Imprecise Probability as an Approach to Improved Dependability in High-Level Information Fusion

Alexander Karlsson, Ronnie Johansson, and Sten F. Andler

School of Humanities and Informatics, University of Skövde, Sweden
{alexander.karlsson, ronnie.johansson, sten.f.andler}@his.se

Summary. The main goal of information fusion can be seen as improving human or automatic decision-making by exploiting diversities in information from multiple sources. High-level information fusion aims specifically at decision support regarding situations, often expressed as "achieving situation awareness". A crucial issue for decision making based on such support is trust that can be defined as "accepted dependence", where dependence or dependability is an overall term for many other concepts, e.g., reliability. This position paper reports on ongoing and planned research concerning imprecise probability as an approach to improved dependability in high-level information fusion. We elaborate on high-level information fusion from a generic perspective and a partial mapping from a taxonomy of dependability to high-level information fusion is presented. Three application domains: defense, manufacturing, and precision agriculture, where experiments are planned to be implemented are depicted. We conclude that high-level information fusion as an application-oriented research area, where precise probability (Bayesian theory) is commonly adopted, provides an excellent evaluation ground for imprecise probability.

1 Introduction

Information fusion (IF) is a research field that has been tightly coupled with defense applications (e.g., [27]) for many years. However, recently researchers in other domains such as manufacturing (e.g., [38]) and precision agriculture (e.g., [34]) have started to recognize the benefits of IF. IF, sometimes also referred to as data fusion, can be depicted as done by Dasarathy [13].

> *"Information fusion encompasses the theory, techniques, and tools conceived and employed for exploiting the synergy in the information acquired from multiple sources (sensor, databases, information gathered by human etc.) such that the resulting decision or action is in some sense better (qualitatively and quantitatively, in terms of accuracy, robustness and etc.) than would be possible, if these sources were used individually without such synergy exploitation."*

From Dasarathy's description, it is seen that the overall goal is to improve decision making, and since there most often exist uncertainty regarding decisions, it

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can be concluded that *uncertainty management* is crucial to IF. In fact, it has even been argued that the main goal of an IF system is to reduce uncertainty [9]. Many methods for handling uncertainty in the IF domain are based on *Bayesian theory*, e.g., *Kalman filtering* [16] and *Bayesian networks* (BNs) [6].

Most research in the IF domain so far has addressed problems in low-level IF, e.g., *target tracking* by *multi-sensor fusion*, while the higher abstraction levels of reasoning, referred to as *high-level information fusion* (HLIF), have been a relatively uncharted research field. Furthermore, those attempts that do exist for HLIF rarely address *dependability* issues (cf. [36]).

In this position paper, we elaborate on HLIF from a generic perspective and a partial mapping from a taxonomy of dependability to HLIF is presented. We argue for imprecise probability as an interesting approach for improved dependability in HLIF, and that more research on this topic is needed. We also argue for the importance of more research on deployment of methods based on imprecise probabilities in "real-world" applications.

The paper is organized as follows: in Sect. 2, we depict the foundations of IF. A thorough description of HLIF is presented in Sect. 3. In Sect. 4, we describe a partial mapping from a taxonomy of dependability to HLIF. Imprecise probability as an approach to improved dependability in HLIF is described in Sect. 5. Three application domains, *defense*, *manufacturing*, and *precision agriculture*, for evaluation of imprecise probability, are presented in Sect. 6. Lastly, in Sect. 7, we argue for the importance of evaluation of imprecise probability in comparison with precise probability (Bayesian theory) through experiments in "real-world" applications.

