Decentralised Fusion of Disparate Identity Estimates for Shared Situation Awareness

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Abstract – *Network-centric warfare (NCW) and the interoperability of joint and coalition forces lie among the future warfighting concepts that have been identified by defence. The purpose behind the introduction of such concepts is to "link sensors, engagement systems and decision-makers into an effective and responsive whole, through shared situation awareness, clear procedures and the information connectivity needed to synchronise the actions of the defence force to meet the commander's intent [1]." To realise the goal of shared situation awareness for NCW, it has long been acknowledged that decentralised data fusion is a key enabling technology, and to this end it has been investigated in terms of distributed target tracking and identification, and the development of distributed agents and ontologies. However, the aspects of interoperability relating to the fusion of disparate types of uncertain (local) data from joint and coalition data fusion systems for shared situation awareness do not appear to have been reported on in the open literature; fusion of disparate types of uncertain data has only been considered for centralised fusion systems. In this paper, these facets of data fusion are considered in tandem for the automatic target identification problem. In particular, a novel Bayesian technique is described and demonstrated for fusing estimates of target identity generated by local data fusion systems which employ a mix of Bayesian probability and Dempster-Shafer formalisms.*

Keywords: Target identification, decentralized data fusion, network-centric warfare, interoperability, disparate uncertainty.

1 Introduction

Network-centric warfare (NCW) and the interoperability of joint and coalition forces are amongst the future warfighting concepts that have been identified by defence[1]. The concept of NCW refers to the "linking of sensors, engagement systems and decision-makers into an effective and responsive whole" and is achieved through "shared situation awareness, clear procedures and the information connectivity needed to synchronise the actions of the defence force to meet the commander's intent [1]". Military interoperability on the other hand refers to "the ability of systems, units or forces to provide services to and to accept services from other systems, units or forces and to use the services so exchanged to enable them to operate effectively together [2]". While the two concepts are distinct, it is evident that NCW relies heavily on interoperability.

From the perspective of shared situation awareness, data fusion has much to offer both NCW and military interoperability. It has long been acknowledged that decentralised data fusion is a key enabling technology for NCW, especially in terms of distributed tracking and identification, and more recently the development of distributed agents and ontologies. For discussions of these topics, see for example [3, 4, 5, 6, 7, 8, 9, 10, 11, 12]. There also exists potential for data fusion to assist in realising interoperability in a distributed system by fusing (local) uncertain data of disparate types from the individual joint and coalition data fusion systems (although, to date, this problem has only been considered for centralised fusion systems; see for example [13, 14, 15]). Ideally, for shared situation awareness in a network-centric environment, the system should be capable of performing both aspects of data fusion. Accordingly, as a first step towards this ideal, this paper proposes a technique for performing distributed target identification in the presence of disparate types of uncertainty. In particular, a novel Bayesian technique is described and demonstrated for fusing estimates of target identity generated by local data fusion systems which employ a mix of Bayesian probability and Dempster-Shafer formalisms.

The remainder of the paper is structured as follows. In Section 2, a review of target identification approaches is presented and the precise nature of the target identification under consideration in the paper is stated. In addition, the standard Bayesian and Dempster-Shafer techniques for fusing attribute data are recalled and a novel Bayesian algorithm for decentralised fusion of local Bayesian target identity estimates is proposed. In Section 3, the problem of fusing probabilistic and evidential data is discussed and several approaches for approximating a Dempster-Shafer body of evidence by a probability distribution are outlined and compared. In Section 4, the overall decentralised target identification algorithm is described and an example drawn from the literature is used to demonstrate it. Finally, some concluding remarks are made on possible avenues for further research.

[1]The remaining concept, which is not considered in this paper, is that of effects-based operations. See [1] for details.

2 Target Identity Estimation

Target identification (alternatively, target identity estimation) refers to the general process of inferring the classification or specification of a target based on selected criteria. What is meant by the identity of a target therefore needs to be interpreted in terms of these criteria. For example, target identity may be based on allegiance, such as friend, foe, neutral, suspect, unknown etc, or on the platform category, such as fighter, bomber, tanker, commercial airliner etc. It may also be further refined in terms of the platform type, for example F/A-18, F-111, C130 etc, or even the specific platform model or tail number, for example the observed aircraft is an F-16A with tail number 7632SC [16, p. 17].

With respect to the US JDL Model of Data Fusion (see [17] for details), target identification is generally regarded as a Level 1 process, typically involving the analysis of sensor data collected from a variety of possible sensors including electronic support measures (ESM), forward-looking infrared (FLIR) and synthetic aperture radar (SAR) to name a few. However, there also exist aspects of target identification that are arguably Level 2 processes, such as the incorporation of intelligence information and the exploitation of contextual information used for identification by origin (IDBO), by location (IDBL) or by adherence to normalcy patterns such as is exhibited by commercial aircraft flying along airlanes (refer to [18, 19]).

