

2 Scientific State of the Art

In this chapter, the theoretical foundations in the scope of the work topics, which have been identified in Section 1.1, are appraised. It summarises the state-of-the-art research and applications of the respective fields in order to identify relevant works and put this dissertation into context.

An analysis of theoretical frameworks applicable to model information in the fusion process is presented in Section 2.2. In Section 2.3, human processes on making a decision are studied. Based on the findings of this chapter, the scientific gap is identified in Section 2.4. This gap defines the contents of the further research presented in the subsequent chapters of this dissertation.

This chapter begins with compiling general research in the field of information fusion. It will clarify the benefits of information fusion over single source information processing from the theoretical and applicative point of view. Knowledge about the basics analysed in the next section is necessary to understand the constraints and circumstances, under which information fusion operates. Special attention is paid to uncertainty and conflict within the information fusion context.

2.1 Information Fusion

Information fusion (IFU) has been researched for more than 40 years and is scientifically well understood. It is nevertheless still a very active field of research. With respect to technical systems, IFU has gained more attention starting in the 1970s. In this decade, new sensors, advanced processing techniques, and increasingly powerful processing hardware became available. From then, data processing models and fusion algorithms have been driven nearly exclusively by applications in the military defence sector. During the 1990s and early 2000s, those algorithms have been adopted by the civil sector for usage in industrial fault diagnosis and condition monitoring applications [HL01]. A brief summary of IFU's history is presented in Appendix H.1.

The concept of IFU is as follows: new or more precise knowledge about physical quantities, events, or situations is created by the utilisation of different information sources. Although IFU is beneficial compared to single-source signal processing, many systems are based on one main sensory apparatus. These systems, called *unimodal systems*, have to contend with a variety of general difficulties. According to [RJ05], these are *raw data noise*, *intra-class variations*, *inter-class similarities*, and *non-universality*. Some of these mentioned limitations can be overcome by *multimodal systems*, which are expected to be more reliable due to the presence of multiple, partly signal-decorrelated, sensors. They address the problems of non-universality and, in combination with information fusion, the problem of inter-class similarities. They can at least inform the

user about problems with intraclass variations and noise. A generic multimodal system consists of four important units (inspired by [RJ05]):

- (i) sensor units, which capture raw data from different measurement modules (resp. sensors);
- (ii) feature extraction units, which extract an appropriate feature set as a representation for the system, from which the raw data is captured;
- (iii) classification units, which compare the current features to their corresponding features stored in a database;
- (iv) decision unit, which uses the classification results to determine whether the obtained results represent the expectations.

A visualisation of this scheme is given in Figure 2.1.

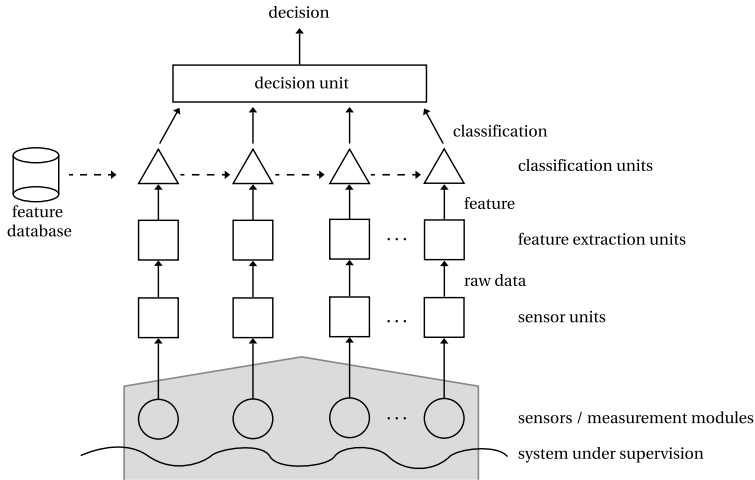


Figure 2.1: Scheme of a generic multimodal system (inspired by [RJ05]).

HALL and LLINAS describe that IFU aims at optimisation of “the accuracy of applications” [HL01, p. 1]. This is the abstract goal for all kinds of applications, regardless of their origin being military, civil, medical, technical, or others. Possible criteria are target position and velocity tracking in the military area [Uhl01], fault detection of a production machine [Ise11], or quality assessment of assembled products [Ise06], but also the avoidance of wrong results in the evaluation of human statements [BSW06], or data compression by mapping a number of input sources to typically 1 output [KKK+11]. What the criterion to be optimised actually is must be defined in advance before creating an IFU application. Afterwards, sources are to be chosen, which provide data containing the necessary information to derive an accurate statement about the criterion under question. After [RP06], the combined *performance* of two sensors S_1 and S_2 ,

which work with complementary physical principles, $\text{Perf}(S_1 \cup S_2)$ regarding the chosen criterion will be increased, such that

$$\text{Perf}(S_1 \cup S_2) > \text{Perf}(S_1) + \text{Perf}(S_2), \quad \text{or at least:} \quad \text{Perf}(S_1 \cup S_2) > \max(\text{Perf}(S_1), \text{Perf}(S_2)).$$

This property, indicating advantages of integration of multiple information sources compared to a single source, is also observed in neurological examinations. All living biological systems constantly make intuitive and subconscious use of IFU, which protects themselves from danger and guarantees survival [DRS04; FOR+14]. MERCIER et al. showed that humans react slower towards an external stimulus acquired by one sense (audio or visual) than if these stimuli appear combined (audio-visual) [MMF+15]. They explain this effect with the *redundant target effect* (RTE) [MMF+15; MBK+15], which describes that neurons are activated to information acquired by multiple senses before every single information would have caused a separate activation (*coactivation*) [Mil82]. Triggered by [MBK+15], TOZZI and PETERS transferred these findings to the area of *algebraic topology* and relate the observed effect to the *Borsuk-Ulam theorem* [Bor33, Satz II] in [TP15]. The Borsuk-Ulam theorem expresses that any *antipodal* points on an n -dimensional sphere¹ are projected onto one point when the sphere is projected to an $(n - 1)$ -dimensional Euclidean space. According to TOZZI and PETERS, the audio and visual sense represent the antipodal points on the sphere, which are both stimulated by the same event (their Euclidean projection). Hence, both share information about the event in their respective stimuli [Pet16, p. 163], [TP15; PT16]. The full information of a stimulus is thus only observable by the combination (*fusion*) of multiple senses, otherwise parts of the information remain hidden resulting in incomplete knowledge.