2 Information Fusion

In order to allow for easy communication among researchers of IF, the *Joint Directors of Laboratories* (JDL) data fusion group has established a model that comprises the IF domain [43]. The model, referred to as the *JDL model*, has been revised many times (e.g., [35, 26]), either due to the lack of some important aspect of IF, or for the purpose of making it more general. Steinberg et al. [35] have presented the following variant of the JDL model, hereafter referred to as the *revised JDL model*, with five functions or levels:

- **Level 0 – Sub-Object Data Assessment:** estimation and prediction of signal observable states
- **Level 1 – Object Assessment:** estimation and prediction of entity states, based on observation-to-track association
- **Level 2 – Situation Assessment:** estimation and prediction of relations among entities
- **Level 3 – Impact Assessment:** estimation and prediction of effects of actions on situations
- **Level 4 – Process Refinement:** continuous improvement of the information fusion process

The claim that uncertainty management is crucial to IF is here reinforced since words such as *estimation* and *prediction* appear in all of the levels except Level 4. With HLIF, we refer to Level 2, 3, and with low-level IF to Level 0, 1, in the revised JDL model. The reason to not include Level 4 in HLIF, is that it may be regarded as a *meta-process* that is a part of all levels, i.e., refinement of processes at each level.

3 High-Level Information Fusion

The aim of high-level information fusion (HLIF) is to establish the current *situation*, and possible *impacts* of that situation conditional on a *set of actions*. Since HLIF mainly has addressed issues in the defense domain, we here elaborate on it from a generic perspective. A terminology for HLIF that captures concepts such as *situations* and *impacts* is presented. It should be noted that there exists a framework, referred to as *situation theory* [14] for which there are some similarities to the terminology that we introduce here, e.g., that situations are about relations (this can also be seen from the revised JDL model). Kokar et al. [24] have developed an *ontology* for situation awareness that is based on situation theory and which is referred to as *situation awareness ontology* (STO). However, uncertainty is not the main focus of the above framework; thus, the concepts introduced here aim at providing a generic and clear understanding of HLIF from the perspective of uncertainty.

3.1 Level 2 – Situation Assessment

As can be seen from the revised JDL model, the main concern in Level 2 – Situation Assessment – is *relations among entities*. As noted by Kokar et al. [23, 24], a binary relation in mathematics, denoted by $\mathcal{R}$, has the following structure:

$$\mathcal{R} \subseteq X \times Y \tag{1}$$

$$X \times Y \overset{def.}{=} \{(x, y) : x \in X, y \in Y\} \tag{2}$$

However, in order to allow other relations than binary, it is necessary to consider *n-ary* relations that can be formally depicted as, cf. [24]:

$$\mathcal{R} \subseteq X_1 \times \ldots \times X_n \tag{3}$$

$$X_1 \times \ldots \times X_n \overset{def.}{=} \{(x_1, \ldots, x_n) : x_i \in X_i\} \tag{4}$$

A relation can be defined *intensionally* by a predicate P that decides which n-tuples that actually belong to the relation [24]:

$$\mathcal{R} \overset{def.}{=} \{(x_1, \ldots, x_n) : P(x_1, \ldots, x_n),\ x_i \in X_i\} \tag{5}$$

The relations that are of interest in HLIF, are usually not observable in a direct way; thus, uncertainty regarding the predicate, and hence the relation, is most often evident. As Kokar et al. [24] have also noted, and which can be seen from the revised JDL model [35], a situation can consist of more than one relation. Consequently, it is necessary to interpret a situation as a *set of relations* denoted by $\mathcal{S}$ and more formally stated as:

$$\mathcal{S} \overset{def.}{=} \{\mathcal{R}_1, \ldots, \mathcal{R}_k\} \tag{6}$$

One may think of the relations as representing different *concepts* that for some reason are needed by a decision maker in order to make a decision about situations in a particular application domain.

Since there most often exists uncertainty regarding which n-tuples that satisfy the predicate for a given relation in HLIF; it is necessary to be able to consider the elements of the relation as *hypotheses*, which we here denote by $(x_1, \ldots, x_n)_j^h$ to indicate that it is a hypothesis with respect to a specific relation $\mathcal{R}_j$, $1 \leq j \leq k$. Since the elements of a given relation $\mathcal{R}_j$ now can be considered as hypotheses, it is also necessary to consider the relation itself as such, a *relational hypothesis*, denoted by $\mathcal{R}_j^h$. Lastly, since a situation $\mathcal{S}$ is defined using relations that may be hypotheses, a situation can also be a hypothesis, denoted by $\mathcal{S}_i^h$, $i \in \mathcal{J}_\mathcal{S}$, where $\mathcal{J}_\mathcal{S}$ is an index set.