Because of the broad nature of target identification, there are numerous algorithms for performing target identification. According to the taxonomy suggested in [20, p. 215], the algorithms may be placed into three major categories, namely *physical models*, *parametric classifi cation techniques* and *cognitive-based models*. The parametric classification techniques category can be further decomposed into the sub-categories of *information-theoretic techniques* and *statistical-based algorithms*. It is the statistical-based algorithms sub-category, which includes Bayesian and Dempster-Shafer reasoning, that is the focus of the current paper.

2.1 Problem Formulation and Notation

Consider a target T that is moving through a surveillance region in which a network of n sensors has been deployed for the purpose of identifying T. For example in an air defence scenario, T may be an airborne target and each node in the sensor network may correspond to the radar warning receiver or ESM kit onboard a fighter in a "networked" n-ship. Let $\Omega = \{x_1, \dots, x_k\}$ denote the set of possible target types and $\{S_1, \dots, S_n\}$ denote the set of sensors in the network. For the sensor data, let $\{y_i^1\}$ denote the current measurement from sensor S_i, Y_i^0 denote the set of all previous measurements from sensor S_i and Y_i^1 $(= \{y_i^1\} \cup Y_i^0)$ denote the set of all measurements from sensor S_i up to and including the current time. Then the problem is to ascertain the target type x_j of T given all the available sensor measurements. For the treatment of the problem in the current paper, the following assumptions are made:

1. (Closed-World Assumption) The set Ω of target types is exhaustive and is used by the (local) target identification algorithms at each node;
2. Each node in the sensor network is connected directly to every other node; and
3. All of the measurements from any given sensor are independent of all of the measurements from every other sensor.

Based on this formulation, it is possible to derive a general Bayesian approach for performing decentralised target identity estimation which does not directly involve measurements, but rather *a priori* and *a posteriori* probabilities. As reasoned in Section 2.4, this may be the preferred option for NCW. However, to be able to employ the algorithm and ensure interoperability across the nodes in the network, it is necessary that the local identity estimates at each node be represented ultimately as an *a posteriori* probability distribution. In reality, it cannot be guaranteed that the local target identity estimates will already be in this form, since the local target identity estimation at any given node may employ some other formalism for its processing. A general treatment of this aspect of the problem is beyond the scope of the paper. Instead, the special case in which local identity estimates at each node are directly determined as an *a posteriori* probability distribution or as a Dempster-Shafer body of evidence is considered. The following sections establish the background on these topics required for the rest of the paper.

2.2 Bayesian Approach

In the standard Bayesian approach [4], the *a posteriori* probability of each target type given the totality of measurements is calculated recursively via Bayes' theorem and then the maximum *a posteriori* probability (MAP) principle is used to declare a target type if a hard decision is required. To illustrate this in more detail, suppose that the local data processing at node i for target identification employs the Bayesian approach. Then, by Bayes' theorem, for each target type x_j

$$
\begin{aligned}
p(x_j \mid Y_i^1) &= p(x_j \mid y_i^1, Y_i^0) && (1)\\
&= \frac{p(y_i^1 \mid x_j, Y_i^0)\, p(x_j \mid Y_i^0)}{p(y_i^1 \mid Y_i^0)} && (2)\\
&= C^{-1} p(y_i^1 \mid x_j)\, p(x_j \mid Y_i^0) && (3)
\end{aligned}
$$

where $p(y_i^1 \mid x_j)$ is the likelihood of observing measurement y_i^1 if the true target type is x_j, and $p(x_j \mid Y_i^0)$ is the *a priori* probability[2] that the target type is x_j. Note that the term $C = p(y_i^1 \mid Y_i^0)$ is constant with respect to x_j and so is easily found by using the fact that the *a posteriori* probabilities must sum to 1.

Having updated the *a posteriori* probabilities, the MAP principle may be invoked to declare the target type as x_κ where

$$\kappa = \arg\{\max_{j=1,\dots,k}\{p(x_j \mid Y_i^1)\}\}. \tag{4}$$

[2] To initiate the process in the absence of any measurements, typically a non-informative (i.e. uniform) *a priori* distribution with $p(x_j \mid \varnothing) = 1/k$ is assumed for the set of target types.