Three fusion types, depending on the abstraction level, are possible in general [LK92; HL97; HL01; RP06]:

- At *signal level*, sensor signals are combined. It is necessary that the signals are comparable in the sense of data amount respectively sampling rate (adaption), dimension, registration, and time synchronisation. If this constraint cannot be fulfilled, fusion on any of the following two levels is appropriate.
- At *feature level*, signal descriptors (features) are combined. Human cognitive functions rely on this association principle for recognition tasks.
- At *symbol level*, classification results are combined. This happens either after obtaining all individual decisions per sensor, or on top of a number of features or signal level fusion steps.

The degree of abstraction increases from signal level to symbol level, whereas the fusion itself is more efficient with increasing abstraction. Nevertheless, additional processing steps in advance to fusion might increase the overall complexity. ROSS and JAIN state that multimodal sensor systems, which integrate information by fusion at an early processing stage, are more effective than those systems, which perform fusion at a later

¹Examples of antipodal points are the poles of the Earth or exactly opposite points on a circle.

stage [RJ05]. Since input signals or features contain more information about the physical data than score values at the output of classifiers, fusion at signal or feature level is expected to provide better results compared to symbol level. Besides, fusion on a high abstraction level is less effective due to the fact that the involved methods inevitably lead to data reduction resulting in information loss (cf. [RP06; HL01]). Fusion in the decision unit, for example, is considered to be rigid due to the availability of only limited information and dimensionality. Table 2.1 summarises the above mentioned fusion association principles.

Table 2.1: Fusion levels and their allocation methods (based on [RP06, p. 7]).

<i>Fusion Level</i>	Signal Level	Feature Level	Symbol Level
<i>Type of Fusion</i>	signals, measurement data	signal descriptors, numeric features	symbols, objects, classes, decisions
<i>Objectives</i>	signal and parameter estimation	feature estimation, descriptor estimation	classification, pattern recognition
<i>Applicable Data Models</i>	data vectors	feature vectors	probability distributions, membership functions
<i>Abstraction Level</i>	low	middle	high
<i>Complexity</i>	high	middle	low

Today, knowledge is mutually transferred between the research areas. Recent research regarding IFU—besides ongoing military research—is carried out in network traffic modelling scenarios [LHW14], in the home care sector (*ambient assisted living* (AAL)) [TFV+12], as well as in the industrial context (machine diagnosis) [Ise11]. ISERMANN provides a comprehensive introduction for an important application field of IFU: fault diagnosis of dynamic technical systems, mainly from a control theoretical point of view for process automation and in the automotive area (driver-assistance systems, autonomous driving, etc.). He provides a taxonomy for fault diagnosis systems and related areas, describes the advantages which can be obtained by fault diagnosis, discusses the relevant approaches, and illustrates a number of applications in this field [Ise06; Ise11]. Other applications contain condition monitoring of rotating electrical machines [KZ15; DC14], electrical power supplies [MAL+14; KTK+14], intelligent transportation systems [BI15; LSG+14], or communication networks [MCC15; HC15].

Comprehensive studies on contemporary research on IFU are found in [KKK+11; SGL15]. KHALEGI et al. identify a number of main challenges posed on IFU systems arising from their input data in their review article. These are data imperfection (such as uncertainty, cf. Section 2.1.1), outliers and spurious data, conflicting data, data modality, data correlation, data alignment/registration, data association, processing framework, operational timing, static vs. dynamic phenomena, and data dimensionality. There is no available IFU approach, which addresses all of the aforementioned challenges [KKK+11].

SNIDARO et al. discuss context-based fusion systems and their benefits [SGL15]. They refer to KOKINOV’s definition in the scope of cognitive science, where *context* is

everything which influences a system's behaviour. It is further distinguished between *external* and *internal context*. The former is the setting or the environment in which the system generates its behaviour, and the latter is the system's current state influencing its behaviour [Kok97]. In their work, SNIDARO et al. characterise a fusion process as a *fusion node* as introduced in [GGP+12]. It consists of data alignment, data association, and state estimation functions. In addition, this original model is augmented by a fusion management function. All functions of the fusion node may be adapted by the available context information. They conclude that systems incorporating contextual information will improve fusion quality and allow for general solutions, which are adaptable to different domains [SGL15]. SNIDARO et al.'s study reveals that no contextual information was included in any fusion system before the 2000s, probably because their inputs were nothing else but sensor data. They list recent research incorporating context information in the form of, e. g., physical descriptions like sensor characterisations including reliability [NBC+00], or spatial information [NBC+00; RGO12] in addition to sensor data. The approaches use the information to adjust the fusion according to the prevailing context in order to improve results by resolving ambiguities, e. g., with respect to an entity's position [RGO12].