Let the set of available information (sensor readings, domain knowledge and stored information) be denoted by ξ. Note that ξ may contain information that is uncertain, e.g., information from an unreliable source, imprecise, i.e., information which in some sense refers to more than one possibility, and inconsistent, e.g., information sources are in conflict [7] (for more detail, see [22, Sect. II-A1]). We will here use *belief* as a generic term for quantifying a rational agent's belief, thus, belief in the above sense is not associated with any particular *Uncertainty Management Method* (UMM). The following belief measure needs to be assessed in Level 2 – Situation Assessment:

$$\mu_\mathcal{S}(\mathcal{S}_i^h = \mathcal{S} | \xi), \tag{7}$$

i.e., the degree of belief for a specific situation hypothesis $\mathcal{S}_i^h$ being the "true" current situation $\mathcal{S}$ conditional on ξ. Depending on the application domain and the type of relations involved in $\mathcal{S}$, it may also be necessary to define belief measures that capture some specific part of a situation in more detail. Examples of such measures are:

$$\mu_{\mathcal{T}_j}((x_1, \ldots, x_n)_j^h \in \mathcal{R}_j | \xi) \tag{8}$$

$$\mu_{\mathcal{R}_j}(\mathcal{R}_j^h = \mathcal{R}_j | \xi), \tag{9}$$

where $\mu_{\mathcal{T}_j}$ denotes the degree of belief for a single tuple $\mathcal{R}_j$, and $\mu_{\mathcal{R}_j}$ depicts the degree of belief for the "true" set that constitutes the relation. In particular scenarios it could be sufficient to define some of these belief measures in terms of the others by for example using the *mean*. As an example $\mu_{\mathcal{R}_j}$ can be defined in terms of $\mu_{\mathcal{T}_j}$ by using the mean, in the following way:

$$\mu_{\mathcal{R}_j}(\mathcal{R}_j^h = \mathcal{R}_j|\xi) = \frac{1}{|X_1 \times \ldots \times X_n|} \left[\sum_{(x_1,\ldots,x_n)_j^h \in \mathcal{R}_j^h} \mu_{\mathcal{T}_j}((x_1,\ldots,x_n)_j^h \in \mathcal{R}_j|\xi) + \sum_{(x_1,\ldots,x_n)_j^h \in \overline{\mathcal{R}}_j^h} \mu_{\mathcal{T}_j}((x_1,\ldots,x_n)_j^h \notin \mathcal{R}_j|\xi) \right], \tag{10}$$

where $\overline{\mathcal{R}}_j^h = (X_1 \times \ldots \times X_n) \backslash \mathcal{R}_j^h$.

The last part of the equation can be simplified if one assumes that the following holds:

$$\mu_{\mathcal{T}_j}((x_1,\ldots,x_n)_j^h \notin \mathcal{R}_j|\xi) = 1 - \mu_{\mathcal{T}_j}((x_1,\ldots,x_n)_j^h \in \mathcal{R}_j|\xi) \tag{11}$$

However, depending on the UMM, this is not always the case (e.g., Dempster-Shafer theory). In the general case one might want to assess the measures $\mu_{\mathcal{T}_i}$, $\mu_{\mathcal{R}_i}$, and $\mu_{\mathcal{S}}$ more specifically by applying some other method than just using the mean over an existing belief measure.