2.3 Dempster-Shafer Approach

In the standard Dempster-Shafer approach [21], evidence about the target identity from each sensor measurement is represented as a body of evidence $\langle \mathcal{F}, m \rangle$ comprising a set of *focal elements* $\mathcal{F}$ and a *basic belief assignment* m on the set of target types Ω (which is referred to as the *frame of discernment*). With each new sensor observation, the body of evidence representing the measurement is typically combined with the previously pooled evidence via Dempster's rule of combination to produce an updated body of evidence that incorporates all the evidence from the totality of measurements to date. Finally, to declare a target type if necessary, the pignistic probability approach described in Section 3.1.1 is often used. To illustrate this in more detail, suppose that the local target identification algorithm at node i employs Dempster-Shafer reasoning. Then, denoting the body of evidence for the current measurement y_i^1 as $\langle \mathcal{F}_{y_i^1}, m_{y_i^1} \rangle$ and the pooled body of evidence from the the previous measurements[3] as $\langle \mathcal{F}_{Y_i^0}, m_{Y_i^0} \rangle$, the body of evidence for the updated target identity evidence is calculated via Dempster's rule of combination as follows. For each subset A of Ω, the updated basic belief assignment is

$$m_{Y_i^1}(A) = \frac{1}{(1-K)} \sum_{F \cap G = A} m_{y_i^1}(F).m_{Y_i^0}(G) \quad (5)$$

where

$$K = \sum_{F \cap G = \varnothing} m_{y_i^1}(F).m_{Y_i^0}(G) \quad (6)$$

and in both cases $F \in \mathcal{F}_{y_i^1}$ and $G \in \mathcal{F}_{Y_i^0}$. The updated set of focal elements is

$$\mathcal{F}_{Y_i^1} = \{F \cap G \mid F \in \mathcal{F}_{y_i^1}, G \in \mathcal{F}_{Y_i^0}, F \cap G \neq \varnothing\}. \quad (7)$$

Having updated the pooled body of evidence, the MAP principle may be applied to its pignistic probability distribution $\{\text{BetProb}_{Y_i^1}(x_j)\}$ (refer to Section 3.1.1) to declare the target type as x_κ where

$$\kappa = \arg(\max_{j=1,\dots,k} \text{BetProb}_{Y_i^1}(x_j)). \quad (8)$$

2.4 Bayesian Fusion with *A Posteriori* and *A Priori* Probabilities

In the last two sections, the Bayesian and Dempster-Shafer approaches to the processing of sensor measurements for updating target identity estimates locally at each individual node were reviewed in brief. To fuse the measurements from all of the nodes to produce a global target identity estimate, there are a number of approaches. One approach is to produce a global estimate by fusing the measurements at a central node; this is aptly named *centralised identity fusion*. To produce a global estimate by any other means is referred to as *decentralised identity fusion*. In the centralised approach, all of the sensor measurements are sent to the central node for processing where they are fused recursively for example by using Bayes' rule or Dempster's rule of combination. The main decentralised option is to fuse the measurements locally at each node as previously described and then fuse the local target identity estimates to produce a global target identity estimate. While the centralised approach is easier to implement, it is more vulnerable than the decentralised option described because the loss of the central node would result in the total breakdown of the network. Under the decentralised approach, the network would continue to function even if multiple $(< n)$ nodes were lost, with the added benefit that each node could continue to function autonomously if necessary. For these reasons it may be argued that, in the context of NCW, the decentralised approach is the preferred option. Accordingly, in the remainder of this section, a novel algorithm is presented for performing decentralised Bayesian target identification in the manner described (subject to the assumptions made in Section 2.1).

To derive an appropriate update equation, suppose that m of the n sensors $S_{i_1}, S_{i_2}, \dots, S_{i_m}$ have each made single observations since the previous global target identity estimate of each target type x_j

$$p(x_j \mid Y_1^0, \dots, Y_n^0) \quad (9)$$

was calculated. To determine the updated global estimate in Expr. 10 from the previous global estimate in Expr. 9, the following reasoning may be employed cf. [22, p. 11]:

$$\begin{aligned} & p(x_j \mid Y_{i_1}^1, \dots, Y_{i_m}^1, Y_{i_{m+1}}^0, \dots, Y_{i_n}^0) && (10)\\ = \ & p(x_j \mid y_{i_1}^1, \dots, y_{i_m}^1, Y_1^0, \dots, Y_n^0) && (11)\\ = \ & C_1^{-1} p(y_{i_1}^1, \dots, y_{i_m}^1 \mid x_j, Y_1^0, \dots, Y_n^0) \times \\ & p(x_j \mid Y_1^0, \dots, Y_n^0). && (12) \end{aligned}$$

The last Expr. 12 follows by Bayes' theorem, where the term $C_1 = p(y_{i_1}^1, \dots, y_{i_m}^1 \mid Y_1^0, \dots, Y_n^0)$ is independent of x_j. Since the measurement $y_{i_r}^1$ for each $r = 1, \dots, m$ is independent of the measurements in each set $Y_k^0 (k \neq i_r)$, Expr. 12 can be rewritten as:

$$C_1^{-1} \left[\prod_{r=1}^{m} p(y_{i_r}^1 \mid x_j, Y_{i_r}^0) \right] p(x_j \mid Y_1^0, \dots, Y_n^0). \quad (13)$$