KHALEGHI et al. point out that decentralised IFU is advantageous compared to centralised IFU, where all measurements need to be communicated to a central processing system before processing them. It is nevertheless crucial to avoid *data incest* resulting in multiple use of single measurements, especially in such distributed scenarios. The authors postulate that increasing formalisation of the IFU approaches will lead to standardised fusion systems and enables automatic developments [KKK+11]. The design and creation of fusion systems is a highly manual task. In addition, every change of a running system must also be implemented manually. As of today, no methodology, framework or tool-chain for designing and re-structuring information processing and fusion systems are available whether open or free, although conceptual techniques have been published [IK09].

In many cases the information captured from the environment and the system is imprecise, incomplete, or inconsistent. Furthermore, signal sources may not be reliable (which is also true for human information, e. g., given in surveys or interrogations [BSW06]). Therefore, it is necessary to apply fusion concepts, which are able to handle and to measure imprecision and (un-)reliability, hence *uncertainty*. Uncertainty occurs due to different reasons. The uncertainty types known in the IFU context are presented in the following.

2.1.1 Uncertainty

This dissertation deals with information fusion of uncertain inputs (cf. work topic WT 2). This section summarises the characteristics and provides a taxonomy of uncertainty, as knowledge about uncertainty is necessary to decide on the appropriate information model applied in this dissertation.

Intelligent behaviour of systems, both technical and living, is defined as

“[...] the ability to understand and adapt to the environment by using a combination of inherited abilities and learning abilities [..., including] the analysis of uncertainty and making decisions under conditions of uncertainties.”

-- BILAL M. AYYUB and GEORGE J. KLIR [AK06, p. 1]

In other words, each system acquires data and processes it to create a model of its environment and adapt to it. The acquired data is prone to uncertainty, hence the systems need to assess the data regarding uncertainty in order to be aware of it and process the uncertain data accordingly. After AYYUB and KLIR’s taxonomy [AK06], uncertainty is a certain type of *ignorance*, conscious ignorance to be precise. That is, one does not know the exact truth, but one knows that something is missing. Thus, uncertainty results from incompleteness, hence lack of knowledge. AYYUB and KLIR define uncertainty being caused by *likelihood*, *ambiguity*, and *approximations*. KHALEGHI et al. define data being uncertain, if the associated confidence degree is smaller than 1 [KKK+11].

Further classification leads to two major types of uncertainty: *aleatory* and *epistemic* uncertainty (cf. Definitions 1.7 and 1.8). KLIR and WIERMAN point out that uncertainty mostly cannot be avoided, especially in the context of real-world applications [KW99]. In engineering, uncertainty is caused by deficiencies in the acquisition of knowledge such as measurement errors, lack of repetitions of an experiment, or production tolerances [LVG11]. Uncertainty, nevertheless, can be kept to a minimum with the necessary information available. This applies to epistemic uncertainty. Aleatory uncertainty is irreducible due to its pure random character, but can be modelled. The classification of uncertainty is summarised in Table 2.2.

Table 2.2: Uncertainty classification and corresponding properties (according to [LVG11, p. 194]).

<i>Class</i>	Aleatory Uncertainty	Epistemic Uncertainty
<i>Type</i>	irreducible	reducible
<i>Origin</i>	intrinsic variations	lack of knowledge
<i>Data</i>	random, stochastic	scarce
<i>Taxonomy</i>	likelihood	ambiguity, approximations

It is important to know and be conscious about ignorance. This is similar to the famous quote in the sense of its original by historian DANIEL J. BOORSTIN²:

“The greatest enemy of knowledge is not ignorance, it is the illusion of knowledge.”

-- STEPHEN HAWKING [AK06, p. 1]

It is only in this case possible to process it accordingly and obtain trustful results.

The basic demand to achieve this goal is the application of appropriate methods and

²“The great obstacle to discovering the shape of the earth, the continents, and the ocean was not ignorance but the illusion of knowledge.” [Boo83, p. 86]

tools to model and process the available information. AYYUB and KLIR propose the framework of *probability theory* (ProbT) in case uncertainty is quantifiable [AK06]. At the same time, they admit that epistemic uncertainty, being the most dominant uncertainty type in risk analysis, can only be modelled with additional effort as a probabilistic variable. In addition, uncertainty is often recognised, but cannot be expressed in statistical, hence probabilistic terms. Such situations are prevalent in the environment of machine and plant engineering (e.g., production processes [Ise06]) or risk analysis (e.g., in the context of radioactive waste repositories [AK06]). Here, only a subset of necessary knowledge for the precise assessment is available.

Another important type of ignorance is described in the next subsection: conflict.

2.1.2 Conflict

The source of conflict is contradiction between sources. That is given whenever the information of at least one source disagrees with the remaining available information. Conflict is a central aspect of this dissertation and thus, research around this topic is appraised in this section. It serves as the foundation for work topic WT 4 and constrains the decision on the applied information model (cf. WT 2).

The possible causes of conflict are numerous. Source deterioration or faults occur especially in real-world problems. Manipulation of the sources (or their information) is also conceivable, especially in security-critical settings. Conflict is formally another form of conscious ignorance. It is namely the cause of *inconsistency* or distorted information [AK06]. Such information inconsistencies lead to results, which do not represent the actual situation, if the conflict has not been recognised and addressed during information processing.

Conflict has been identified as one of the most challenging topics in IFU by KHALEGHI et al. [KKK+11]. Measures of conflict are well-known in literature. One example is SHANNON's *entropy measure* (defined as a measure of information [Sha48]), which can also serve as a conflict measure [AK06].

A number of publications work on the improvement or substitution of the conflict measured and processed in the combination rule of *Dempster-Shafer theory of evidence* (DST) [Sha76]. MARTIN et al. propose a conflict measure based on the distance between belief functions. This new measure serves additionally to determine *a posteriori* the reliability of the recently processed data [MJO08; Mar12]. SMARANDACHE et al. put this new approach into context and benchmarked it against other conflict measures (which they call "contradiction measures") [SHM12]. A measure based on vector distances between the data to be fused is introduced in [LHZ14].