3.2 Level 3 – Impact Assessment

Consider Level 3 – Impact Assessment – where the aim is to estimate effects on situations given certain actions [35]. The representation of situations still applies since *"estimation and prediction of effects on situations"* as stated in the revised JDL model can be interpreted as estimation and prediction of "future situations", *impacts*, which we here will denote by $\mathcal{I}$, and $\mathcal{I}_i^h$, $i \in \mathcal{J}_{\mathcal{I}}$, when considered as a hypothesis. From a decision maker's point of view, a certain set of planned actions is expected to lead to a desirable impact. Now, since there most often exists uncertainty regarding the *current situation*, something that is reflected in the belief measure $\mu_{\mathcal{S}}$, it is also necessary to incorporate this uncertainty when estimating future situations, impacts $\mathcal{I}_i^h$. Consequently, a belief measure for Impact Assessment, $\mu_{\mathcal{I}}$, has the following appearance:

$$\mu_{\mathcal{I}}(\mathcal{I}_i^h = \mathcal{I}|\mathcal{A}, \mu_{\mathcal{S}}, \xi), \tag{12}$$

i.e., the degree of belief regarding a possible impact $\mathcal{I}_i^h$ is conditional on: a set of actions $\mathcal{A}$, the belief measure for the current situation $\mu_{\mathcal{S}}$, and the set of available information ξ. Additional belief measures that capture some specific part of an impact in more detail, similarly to expressions (8) and (9), may also be defined for Impact Assessment.

4 Dependable High-Level Information Fusion

One of the main issues in HLIF is to assess the belief measures $\mu_{\mathcal{S}}$ and $\mu_{\mathcal{I}}$ over possible current situations, $\{\mathcal{S}_i^h\}_{i \in \mathcal{J}_{\mathcal{S}}}$ and possible impacts $\{\mathcal{I}_i^h\}_{i \in \mathcal{J}_{\mathcal{I}}}$. Since these quantifications constitute a basis for *HLIF-based decision making*, human or automatic, a question one can pose is how *trustworthy* such quantifications are? However, a clarification on what is actually meant by "trustworthiness" or "trust" in HLIF is necessary since there is a lack of research on that topic. Avižienis et al. [5] define trust as *"accepted dependence"* and have presented a taxonomy of *dependability* that is well-accepted within the dependable computing domain. In HLIF, however, some of these concepts, e.g., *reliability* and *robustness*, are also utilized but with no consistent meaning; thus, researchers have adapted their particular interpretation in a specific application domain and problem. We will here present a partial mapping from this taxonomy to HLIF that preserves as much consistency as possible with respect to how concepts have been utilized in HLIF. Since specific characteristics of dependability is application dependent, this partial mapping should be seen as a guideline for interpreting dependability in HLIF. We will later use this terminology when we discuss why imprecise probability seems to be an interesting approach to improved dependability in HLIF (Sect. 5).

4.1 High-Level Information Fusion as a Service

The basis for the concepts in the dependability taxonomy is a *service*; thus, we need to clearly state what type of service the involved functions in HLIF provide. By the description of HLIF in Sect. 3, it can be argued that a *HLIF service* provides the artifacts listed in the introduction of this section, i.e., $\{\mathcal{S}_i^h\}_{i\in\mathcal{J}_\mathcal{S}}$, $\{\mathcal{I}_i^h\}_{i\in\mathcal{J}_\mathcal{I}}$, $\mu_\mathcal{S}$, and $\mu_\mathcal{I}$. These artifacts are utilized by a decision maker (human or automatic) in order to make a decision concerning situations, in other words, a HLIF service aims at providing decision support regarding situations.

4.2 Reliability

We start this partial mapping with the attribute of dependability referred to as *reliability*; an attribute that has many different interpretations [30, 26, 42]. Svensson [36] has proposed the following interpretation of reliability for HLIF-based decision-support systems:

> *"Technical system property of delivering quantitative results which are reasonably close to best possible, subject to known statistical error distributions"*.

However, *"...results which are reasonably close to best possible..."* could be hard to interpret since *"best possible"* needs to be more clearly defined, and *"...statistical error distributions"* is too specific in many circumstances, e.g., when subjective opinions (from domain experts) are utilized.