Applying Bayes' theorem once more to each of the terms in the bracketed product gives

$$\begin{aligned} & C_1^{-1} \left[\prod_{r=1}^{m} \frac{p(x_j \mid y_{i_r}^1, Y_{i_r}^0) p(y_{i_r}^1 \mid Y_{i_r}^0)}{p(x_j \mid Y_{i_r}^0)} \right] \times \\ & p(x_j \mid Y_1^0, \dots, Y_n^0) && (14)\\ = \ & C_2 \left[\prod_{r=1}^{m} \frac{p(x_j \mid Y_{i_r}^1)}{p(x_j \mid Y_{i_r}^0)} \right] p(x_j \mid Y_1^0, \dots, Y_n^0) && (15) \end{aligned}$$

[3] Unlike the Bayesian approach which requires an initial *a priori* distribution of target types to be set, no such initial conditions are required for the Dempster-Shafer approach because the body of evidence for the first measurement is regarded as the first update. However, if desired, the *vacuous* body of evidence $\langle \mathcal{F}_\varnothing, m_\varnothing \rangle$ with $\mathcal{F}_\varnothing = \{\Omega\}$ and $m_\varnothing(\Omega) = 1$ may be used to represent the "initial pooled evidence" in the absence of any measurements [21, p. 38]. The results are the same either way.

where $C_2 = C_1^{-1} \prod_{r=1}^{m} p(y_{i_r}^1 \mid Y_{i_r}^0)$ is independent of x_j. Since Expr. 15 is equal to the global *a posteriori* estimate of x_j in Expr. 9 and it involves only the local *a posteriori* and *a priori* estimates and the global *a priori* global estimate of x_j, together the two expressions provide a suitable update equation. (It is noted that, as in the standard Bayesian approach, the value of C_2 can be found by using the fact that all of the *a posteriori* probabilities must sum to 1.)

3 Fusion of Discrete Uncertain Data of Disparate Types

In Section 2, the network-centric aspects of the decentralised target identification problem were discussed. In this section, the interoperability issue of fusing finite datasets with disparate types of uncertainty is addressed.

In the literature, two main techniques for handling disparate uncertain data have been reported. The first is the unified approach such as that taken in random set theory [14, 23] which seeks to represent different forms of uncertainty, for example probabilistic, evidential and possiblistic (fuzzy), as specialisations of a general theory of uncertainty. The other approach involves transforming data from one type of uncertainty to another [15, 24, 25, 26].

In the particular case of fusing a finite Bayesian probability distribution $\{p(x_j \mid Y_{i_1}^1)\}_{j=1}^k$ and a Dempster-Shafer body of evidence $\langle \mathcal{F}_{Y_{i_2}^1}, m_{Y_{i_2}^1} \rangle$ defined on the same frame of discernment Ω, there are several options. One is to ignore the *a priori* information available from the Bayesian distribution and simply regard it as a body of evidence $\langle \mathcal{F}_{Y_{i_1}^1}, m_{Y_{i_1}^1} \rangle$ which may then be fused with $\langle \mathcal{F}_{Y_{i_2}^1}, m_{Y_{i_2}^1} \rangle$ using Dempster's rule of combination. A second option is to try to incorporate the *a priori* information as generalised likelihoods in the fusion of the Bayesian distribution and the body of evidence either by regarding them both as random sets and using techniques described in [14] or [23], or by regarding them both as belief functions and using techniques described in [7]. A third option is to transform the body of evidence $\langle \mathcal{F}_{Y_{i_2}^1}, m_{Y_{i_2}^1} \rangle$ into a probability distribution on Ω. By regarding each term in this distribution as an *a posteriori* probability $p(x_j \mid Y_{i_2}^1)$ for the appropriate x_j, it may be fused with $p(x_j \mid Y_{i_1}^1)$ using the technique in Section 2.4. This is the approach that is investigated in the remainder of the paper.

In the sequel, three techniques for transforming a body of evidence into a probability distribution are outlined and compared.

3.1 Approximating Bodies of Evidence by Probability Distributions

3.1.1 Pignistic Probability Approach

The first of the techniques for approximating a body of evidence by a probability distribution is that based on *pignisitic probabilities*, which play an integral part in Smets and Kennes [27] *transferable belief model* (TBM). The TBM is their interpretation of the Dempster-Shafer model and employs the same representation of beliefs via bodies of evidence (or equivalently belief functions), but it incorporates additional conjunctive, disjunctive and conditioning functions for manipulating evidence beyond Dempster's rule of combination alone. The TBM is a two-level model. The *credal level* is used to represent and manipulate beliefs using belief functions and Dempster's rule of conditioning as has already been outlined, while the *pignistic level* is used for decision making. At the pignistic level, the process for decision making is to use the beliefs at the credal level to construct a probability distribution on Ω - the *pignistic probability distribution* - and then to apply the MAP principle to the distribution for making the decision. The pignistic probability distribution BetProb is constructed by setting

$$\mathrm{BetProb}(x_j) = \sum_{F \in \mathcal{F} \mid x_j \in F} m(F)/|F|, \tag{16}$$

for each $x_j \in \Omega$, where $\mathcal{F}$ denotes the set of all focal elements in the body of evidence [27, p. 202].