MINOR and JOHNSON do not consider conflict as uncertainty originating from data source reliability issues, but from uncertainty in the frame of discernment. They allow the existence of yet unknown elements, which are not part of the considered frame of discernment. Here, reliable sources are assumed along with an augmented frame of discernment. The sources' reliability must be questioned in this case as they are then applied to observe an inappropriate situation (the *augmented* frame of discernment) [MJ15].

MA et al. propose a conflict measure based on Dempster-Shafer theory of evidence

to evaluate inconsistencies in knowledge bases and weigh their items accordingly. With help of these measures, knowledge bases can be merged while preserving the most relevant items in case of conflicts [MLM12].

A combination rule along with a conflict measure, based on the average of the individual beliefs, is introduced in [DST+14]. This paper concludes that the arithmetic mean is typically the best combination rule, but admits at the same time that the choice of the correct combination rule is context-sensitive. Another conflict measure is developed in [Dan13b; Dan13a; Dan14]. It is based on the internal conflict between belief functions, which increases when decreasing belief is assigned to the evaluated propositions. To date, this concept is developed axiomatically [Dan14].

A study about human conflict perception is presented in [GSL+14]. The authors investigate museum visitors' reflections on exhibition samples, where information about the samples conflict. The inconsistency was recognised by more than 90 % of the visitors, but less than 70 % processed it.

Once determined, conflict is to be recognised, incorporated, and processed accordingly. The importance of such procedures in real-world applications should not be underestimated: it might have lethal consequences. On May 9th, 2015, Airbus suffered from a crash of one of its A400M military aircrafts during a test flight shortly after takeoff: four crew members died and two were severely injured [o.Kur15]. Preliminary results of the case's investigation led to the conclusion that the engines received conflicting commands from the aircraft's control unit. This resulted in the crash either due to a limitation of the engines' thrust level or a complete engine shutdown [Geb15]. Another critical case with luckily no victims was Lufthansa flight LH 1829 on November 5, 2014 [Tra15a]. This list of incidents can be continued by the Air France crash on the way from Rio de Janeiro to Paris in May 2009 with 228 victims [Tra10], or the crash of an Air Asia Airbus A320 close to the Indonesian coastline in December 2014 (162 people died) [Tra15b]—the importance of conflict handling (also of course in other areas) should be clear at this point.

To a certain extent, conflict handling is independent from the model applied to represent the information. Whereas probability theory, fuzzy set theory, and possibility theory need to incorporate further processing steps for conflict handling, Dempster-Shafer theory of evidence is inherently designed to handle conflicts. The information models are described in the next section.

2.2 Information Models

In order to incorporate uncertainty and conflict handling in the fusion process, the processed information needs to be modelled by supporting means. Another important constraint is the variety of inputs and their characteristics, which this dissertation deals with. In order to incorporate arbitrary inputs in the information fusion process, the applied information model must transform the inputs into a coherent space. A number of approaches is found in the literature, which fulfils the said constraints and qualifies as a candidate modelling technique. The most prominent and promising approaches analysed in the context of information fusion are probability theory, Dempster-Shafer

theory of evidence, fuzzy set theory, and possibility theory along with hybrid and less prominent approaches. The results of the state-of-the-art analysis presented in this section serve as the scientific basis for work topics WT 2–4.

2.2.1 Probability Theory Fusion Approaches

The technique for modelling uncertain information with the oldest history is ProbT. It is nowadays intuitively used in everyday language to express degrees of belief or uncertain situations quantitatively (“Tomorrow it will rain with a probability of 80%.”). According to SHAFER, the term *probability* was first mentioned in *Port Royal’s* “Logic” [Sha96, p. 16], which was published anonymously in 1662, and which PASCAL is believed to have significantly contributed to. It was nevertheless BERNOULLI in 1705, who posthumously introduced the first mathematical definition of probability, which previously had only a philosophical meaning and had already been used in legal arguments [Jay03; Sha96]:

“Probability is a degree of certainty, and differs from certainty as a part from a whole.”

-- JACOB BERNOULLI (according to [Sha96, p. 19])

Excellent text books describing the history and manifold aspects as well as a number of application fields of ProbT are [Jay03; Hal05; Bis09]. A summary of the basic ProbT formalisms is included in this dissertation in Appendix A.

Under the common notion of probability theory a number of interpretations exist, of which the most prominent are described in the following. Though different in their individual characteristics, central concepts of ProbT are shared between the interpretation forms. One is the concept of *conditional probabilities* (cf. Definition A.9): it expresses the probability of an event under a given condition.

Probability theory is applicable to model information, which is affected by aleatory uncertainty, as probability distribution by a *probability density function* (pdf). An exemplary pdf is displayed in Figure 2.2.

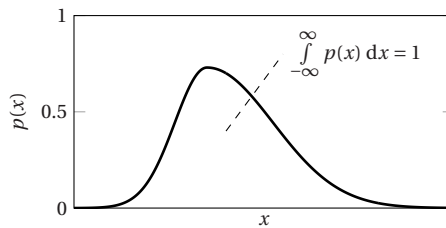


Figure 2.2: Exemplary probability density function $p(x)$. Note its basic property $\int_{-\infty}^{\infty} p(x) dx = 1$.

Probability distributions are applied in all of the different forms of interpretation. *Frequentist probability* is one form of interpretation and based on repetition of an experiment, observation, etc. under identical conditions. A basic assumption is that repeti-

tions are carried out infinitely, hence $N \rightarrow \infty$ [Jay03]. Often, this is implicitly presumed [Bis09].