In the dependability taxonomy, it is seen that reliability is defined as *"continuity of correct service"*. Llinas [25] has listed *"Correctness in reasoning"* as an important criteria for evaluation of fusion performance in a context of HLIF. Thus, one can argue that the key to think about reliability is *correctness*. The question then becomes what a correct HLIF service is, and a natural answer is that correctness refers to what such service actually delivers, i.e., correctness of the artifacts: $\{\mathcal{S}_i^h\}_{i\in\mathcal{J}_\mathcal{S}}$, $\{\mathcal{I}_i^h\}_{i\in\mathcal{J}_\mathcal{I}}$, $\mu_\mathcal{S}$, and $\mu_\mathcal{I}$.

For the sets of hypotheses, correctness refers to the extent of all plausible hypotheses actually being in the sets (cf. [31]), i.e., *exhaustivity*. For the belief measures, it can be argued that correctness is achieved when the measures reflect the character of the available information (cf. [39, Section 1.1.4]). As an example, if information is scarce, uncertain, imprecise or conflicting (see further [22]), this should be reflected in the belief measure.

Lastly, if we assume that ξ continuously gets updated, e.g., via a sensor stream, then it is necessary for the belief measures to continuously reflect ξ, thus in agreement with *"continuity..."* in the definition of reliability found in the taxonomy.

4.3 Fault

A *fault* in the dependability taxonomy is defined as the cause of an *error* that in its turn is something that may cause a *failure*, i.e., a deviation from correct service [5]. Since we have already argued that a correct HLIF service delivers an exhaustive set of plausible hypotheses and belief measures that reflect the character of ξ, the negation of this statement, i.e., a service that provides a non-exhaustive set of plausible hypothesis or belief measures that do not reflect ξ, is considered to be a service that is *not* correct.

Based on these arguments, faults can be defined as: uncertain, imprecise, inconsistent, and lack of information (for more detail, see [22, Sect. II-A1]), since if inadequately handled, all of these may lead to service incorrectness. For a non-exhaustive set of hypotheses, *insufficient or inaccurate domain knowledge* about the process can also be considered as a fault since design of hypotheses most often rely on domain knowledge. Another important fault in HLIF concerns *unreliable sources*. If we consider a source as providing a service, reliability of this service would be correctness of the source output. It is possible to account for unreliable sources by introducing *reliability coefficients* that quantify the degree of reliability for the sources [30]. Thus, one can say that a service, based on unreliable sources, is still reliable as long as one know the *quality of sources*, e.g., reliability coefficients, and compensate for this.

4.4 Safety

The next concept in the taxonomy that we will consider is *safety*, which is defined as *"Absence of catastrophic consequences on the user(s) and the environment"* [5]. Seen from a decision maker's point of view, one can aim at a minimized number of *possible catastrophic consequences*. In essence, when a decision is taken by utilizing a HLIF service, a possible catastrophic consequence may be interpreted as an *unexpected impact* of such decision. There are two important so called *secondary attributes* (attributes that refine primary attributes [5]) that we consider to be a part of safety: *robustness* and *stability*.

Robustness

Svensson [36] has proposed the following definition of robustness for HLIF-based decision-support systems:

> *"Property of a system to react appropriately to exceptional conditions, including to avoid making large changes in recommendations as a consequence of small changes in input data."*

Bladon et al. [6] have proposed the following description of robust in conjunction with a Situation-Assessment system:

> *"Robust: able to handle inconsistent, uncertain, and incomplete data."*

Llinas [25] has listed the following criteria for evaluation of HLIF performance:

> *"Adaptability in reasoning (robustness)"*

Antony [3] claims that:

> *"Robustness measures the fragility of a problem-solving approach to changes in the input space."*

Avižienis et al. [5] define robustness as a secondary attribute in the following way:

> *"...dependability with respect to external faults, which characterizes a system reaction to a specific class of faults."*

When looking at the statements above, it can be argued that most of them relate to a *reaction*. The description of robustness by Avižienis et al. [5] suggests that we need to find a class of faults that the reaction refers to. In order to be able to distinguish "robust" from "reliable", we partially adopt Svensson's interpretation that robustness is about *"...exceptional conditions..."*. Consequently, we define the class of faults as *exceptional* which in HLIF may be *exceptional degrees* of:

- Uncertain, imprecise, and inconsistent information
- Lack of information
- Insufficient or inaccurate domain knowledge
- Unreliable sources

Exceptional degrees is something that is dependent on the application domain at hand, and must therefore be defined accordingly. The desired reaction to exceptional faults, from a decision maker's point of view, would be to expect that the service still fulfill reliability, i.e., correctness. Altogether, robustness in HLIF is about being able to provide a reliable service even though exceptional faults are present.