3.1.2 Bayesian Approximation Approach

The second technique is based on Voorbraak's approximation of a body of evidence [28]. The associated probability distribution is similar in form to the pignistic probability distribution. The motivation for its definition was not decision making though, but rather the problem of reducing the computational complexity of reasoning with bodies of evidence. While a more common strategy for this problem is to prune the set of focal elements and redistribute the masses from the pruned elements [29], Voorbraak instead approximated the body of evidence by replacing its basic belief assignment m with a Bayesian basic belief assignment[4] $\underline{m}$ such that for each subset A of Ω

$$\underline{m}(A) = \begin{cases} \frac{\sum_{A \subseteq F \in \mathcal{F}} m(F)}{\sum_{F \in \mathcal{F}} m(F)|F|} & \text{if } |A| = 1, \\ 0 & \text{otherwise} \end{cases} \tag{17}$$

where $\mathcal{F}$ denotes the set of all focal elements in the body of evidence. The basic belief assignment $\underline{m}$ is referred to as the *Bayesian approximation* of m and the denominator $\sum_{F \in \mathcal{F}} m(F)|F|$ in each term is known as the *Bayesian constant* for m. It can be shown that $\underline{m}$ possesses the property that

$$\underline{m_1 \oplus m_2} = \underline{m_1} \oplus \underline{m_2}, \tag{18}$$

where $\oplus$ denotes the operator for Dempster's rule of combination, and so the order in which the approximations and combinations are performed does not influence the final result [30]. Strictly speaking, the function $\underline{m}$ is a basic belief assignment defined on the power set $\wp(\Omega)$, but in Section 3.1.4 it is regarded as a probability distribution on Ω.

3.1.3 Aggregated Uncertainty Approach

The final technique arises from the aggregated uncertainty (AU) measure in Dempster-Shafer theory (based on the

[4] A basic belief assignment is said to be *Bayesian* if and only if all of its focal elements are singletons [21, pp. 19, 54].

Shannon entropy) which was proposed independently by Maeda, Nguyen and Ichihashi [31] and Harmanec and Klir [32]. Given a body of evidence $\langle \mathcal{F}, m \rangle$, its aggregated uncertainty is defined to be [31, 32]

$$AU(m) = \max\{\sum_{j=1}^{k} f(x_j)\} \tag{19}$$

where

$$f(x_j) = \begin{cases} -p(x_j)\log_2 p(x_j) & \text{if } p(x_j) > 0, \\ 0 & \text{if } p(x_j) = 0. \end{cases} \tag{20}$$

and the maximum is taken over all $\{p(x_j)\}$ such that $p(x_j) \in [0, 1]$ for all $x_j \in \Omega$, $\sum_{j=1}^{k} p(x_j) = 1$, and for all $A \subseteq \Omega$, $Bel(A) \leq \sum_{x_j \in A} p(x_j)$. The unique set $\{p(x_j)\}$ at which the maximum is realised is the *AU probability distribution*. It is noted that the aggregated uncertainty $AU(m)$ of $\langle \mathcal{F}, m \rangle$ is simply the Shannon entropy of the AU probability distribution. An algorithm for computing the AU probability distribution is presented in Appendix A (for further details, refer to [25, 32, 33]).

3.1.4 Comparison of the Three Approximation Techniques

To date, attempts at meaningfully comparing the three techniques theoretically have been fruitless, so the comparisons made here are mainly qualitative and are based on empirical results and properties of the individual techniques.