Frequentist probabilities rely on sampling only and provide no means to include prior knowledge. These drawbacks are eliminated in the framework of *Bayesian probability*, expressing *subjectivist probabilities* [Jay03]. Bayesian methods are capable to assess uncertain events, for which an experiment or evaluation cannot be repeated several times. Examples are the question of the vanishing of the Arctic ice cap until the end of the century [Bis09] or the meltdown of a nuclear plant within the next five years [Hal05]. *Bayesian fusion* is the most prominent probabilistic fusion method and is well-studied both theoretically and practically (cf. [Jay03; Bis09; KKK+11]). It applies *Bayes' theorem* (cf. Theorem A.12) to determine a *posterior* probability distribution based on a *prior* probability distribution and current measurements modelled by the *likelihood function*. Every time new measurements (or data) are obtained, the posterior is updated by recursive application of Bayesian fusion, whereas the old posterior serves as current prior. All methods based on Bayes' theorem necessarily assume that data is acquired from independent sources, whose statistical behaviour is identical. In addition, the prior must be determined before any application, whereas statistical information is not available for every application [Zad62]. As a last resort, assumptions have to be made resulting in the prior to be uniform (in case of total ignorance) or Gaussian (due to its properties).

Whereas no general analytic solution exists for the determination of the posterior in the classical Bayesian approach, one exists in the form of *Kalman filters*, which constrain the evaluated systems to be linear and are only affected by Gaussian noise [Kál60]. Kalman filters are on the one hand well-studied and popular in fusion applications due to their optimality in terms of mean-squared error. On the other hand, Kalman filters are influenced by outliers in the data and not appropriate in applications with ill-known or non-Gaussian uncertainty characteristics [KKK+11].

Particle filters [Del96] are also based on Bayesian fusion, but are able to work with non-Gaussian uncertainties and non-linear systems. They apply *Monte Carlo simulation* models [HT78] to determine the posterior probability and make no assumptions about the applied probability distribution. It is a recursive implementation of a method later denoted by *sequential Monte Carlo* by LIU and CHEN [LC98]. Besides its advantages compared to Kalman filters, particle filters' greatest disadvantage is its exponential computational complexity of $\mathcal{O}(c^n)$ along with the possible need of a large number of samples n necessary to determine the appropriate posterior [KKK+11; SGL15]. *Markov chain Monte Carlo* methods are alternatives of lower complexity, which generate samples according to the transition probabilities of the applied Markov chain instead of generating independent samples. The most popular representative of this family of methods is the *Gibbs sampling* algorithm [GG84], a special case of the *Metropolis-Hastings algorithm* [Has70].

A local Bayesian fusion approach is proposed in [BSW06] to provide a solution tackling the exponential computational complexity of Bayes' theorem with respect to the dimension of the input values. The approach concentrates on fusing only those parts of the inputs where the information is concentrated, the rest is disregarded. This does not lead to a dimension reduction of the input vector, but each dimension is restric-

ted to a smaller number of elements resulting in a more efficient determination of the result.

In the *maximum likelihood principle*, the likelihood function is maximised based on the observed data [Bis09]. No explicit prior information about the model at hand is incorporated in the likelihood function. It must nevertheless be guaranteed that the evaluations must not leave the context of the application such that maximum likelihood is effective [Jay03]. Fundamentally different, prior information is modelled explicitly in the prior distribution of Bayesian fusion, in which the likelihood function also has a central role.

One phenomenon that KISEON and SHEVLYAKOV have recognised is the ubiquitous assumption and application of the *normal* or *Gaussian probability distribution*. They present reasons for this phenomenon (the Fourier transform of a Gaussian is a Gaussian, the convolution of two Gaussians is a Gaussian, etc.), but at the same time list the disadvantages resulting from effects like outliers or limited amounts of data when it comes to a practical application of the Gaussian distribution [KS08].

To conclude, the quality of the solution always depends on the quality of the underlying model. This model is created from available data, which is only rarely available in a sufficient amount [HS01]. Frequentistic probability models will thus fail immediately in the case of a small data base. Also most Bayesian models are not appropriate. They assume independent and identically distributed data. Independence must be questioned in most real-world applications, as data sources used in the same applications are at best partly decorrelated [HS01; m.LM10a]. The same applies to identical distribution of the data, which in real-world applications can at best be approximately assumed due to the high variety of possible data sources.

Due to their comprehensive theoretical foundation, probability theory methods such as Bayesian fusion naturally seems nevertheless to be an adequate candidate to represent the acquired data [Car01; AK06]. Uncertainties in machine condition monitoring are contrarily mainly of epistemic nature, but probabilistic methods are able to model only aleatory (random) uncertainties. Besides, KOLMOGOROV's axiomatic foundation of probability theory contains the additivity axiom [Kol50], which is often not practicable in real-world applications: In case a hypothesis (e. g., "The machine is intact") is denied, this axiom implicitly leads to the acceptance of its complement (the machine's defect) [JMB07]. This drastic view is inappropriate in many cases, everything in between represents the actual physical situation more adequately (e. g., a part of the machine is worn out and not working properly).

The importance of ProbT in the scientific community is nevertheless underlined by current application-oriented research, within which condition monitoring is an important topic. ZHAO et al. propose a prediction approach for gear tooth cracks, in which they apply Bayesian fusion to cope with uncertainty in form of measurement errors. The prior distribution is determined from historical failure data, while current measurements update the likelihood function. The resulting posterior (modelling information about the current load exposed to the gear) serves as input for a degradation model, from which a failure time distribution is determined. On this base, the next inspection time is scheduled in order to facilitate condition-based maintenance [ZTB+15].