Stability

Stability is included in the definition of robustness by Svensson [36]:

> *"...avoid making large changes in recommendations as a consequence of small changes in input data."*

In order to allow for as precise and clear meaning as possible for both robustness and stability, we prefer to view stability as a separate secondary attribute to safety. It is somewhat unclear what Svensson exactly means by *"...large changes in recommendations..."*. When are recommendations of actions considered to be different from each other? One may even think of two very different recommendations that are expected to lead to essentially the same impact. Thus, we rephrase stability as: small variations in input should not cause changes in actions that are expected to lead to different impacts. Here, "expected" and "different impacts", needs to be more clearly defined, something that must be done with respect to a specific problem and application domain.

As an example, assume that one has two different sets of actions, $\mathcal{A}_1$ and $\mathcal{A}_2$, which for some reason are expected to lead to different impacts. Assume that the following holds for an impact $\mathcal{I}_i^h$:

$$\mu_{\mathcal{I}}(\mathcal{I}_i^h = \mathcal{I}|\mathcal{A}_1, \mu_{\mathcal{S}}, \xi) - \mu_{\mathcal{I}}(\mathcal{I}_i^h = \mathcal{I}|\mathcal{A}_2, \mu_{\mathcal{S}}, \xi) = \kappa \tag{13}$$

Let the input in our interpretation of stability refer to ξ, more concretely, let ξ constitute a sensor stream of information. Now, assume that the stream becomes noisy, i.e., small random variations in the information are present, denoted by ξ'. Such variation may cause, at a given time instant, the following equation to hold:

$$\mu_{\mathcal{I}}(\mathcal{I}_i^h = \mathcal{I}|\mathcal{A}_1, \mu_{\mathcal{S}}, \xi') - \mu_{\mathcal{I}}(\mathcal{I}_i^h = \mathcal{I}|\mathcal{A}_2, \mu_{\mathcal{S}}, \xi') = \kappa' \tag{14}$$

By fulfilling stability the following is prevented:

$$|\kappa - \kappa'| > \epsilon \tag{15}$$

In other words, the difference in belief is not allowed to deviate "too much" due to random variations in ξ'. Here ϵ is a parameter that quantifies an *acceptable deviation* with respect to the variation in ξ'. In the worst case, a decision maker may choose to implement $\mathcal{A}_1$ when Eq. (13) holds and $\mathcal{A}_2$ when Eq. (14) holds. Since the action sets were expected to lead to impacts that are in some sense different from each other, such behavior is considered to be "unsound". In this example, the input was the set of available information ξ, but one may equally well consider the belief measure $\mu_{\mathcal{S}}$ as the input, i.e., small variations in $\mu_{\mathcal{S}}$ should not cause the behavior defined by Eq. (15).

5 Imprecise Probability - Dependable High-Level Information Fusion

Imprecise probability [41] refers to a family of theories that allow imprecision in the belief measures, e.g., a probability interval. Walley [39, 40, 41] has argued extensively for the importance of imprecision in probabilities and describes several different sources of it such as: *lack of information*, *conflicting information* (inconsistent information), and *conflicting beliefs* (e.g., conflict amongst a group of domain experts), to name a few of them. Lack of information is related to a specific type of uncertainty referred to as *epistemic* or *reducible* [33], since gathering more information may reduce this type of uncertainty; closely related to one of the goals of IF, i.e., reducing uncertainty. The two latter sources of imprecision in probabilities: conflicting information and conflicting beliefs, are also obvious in an IF context, since utilizing multiple sources of information typically lead to conflict.