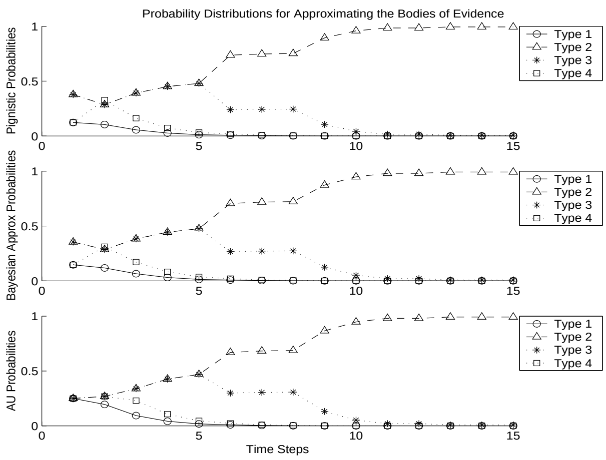

Fig. 1: Probability distributions for Sensor 1 in the example given in Section 4

First, it is noted that in practice the probability distributions produced by the three techniques appear to be very similar. This similarity has been observed repeatedly without exception over a large number of runs and is illustrated for a single case in Fig. 1 using the model for sensor 1 in the problem analysed in Section 4. However, despite this similarity, it has also been repeatedly observed that for the most strongly supported target type $x_j \in \Omega$, its probability is greatest in the pignistic probability distribution, followed by the Bayesian approximation and finally the AU probability distribution. This may possibly be explained in part by the fact that the pignistic probability distribution has been developed specifically for decision-making purposes, and so would be expected to give the best discernment. Furthermore, with regard to the AU measure, examination of the algorithm for its calculation (refer to the Appendix) reveals that in Step 2, multiple target types x_j may be assigned the same probability and so the AU probability distribution may be expected to give the poorest discernment. Ultimately though, these distinctions are at best marginal and soon vanish after several iterations.

Therefore the selection of an approximation technique is best made based on the individual properties of the probability distributions. The AU probability distribution has the benefit that there is no loss of uncertainty-based information (as measured by the AU uncertainty) in using it to approximate the body of evidence. However, it is far more computationally expensive to calculate than the other two distributions because it requires knowledge of the belief of each subset of Ω, while the other two only require knowledge of the basic belief assignment. The pignistic approximation is desirable because it has a sound theoretical basis. Finally, the Bayesian approximation is desirable because of the property stated in Eq. 18 which is useful for data fusion systems that may be susceptible to data latency (out of sequence data) problems.

Given all these considerations, a single approximation technique is used for testing in the next section because the results are expected to be similar across all the techniques. In particular, the AU probability distribution is used in the fusion problems for two reasons. First it provides the most conservative approximation and is therefore less likely to furnish overly optimistic results and second data latency is not an issue.

4 Decentralised Target Identification Algorithm

The results established in Sections 2 and 3 can now be combined to give the following algorithm for decentralised target identification involving the fusion of local target identity estimates based on either Bayesian or Dempster-Shafer reasoning.

Initialisation: Initialise the values of each of the *a priori* probabilities $p(x_j \mid Y_1^0, \ldots, Y_n^0)$ and $p(x_j \mid Y_i^0)$ for all $i = 1, \ldots, n$ and $j = 1, \ldots, k$ and disseminate them throughout the whole network. Then proceed to Step 1 if an observation is made at one of the nodes.

Step 1: If the observation is made at node i_1, use the measurement $y_{i_1}^1$ to calculate the local *a posteriori* probability distribution $\{p(x_j \mid Y_{i_1}^1)\}_{j=1}^k$ or body of evidence $\langle \mathcal{F}_{Y_{i_1}^1}, m_{Y_{i_1}^1} \rangle$, in accordance with the reasoning scheme in use at that node.

Step 2: If node i_1 employs Dempster-Shafer reasoning, transform the body of evidence in Step 1 to an *a posteriori* probability distribution $\{p(x_j \mid Y_{i_1}^1)\}_{j=1}^k$ using one of the techniques in Section 3.

Step 3: Communicate the local *a posteriori* probability distribution to each of the other nodes.

Step 4: Use the update equation that was developed in Section 2.4 to calculate the global *a posteriori* probabilities $p(x_j \mid Y_{i_1}^1, Y_{i_2}^0, \ldots, Y_{i_n}^0)$ for each $j = 1, \ldots, k$.
Step 5: Reset the values of each of the *a priori* probabilities $p(x_j \mid Y_{i_1}^0, \ldots, Y_{i_n}^0)$ and $p(x_j \mid Y_i^0)$ for all $j = 1, \ldots, k$ to $p(x_j \mid Y_{i_1}^1, Y_{i_2}^0, \ldots, Y_{i_n}^0)$ and $p(x_j \mid Y_i^1)$ respectively for the next iteration.
Step 6: If a new observation is made at one of the nodes, return to Step 1 and repeat the process.

In what follows, the algorithm is tested and evaluated using a problem drawn from the literature.

4.1 Example

The example in this section is drawn from [34, pp. 533-551] and involves the identification of a target which is one of four different types. Two fictitious sensors are used in the identification process. For each i, sensor i observes a single fictitious feature f_i of the target. The partial probability databases for the features are illustrated in Figs. 2 and 3. In each figure, the horizontal axis indicates the range of possible values that the feature may assume. For each type, the light and dark bars indicate possible modes that a target of that type may operate in and the vertical heights of the bars indicate the probabilities of those modes being used; for each target type in this example the use of the modes is equiprobable.