A fusion method based on probabilistic finite state automata learned from captured

time series for the semantic model generation of a distributed application is presented in [SSV+14]. KLERX et al. apply probabilistic timed automata based models for condition monitoring of *automated teller machines* (ATMs) as discrete event systems [KAK+14; KAK14; AKP+14].

A Bayesian approach to suppress faulty sensor signals, in which the independence of sensor location and sensor observation is assumed, is proposed and evaluated for a robot navigation scenario in [KKR15].

2.2.2 Dempster-Shafer Theory of Evidence Fusion Approaches

The *Dempster-Shafer theory of evidence* (DST) is a theory, which is applied to quantitatively express degrees of belief about propositions. DST is often denoted by “theory of belief functions” [YL08; KKK+11; Mar12; SHM12], but also (much simpler) “belief theory” [Pra83; Jøs02; NB05] or “evidence theory” [MM14; SS14; YQ14; Den15]. The latter denomination is too specific as probability theory (cf. Section 2.2.1), fuzzy set theory (cf. Section 2.2.3), or possibility theory (cf. Section 2.2.4) are also justified candidates to express evidence mathematically. A brief summary of DST’s formalisms is included in Appendix B.

DST’s roots are in DEMPSTER’s article “Upper and Lower Probabilities Induced by a Multivalued Mapping” from 1967 [Dem67]. Here, DEMPSTER describes his idea of assigning upper and lower probability bounds to a *proposition* being a set of *elementary elements* from the *frame of discernment*, with *power set* denoting the exhaustive set of all subsets of the frame of discernment. DEMPSTER proposes to interpret a probability measure as *degree of belief* quantifying a state of partial knowledge. For the combination of several degrees of belief, it must be assumed that they originate from independent sources, interpreted as non-overlapping random sample propositions from the frame of discernment [Dem67]. For such degrees of belief, no simple product rule of combination existed. Hence, DEMPSTER developed a combination rule for two independent sources, which is valid to combine individual degrees of belief to determine upper and lower probabilities, respectively. This combination rule, denoted by *Dempster’s rule of combination* (DRC) (cf. Definition B.17), is mathematically the conditional probability for the first source’s observation given the second source’s observation, as DEMPSTER briefly justifies in [Dem67]: it represents a Bayesian posterior in case the first source represents information about the sampled data, the second source represents prior information, and both sources are *sharp*, i. e., upper and lower probabilities are equal.

Dempster’s rule of combination is a central concept in SHAFER’s monograph “A Mathematical Theory of Evidence” from 1976 (in which DEMPSTER wrote the foreword) [Sha76]. This is the basic publication introducing what later was named after its main contributors DEMPSTER and SHAFER³. Belief and plausibility functions are the central measures of DST and based on the *lower* and *upper probabilities* P_* and P^* introduced by DEMPSTER [Dem67]. These are applied in a new interpretation, as DEMPSTER acknowledges in his foreword to SHAFER’s work [Sha76]. SHAFER also introduced a term

³It was BARNETT in 1981, who called this theory “Dempster-Shafer theory” for the first time (cf. [Bar81, p. 868], reprinted in [YL08]) according to DEMPSTER and SHAFER in their foreword to [YL08].

in DRC's denominator, which is necessary for normalisation [Sha76, p. 60]. This normalisation factor is provided with a physical meaning some pages later in the monograph: it is a measure of the extent of conflict between two beliefs [Sha76, p. 65]. The conflict's extent is quantified ranging from 0 in the case of no conflict to 1 in the case of total conflict.

A clear distinction of the term “probability” is made between *chance* and *degree of belief* in DST. Everything related to *aleatory* (or random) experiments is considered as chance. Chance may serve as a degree of belief, but this relation is not bijective: a degree of belief may have been determined differently, and in case no aleatory information is represented by a degree of belief, it cannot be considered as chance. This is the case when the degree of belief represents *epistemic* information, which has been obtained from everything else but an aleatory experiment. For the rest of this document, *probability* will be used synonymously for the aleatory concept of *chance*, while *degree of belief* denotes SHAFER's epistemic concept.

The individual degree of belief assigned to *exactly* one proposition is denoted by *basic belief assignment* (BBA) (cf. Definition B.1), or sometimes as *mass*. No basic belief assignment is assigned to the empty set, whereas the sum of all BBAs must be 1—in other words, not more than 100% of the individual belief can be assigned. It is not necessary in DST to assign a BBA to every element of the power set. Only elements, to which belief exists, have a BBA assigned. The remaining belief is assigned to the frame of discernment. Total ignorance is modelled by the *vacuous belief function*, which assigns all belief to the frame of discernment. Each subset of the power set, which is assigned a nonzero basic belief, is called *focal element* of the frame of discernment.

Recent research by DEZERT et al. analysed Dempster's rule of combination. They conclude that DRC is only compatible to Bayesian fusion under the constraints that the BBAs to combine are either non-conflicting or Bayesian, and the prior distribution is uniform or vacuous at the same time [DTH+14].

Since DST's introduction, its core concepts of basic belief assignment as well as belief and plausibility function are widely accepted in the scientific community. This is objectively manifested in a comparably small amount of scientific work in this context over the past decades. The only facet investigated is the determination of BBAs from observed data in a machine learning sense. SHAFER does not provide a supervised or unsupervised learning approach for the BBAs in [Sha76]. Besides, BBA's definition on sets, and not on single elements, makes the determination of BBAs a nontrivial task. This becomes apparent, when BBA definitions are based on measurements, where single elements are measured. Therefore this topic is actively researched [BGW13; Cho13; HDM+14; KMW14; QHZ+14; XSM+14; YLH14; HDY15; HH15].