As pointed out by Walley [39, Section 5.1.5], a significant difference between Bayesian theory and imprecise probability, is the way the amount of information is reflected in the belief measure. If little or no prior information concerning some process is available, Bayesian theory propose a *non-informative prior*, e.g., *maximum entropy* [20], while imprecise probability utilize the degree of imprecision to reflect the amount of information; substantial information implies a small interval of possible probabilities, and scarce information a large interval of possible probabilities. Thus, when utilizing imprecise probability, the information can actually be seen in the belief measure itself, while in Bayesian theory the same belief measure can be adopted before any information is available, as well as later when a large amount of information is available. Subsequently, if we consider reliability in HLIF as a correctness criterion, where the belief measure should reflect the character of the available information, even in exceptional cases when there is a severe lack of it (related to robustness), Bayesian theory cannot adequately fulfill this. From a decision maker's point of view, reliability can be thought of as a sort of "soundness" criterion, i.e., the decision maker will be aware of the quality of the belief measure.

Imprecise probabilities also allow a direct way of handling the problem of stability. Consider *Bayesian networks* (BNs) [17], a method that is commonly proposed for HLIF [6, 12, 21], where precise probabilities, usually referred to as *conditional probability tables* (CPTs) needs to be assessed from data, or elicited from a domain expert. A problem with such networks, besides assessment or elicitation of precise CPTs, is that it is necessary to perform *sensitivity analysis*, i.e., examine for chaotic behavior [37] by perturbation of the CPTs. By utilizing imprecise probability (e.g., [10, 11]) it is possible to account for "possible" values of the CPTs in a direct way. Thus, instead of assessing or eliciting precise probabilities followed by sensitivity analysis, where the CPTs are perturbed; imprecise probability account for this from the start, i.e., the imprecision constitutes "possible" probabilities that potentially could have resulted from a perturbation of precise probability.

6 Application Domains

Information fusion (IF) has its roots in the defense domain and is still tightly coupled to it. In this section, we first depict the current state of IF techniques and applications within defense. Then, we describe two “civilian” application domains, *manufacturing* and *precision agriculture*, where researchers have started to recognize the benefits of IF, mainly through initial studies in low-level IF.

6.1 Defense

There exist a number of different IF applications within the defense domain such as: *ocean surveillance*, *air-to-air and surface-to-air defense*, *battlefield intelligence*, *surveillance*, *target acquisition*, and *strategic warning and defense* [16]. In a defense context, Level 1 – Object Assessment – concerns the problem of detecting objects and their corresponding physical attributes, e.g., vehicle type (e.g, tank or jeep), position, velocity, and heading.

The goal of Level 2 – Situation Assessment – is to establish relationships among the identified objects and events, which belong to the environment under consideration [16]. A common relation applied at this level is clustering, e.g., clustering of vehicles into *platoons*, *companies*, and *battalions* [32]. Lastly, in Level 3 – Impact Assessment – predictions are made about future situations, e.g., different threats of enemies [16].

So far in the defense domain, most of the research has concerned Level 1 – Object Assessment –, e.g., *target tracking* with multi-sensor fusion. Most attempts to HLIF in defense involves Bayesian theory and especially BNs [6, 12, 21]. Other approaches to HLIF in the defense domain are: *Dempster-Shafer theory* [32], *genetic algorithms*, *fuzzy logic*, *neural networks* [18], *case-based reasoning*, and *fuzzy belief networks* [27].

6.2 Manufacturing

A well-known problem in manufacturing is planning of *maintenance* such that the cost and risk of failure are minimized. According to Jardine et al. [19], maintenance can be divided into: *unplanned maintenance* (breakdown maintenance) and *planned maintenance*. In unplanned maintenance, utilization of a physical asset occurs until breakdown, an approach that enables for maximum amount of utilization while there are no serious failures, but on the other hand, a breakdown can potentially cause a halt in production or even more serious failures, leading to severe economic loss. In planned maintenance, a schedule is utilized for each physical asset. The advantage of this approach is that it reduces the number of breakdowns, but for a cost of decreased utilization, since maintenance is performed independently of the actual condition of the physical asset. Due to an increased complexity in machines, planned maintenance has become a costly activity [19].