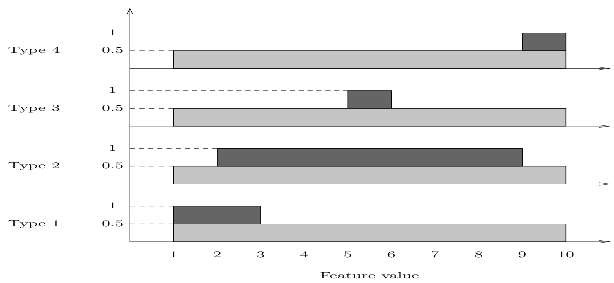

Fig. 2: Partial Probability Database for Sensor 1

It is noted that based on feature f_1, type 3 is a subclass of type 2, type 1 is partially distinguishable from type 2 and type 4 is the most distinct. Similarly, based on feature f_2, type 1 is a subclass of type 4, type 3 is partially distinguishable from type 4 and type 2 is the most distinct class. If the true target type is type 3, using sensor 1 alone it is not possible to identify it uniquely. However, with the help of sensor 2's data, this ambiguity can be resolved.

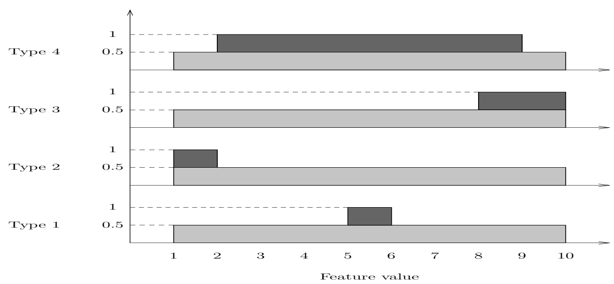

Fig. 3: Partial Probability Database for Sensor 2

The example as described has been adapted for the purposes of the paper in the following way. The two sensors are regarded as the two nodes in a network. At each node, local target identity estimates are generated in the form of Dempster-Shafer bodies of evidence. At each time instant, the sensor at each node makes a single observation and the updated local estimates are used in turn to update the global target identity estimates via the algorithm at the beginning of Section 4. In [34], two distinct techniques are described for generating synthetic data in the form of bodies of evidence which conform to the partial probability databases. These are known as the *power set* (PS) and *typical set* (TS) approaches (for detailed explanations of the approaches, refer to Sections 8.5.7 and 8.5.8 of [34]). Hence, three separate cases have been considered. In each case the true target type is known to be type 3. For case 1, the typical set approach is employed for generating the synthetic measurements and target identity estimates at both nodes. For case 2, the power set approach is employed at both nodes; and for case 3, the power set approach is employed at node 1 and the typical set approach is employed at node 2. The results of these simulations are displayed in Figs. 4, 5 and 6. In each case, sensor 1 has misclassified the target as expected. For cases 1 and 3, sensor 2 has not been able to decide between types 2 and 3. However, in all three cases, the results from the fused identity estimates from the two sensors have correctly identified the target type (although in case 2, this decision has taken substantially longer to make).

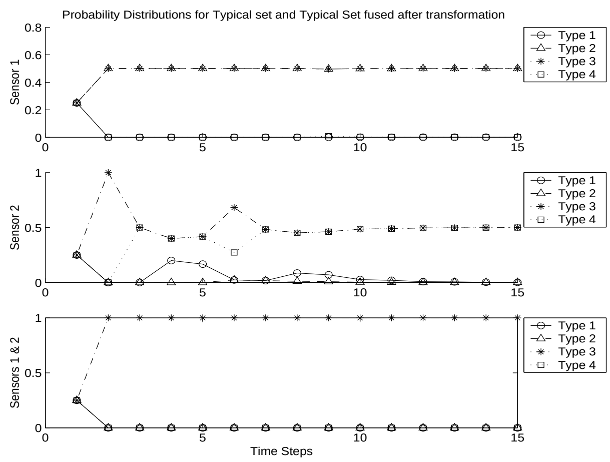

Fig. 4: *A posteriori* probability distributions (TS-TS case) following decentralised Bayesian fusion

Finally, for the sake of comparison, in each case the local estimates from each sensor were also fused using Dempster's rule of combination and then transformed into a probability distribution. In cases 1 and 2, the results were almost identical to those obtained for the decentralised Bayesian fusion approach. However, the results in case 3 shown in Fig. 7 were markedly worse when Dempster's rule of combination was used. The correct target identification of type 3 was eventually made, but long after it had been made by the decentralised Bayesian fusion approach which identified the target correctly at the second time step. In summary, the results of the testing on the decentralised Bayesian fusion algorithm are very encouraging.