In contrast, Dempster's rule of combination has been discussed controversially almost right from the beginning. Criticism and research on alternatives compensating identified deficiencies is found in literature up to date (cf. [Yag87; Sme90; DTH+14; CMY15]). The first discussion was raised by ZADEH and made public in 1984 [Zad84], although the argumentation was already recorded in a technical report from 1979 [Zad79]: Due to the normalisation applied in DRC, the combination result is counter-intuitive in conflicting situations, in which experts are confident a certain proposition does not exist. He illustrates this situation with the following case of two physicians

examining a patient, which in the literature is denoted by “ZADEH’s example”.

Example 3: ZADEH’s *example*. Two physicians are asked to assess a patient’s disease. Each express their belief as presented in Table 2.3.

Table 2.3: Physicians’ beliefs about a patient’s disease (according to [Zad84]).

<i>Disease</i>	Meningitis	Brain Tumor	Concussion
<i>Doctor A</i>	0.99	0.01	0.00
<i>Doctor B</i>	0.00	0.01	0.99

Thus, each physician certainly rejects one of the three possible diseases and believes in brain tumor only to 1 %.

Applying DRC will lead to the conclusion that the patient has a brain tumor with 100 % belief (cf. Table 2.4).

Table 2.4: Fusion result of Dempster’s rule of combination (DRC) given the individual beliefs presented in Table 2.3.

<i>Disease</i>	Meningitis	Brain Tumor	Concussion
<i>DRC</i>	0.00	1.00	0.00

ZADEH hence arguments that DRC yields counterintuitive fusion results in such a high-conflicting setting, as brain tumor has been excluded almost completely by both physicians [Zad84]. His conclusion is supported by the “Real Z-box Experiment” of DEZERT et al. [DTD15]. The intention was to evaluate how a physical phenomenon treats such a high-conflicting situation in an electric circuit, in which electric currents are configurable to represent each expert’s belief in each proposition. Their electric circuit denoted by “Z-box” contains light-emitting diodes representing the three possible diseases. When configuring the flowing currents compatible to the beliefs in ZADEH’s example,⁴ it turns out that the diodes representing meningitis and concussion glow equally bright, while that representing brain tumor is dimmed. Transformed into beliefs, the physical experiment yields the fusion results presented in Table 2.5. DEZERT et al. conclude, that DRC fusion results in the example are incompatible to physical “fusion” and thus counterintuitive.

Other research defends DRC and argues that counterintuitive results occur due to improper application of DRC. It is instead a problem of uncertainty in the constraints, under which DRC may be applied [Lem85; Kyb87; Voo91]. Instead of replacing the combination rule, MAHLER votes for a transformation of the input data [Mah07]. As

⁴DEZERT et al. deviate from ZADEH’s original example insofar as that they apply beliefs (i. e., electric currents) of 0.90 and 0.10 instead of 0.99 and 0.01, but obtain results equal to ZADEH in the case of DRC fusion. The deviation is not motivated in [DTD15]. Presumably it is due to the design of their electric circuit, whose currents need to be within certain limits, which cannot be satisfied using exactly those beliefs presented by ZADEH.

Table 2.5: Fusion result of DEZERT et al.'s Z-box experiment [DTD15].

<i>Disease</i>	Meningitis	Brain Tumor	Concussion
<i>Z-box</i>	0.45	0.10	0.45

is pointed out in [KKK+11], MAHLER argues that the assignment of an arbitrary small non-zero mass to every proposition will circumvent counterintuitive results. SMETS acknowledges the counterintuitive result, but points out that the counterintuitivity arises due to the *closed-world* assumption, i. e., the assumption that one of the elements in the frame of discernment must be true. In an open-world setting, where an element outside the frame of discernment might be true, the problem would not arise [Sme90]. HAENNI argues that a concept should not be abandoned just because it does not yield the desired result in a special situation. He furthermore underlines DRC's validity by following SHERLOCK HOLMES' argumentation that something must be true, even if it is improbable, if all other alternatives turn out to be impossible [Hae02; Hae05]. Compared to ZADEH's example the latter argumentation is not valid as each of the alternatives is *possible* as at least one physician assigns them belief, i. e., none of the alternatives have assigned zero belief considering it completely impossible. HAENNI also invalidates ZADEH's example by pointing out that ZADEH applied DST incorrectly by limiting the frame of discernment only to the given three diseases. He instead argued that the frame of discernment must be augmented with combinations of the diseases as these are not mutually exclusive [Hae05]. This argumentation depends on the semantics of the application and is thus not generally applicable. That is, whilst the frame of discernment defined in ZADEH's example is justifiably inappropriate, applications in which three mutually exclusive alternatives form the frame of discernment may exist. The observed counterintuitivity of DRC will be present in such cases.

Other authors discovered deficiencies of DRC similar to ZADEH's findings (cf. [SD06; LL08]), which led to a number of alternative combination rules [KKK+11]. MURPHY's rule computes the arithmetic mean of the masses [Mur00]. YAGER's alternative distributes the conflicting belief among all elements rather than only among the focal elements [Yag87]. Campos' rule renormalises the initial DRC result with respect to the conflict and thus avoids counterintuitive fusion results [Cam06]. DUBOIS and PRADE introduced a combination rule, which assigns conflicting mass to their focal elements' union [DP86].

