1}^{\tilde{M}} p(d_1, \ldots, d_{i-1}, d_{i+1}, \ldots, d_N|O_j)\right)}{\sum_{j=1}^{\tilde{M}} p(d_1, \ldots, d_N|O_j)} > (1 + \varepsilon_{ext}) \cdot \tilde{M} \quad (3)$$

for a given threshold $\varepsilon_{ext} > 0$. The underlying idea of the Extended Coherence Approach is as follows: Scaling SLV_i and CLV_{-i} to sum up to one, does not influence the definition of conflicts by the Coherence Approach. Since most information is coded in the high values of likelihood vector components, at least one of the highest components is involved in a potential conflict. Therefore, a component can be discarded from both likelihood vectors without influencing a conflict if both component values are small. This discarding can be repeated recursively until $\tilde{M} = 2$. If a conflict appears between the reduced likelihood vectors, it has to be considered also as conflict between the full likelihood vectors SLV_i and CLV_{-i}. It can be easily shown, that unlike the two former approaches, this new Extended Coherence Approach appropriately handles the uniform distribution or equal likelihood vectors. By its definition, the Extended Coherence Approach is designed to handle the problem of the Coherence Approach concerning large M.

4 Experimental Comparison of Conflict Definitions

In order to compare the different approaches with the intuitive conflict understanding of experts and with each other, we conducted an experimental comparison. We set up a fictive technical and operational scenario and asked experts to judge combinations of two declarations from different sources, whether they would consider a particular combination as conflict or not. Obviously, without knowledge of the numerical configuration data, the decisions were intuitive, but turned out to be very similar. Using predefined Bayesian configuration data combined with different source/sensor measurement uncertainty levels $\alpha = 1.0, 0.9, 0.8, 0.7, 0.6, 0.5$, each combination of two declarations corresponds to a pair of likelihood vectors SLV_i and CLV_{-i}. We denote, that $\alpha = 1.0$ represents a low and $\alpha = 0.5$ a high measurement uncertainty. Altogether we had 804 pairs of likelihood

Approach:	Threshold	Distance	Coherence	Extended Coherence
Parameter:	$\varepsilon_{up} = 0.369$ $\varepsilon_{low} = 0.151$	$\varepsilon_{dist} = 0.433$	$\varepsilon_{coh} = 0.057$	$\varepsilon_{ext} = 0.254$
$\alpha = 1.0$	(6 / 3 / 3)	(34 / 34 / 0)	(5 / 3 / 2)	(7 / 7 / 0)
$\alpha = 0.9$	(6 / 3 / 3)	(23 / 23 / 0)	(5 / 3 / 2)	(5 / 5 / 0)
$\alpha = 0.8$	(6 / 3 / 3)	(7 / 7 / 0)	(5 / 3 / 2)	(3 / 3 / 0)
$\alpha = 0.7$	(6 / 3 / 3)	(5 / 3 / 2)	(4 / 1 / 3)	(3 / 3 / 0)
$\alpha = 0.6$	(6 / 3 / 3)	(18 / 1 / 17)	(4 / 1 / 3)	(2 / 2 / 0)
$\alpha = 0.5$	(10 / 3 / 7)	(48 / 0 / 48)	(6 / 1 / 5)	(5 / 2 / 3)
Sum for all α	(40 / 18 / 22)	(135 / 68 / 67)	(29 / 12 / 17)	(25 / 22 / 3)

Table 1: Number of deviations (*total / false positive / false negative*) for approach vs. intuition

vectors resulting from fictive but realistic scenarios. Based on the expert's judgements as reference, each pair of likelihood vectors was marked as intuitively conflicting or not. We used the total number of deviations between these intuitive conflicts and the outcome of a conflict-definition approach as quality measure. Note, that the total number of deviations is the sum of false positive and false negative deviations.

By minimizing the total number of deviations for each approach as primary criterion and the number of false negative deviations of the approaches outcome as secondary criterion, the ε-parameters were calibrated. This is due to the fact, that a conflict definition is intended to point out possible problems in identification, and a false positive is far more acceptable than a false negative.

Table 1 shows the four approaches with its ε-parameters as well as the number of deviations between the approach's outcomes and the expert-provided intuitive conflicts. The first entry in the parentheses is the total number of deviations, the second reflects the number of false conflicts provided by the approach (i.e., false positives), and the third entry numbers the conflicts not detected by this approach (i.e., false negatives).

All three of Threshold, Coherence, and Extended Coherence Approaches show good performance with total deviation rates of 4.9%, 3.6%, and 3.1%, whereas the Distance Approach rate of 16.7% is much worse. In addition, the Distance Approach seems to depend more on the level of measurement uncertainty, whereas the other three approaches are very stable. The Coherence Approach is only slightly worse than its extended version. Obviously, the potential problem of the Coherence Approach becomes relevant only for larger M. For $M \leq 6$ the Coherence Approach can be used instead, which is easier to implement. A very low false negative rate is achieved by the Extended Coherence Approach, i.e., almost all conflicts are detected while having only little false positives. Note that changing the parameter ε_{ext} to 0.23 actually provides no false negative at all and only 28 false positive deviations in the 804 cases. This is a very welcome property, on the one hand due to the fact that all problem cases can be detected with only little overhead by false conflicts. Heading for a low false-negative rate calibration criterion on the other hand, it provides an easy proceeding for determination of the ε_{ext}-parameter: Given a Bayesian configuration, an operational user can provide a set of intuitive conflict cases as described above. Then the parameter can be calculated with little effort using formula (3).

5 Conclusions

The considered established approaches of source-conflict definition in Bayesian identification show room for improvement concerning some details. The Coherence and the Extended Coherence Approach were newly proposed as alternative definition of source conflicts. An experimental comparison showed encouraging results for these newly-proposed approaches. In particular, the Extended Coherence Approach appears as a promising candidate for definition of source conflicts, which deserves further research and extended evaluation.

References

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