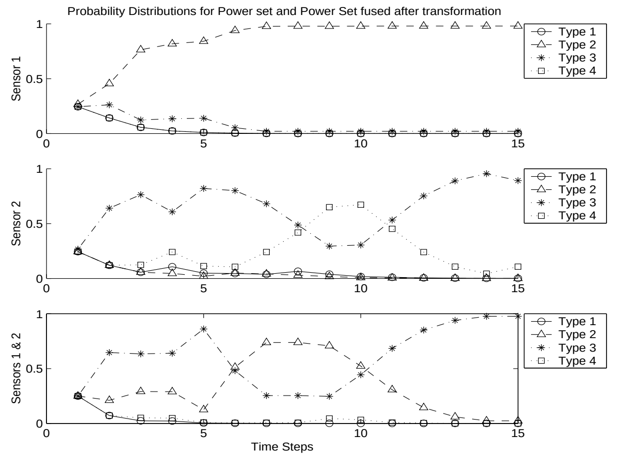

Fig. 5: *A posteriori* probability distributions (PS-PS case) following decentralised Bayesian fusion

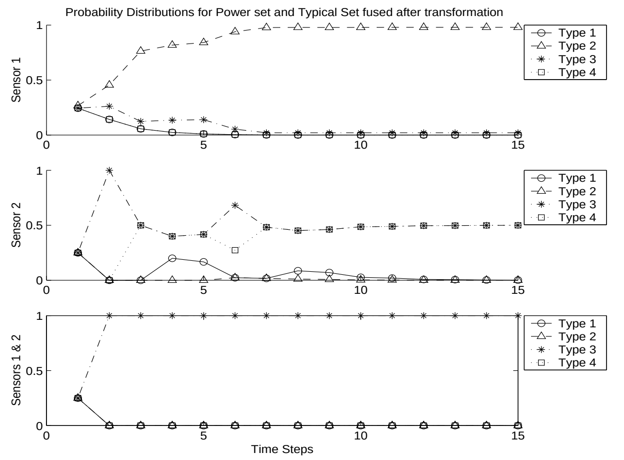

Fig. 6: *A posteriori* probability distributions (PS-TS case) following decentralised Bayesian fusion

5 Conclusion

In the context of network-centric warfare and military interoperability, the problem of performing decentralised target identification using disparate uncertain data has been investigated. In particular, a target identification algorithm has been proposed for fully connected networks in which local target identity estimates at each node are directly calculated as either *a posteriori* probability distributions or Dempster-Shafer bodies of evidence. The main features of the algorithm include a novel formulation for updating global identity estimates from local *a posteriori* and *a priori* estimates and a technique for fusing finite Bayesian probability distributions with Dempster-Shafer bodies of evidence based on uncertainty transformations. The algorithm has been tested on a small, yet challenging, problem drawn from the literature with encouraging results being achieved. Finally, it is noted that the technique may be extended to accommodate other forms of uncertainty, such as possibilistic uncertainty, providing suitable uncertainty transformations exist (for examples of possibility-probability transformations, see [15, 24, 25]).

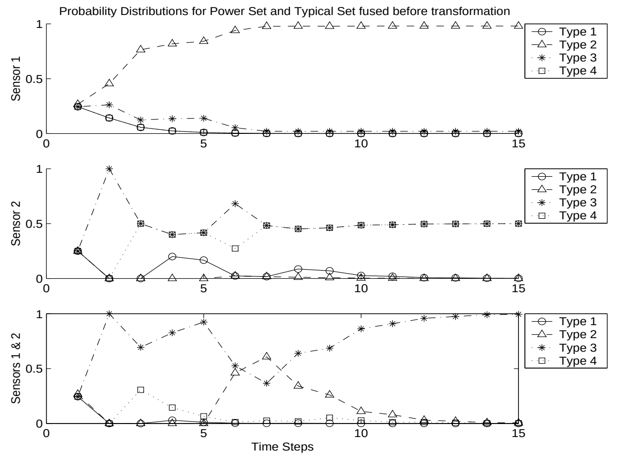

Fig. 7: *A posteriori* probability distributions (PS-TS case) following Dempster-Shafer fusion

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A Appendix: Algorithm for Calculating the Aggregated Uncertainty

Input: A frame of discernment Ω and a belief function Bel on Ω.
Output: The measure $AU(m)$ and the probability distribution $\{p(x_j)\}$ giving rise to the value of AU.
Step 1: Find a non-empty set $A \subseteq \Omega$ such that $\frac{Bel(A)}{|A|}$ is maximal. If more than one such set exists, select the one with maximal cardinality.
Step 2: For each $x_j \in A$, set $p(x_j) = \frac{Bel(A)}{|A|}$.
Step 3: For each $B \subseteq (\Omega \setminus A)$, set $Bel(B) = Bel(B \cup A) - Bel(A)$.
Step 4: Set $\Omega = \Omega \setminus A$.
Step 5: If $\Omega \neq \varnothing$ and $Bel(\Omega) > 0$, then go to Step 1.
Step 6: If $Bel(\Omega) = 0$ and $\Omega \neq \varnothing$, then set $p(x_j) = 0$ for all $x_j \in \Omega$.
Step 7: Calculate $AU(m) = \sum_{j=1}^{k} f(x_j)$ where $f(x_j)$ is the function specified in Eq. 20.
Stop.

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