Recently, there has been an increased interest in multi-sensor fusion as a means to achieve more reliable prognosis and diagnosis in maintenance [19], and researchers have started to notice the commonalities between the IF domain and manufacturing [38, 19].

6.3 Precision Agriculture

The aim of precision agriculture is to account for large *within-field spatial and temporal variations* of different *crop* and *soil* factors [34]. By measuring different *soil properties* such as texture, moisture content, nitrogen (N) content and pH [1], the field can be divided into zones that have different needs, e.g., of fertilization or pesticides. When combining a *geographical information system* with a global positioning system, each zone can be targeted, through model simulation, with its corresponding need of for instance N-fertilization, pesticides, or watering. In the case of fertilization, it is also common to utilize so called *on-the-go sensors* (e.g., radiometric sensors) where sensor readings are used as further input for fertilization calculations. Since these calculations are performed during the actual fertilization process, they need to meet certain time constraints. Precision agriculture is both economical and environmentally friendly since the purpose is to estimate the exact need for optimal yield and minimum influence on the environment [28].

7 Discussion and Future Work

While there are many articles that describe theoretical aspects of imprecise probabilities (e.g., [41]), and comparative studies of uncertainty management methods addressing "artificial" (toy) problems (e.g., [15]), the more practical aspects where such methods are implemented and evaluated in "real-world" applications seem to be to a large extent overlooked (there are exceptions, e.g., [4, 8, 29]). We believe that the only way for imprecise probability to gain recognition by researchers in HLIF in particular and other research communities in general, is to conduct experiments that actually demonstrate benefits of such approach in comparison with precise probability. We have here described three application domains which will be utilized for this purpose. The exact theories to be evaluated in the family of imprecise probability will be selected in accordance to characteristics of the specific problem in each of these application domains. A common feature of all these domains, and most IF applications, is that decisions must be made within a certain period of time, i.e., certain time constraints need to be met. Such constraints may be challenging to meet when using imprecise probability, due to the additional complexity introduced by imprecision (sets of probability measures instead of a single probability measure).

Since many attempts to address HLIF rely on Bayesian theory such as BNs; imprecise probability will naturally be evaluated against existing precise solutions. Consequently, HLIF provides an excellent evaluation ground for imprecise probability. There is also genuine need for addressing dependability issues in HLIF, an area that has been more or less neglected, or as Svensson [36] puts it:

> *"Indeed, unless concepts and methodologies are found and generally applied which enable researchers and developers to achieve and demonstrate reliability of high-level information fusion methods and algorithms, operational decision makers are unlikely to be willing to trust or use decision support systems based on such techniques."*

In a recent publication, Antonucci et al. [2] have recognized the benefits of utilizing imprecise probability – *credal networks* [10, 11] – in IF. The application of credal networks to HLIF is definitely something that should be further investigated and contrasted against BNs.

8 Conclusions

In this position paper we have reported on ongoing and planned future work on deployment and evaluation of imprecise probability in high-level information fusion (HLIF) applications. A detailed description of HLIF and a partial mapping from a dependability taxonomy to HLIF were presented. There is a need to find more dependable methods within HLIF, and imprecise probability seems to be an interesting approach to improve dependability. We have also argued that it is important to implement and evaluate imprecise probability in "real-world" applications, if such methods are going to be acknowledged. Since HLIF is an application oriented research area, where most methods are based on Bayesian theory, we have also concluded that HLIF is an excellent evaluation ground for this purpose. Three application domains: defense, manufacturing, and precision agriculture, for evaluation of imprecise probability as an approach to improved dependability in HLIF, were described. Design of experiments in these domains, which contrasts the benefits and drawbacks of imprecise probability to precise probability, is our next step, something that in itself is challenging and valuable to the dissemination of research on imprecise probability.

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