The above mentioned are the most prominent among the alternative approaches, from which at least one serves as a benchmark approach in nearly every other publication introducing a DRC alternative. One example is the *Two-Layer Conflict Solving* (TLCS) fusion approach proposed by LI and LOHWEG. It includes two layers to combine pieces of evidence, and possible inherent conflict is decreased during combination. The first layer resolves the conflict to some extent, and then the second continues to solve it and achieves more stable results [LL08]. SEBBAK et al. present a combination rule to obtain "normal behavior in combination of bodies of evidence" [SBM+14, p. 1]. The proposed approach redistributes the conflicting belief to the non-conflicting pro-

positions, preferring the one with the highest belief assigned. Though, this contribution has been criticised for the presented combination rule benchmark [SDM14]. Examples of other alternatives are presented in [SHM08; HH14; LJ14; SDM14; SWL+14b; Wie14; YX14; CMY15; Den15]. An analysis of DRC alternatives, which at that time was contemporary and is today still comprehensive, was carried out by SMETS in 2007. It concludes that most of the alternatives are ad hoc solutions, which are merely theoretically justified [Sme07].

Another drawback of DRC is its computational complexity of $\mathcal{O}(c^n)$ with respect to the number of BBAs n to combine [Bar81]. An architecture applicable for parallel computation of DRC to handle its exponential complexity is presented in [IT96]. DENÈUX and YAGHLANE present a different approach which concentrates on hierarchical clustering of the focal objects (*coarsening*) in the frame of discernment, leading to a more efficient, though approximated, combination [DY02]. An approach benchmarked against the previously mentioned is based on the idea that the processing of set labels during the combination leads to inefficient implementations. By a more efficient finite field theory-based representation for the labels of the sets forming the power set, the approach outperforms that from [DY02] especially in cases of small frames of discernment (< 4 propositions) [Oxe08].

The importance of DST (and the concepts based on it) is manifested in a large number of successful information fusion applications known in literature. The first IFU application appeared in [GLF81]. The most recent applications are found in, e.g., condition monitoring and fault diagnosis of technical systems [Cho13; QLP14; WTL14; Krü15], communication networks [LHW14; YTT14], automotive driver assistance [PDB+14; XWX+14], image processing [HZM14], and risk assessment [DPL+14; JH14; SFP15] besides other decision-making applications [JDC12; JPL+13]. Nearly all authors emphasise that the theoretical foundations have been advantageous in ambiguous and conflicting situations compared to other approaches. A theory, which breaks completely with classical probabilistic methods, is the fuzzy set theory, presented in the following section.

2.2.3 Fuzzy Set Theory Fusion Approaches

Fuzzy set theory (FST) was constituted publicly by ZADEH with his famous article ‘Fuzzy Sets’ [Zad65]. Despite this, the theory’s roots are within ZADEH’s early scientific work. The history of the FST has been compiled and set into context by SEISING in [Sei05].⁵ Based on his book, FST’s history is briefly summarised in Appendix H.2. Excellent and comprehensive works on FST’s formalism, aspects, and properties are contained in [KY95; AK06]. Basic formalisms of fuzzy set theory are included in Appendix C of this dissertation.

ZADEH considers sets with unsharp boundaries and denotes these as *fuzzy sets*, “a «class» with a continuum of grades of membership” [Zad65, p. 339]. These sets are used to model the uncertainties he encountered during his research in the past years before the publication, which arise from imprecision, not from random variables or stochastic

⁵An English translation [Sei07] is also available.

processes. This imprecision denoted by *fuzziness* is also present in the human language [Sei05; Zad65].

In FST, the *universal set* (semantically comparable to DST's frame of discernment) is formed by *generic elements*. The subsets of the universal set are called *fuzzy sets*. Each fuzzy set is characterised by a *membership function* [Zad65]. Its value represents the *grade of membership*, to which an element belongs to the respective fuzzy set. Whereas membership functions can be defined manually, procedures for automatic creation of membership functions based on measurement data are also known in the literature [Wol98; LDM04; HB09]. Subsequent adjustments, such as the integration of expert knowledge, are possible.

ZADEH has also introduced another concept of fuzzy sets. In *fuzzy sets of type 2*, the membership grades of an element belonging to a set are fuzzy sets themselves [Zad75]. This concept is applied by an Italian research group led by SALICONE and FERRERO for the integration of random uncertainties in the framework of fuzzy sets to model measurement errors in electrical systems [FS02; FS06; FPS13; FPS14]. The basic concept of their solution denoted by *random fuzzy variable* (RFV) relies on the construction of fuzzy sets of type 2 by joining two distinct fuzzy membership functions. One membership function represents the epistemic part of uncertainty (coming from systematic measurement errors). The other one is constructed by transforming aleatory uncertainty (or random measurement errors) modelled as a probability density function into a membership function. Subsequently, both membership functions are joined to one fuzzy set of type 2 [FS06]. Example membership functions of both types are depicted in Figure 2.3.

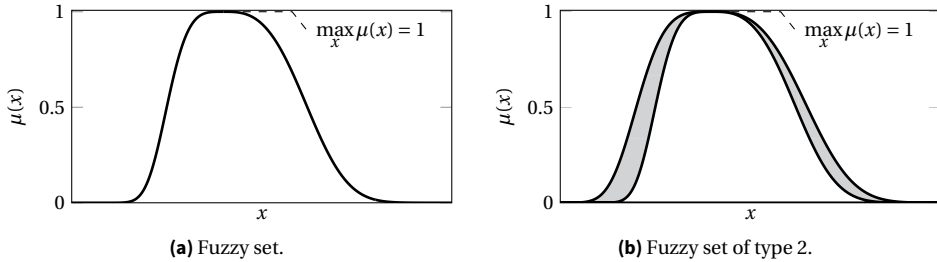


Figure 2.3: Exemplary fuzzy membership functions $\mu(x)$ representing (a) a fuzzy set, and (b) a fuzzy set of type 2. Note the normal fuzzy set's basic property $\max_x \mu(x) = 1$.

The aggregation or fusion, respectively, of the information is carried out by fuzzy logic methods:

“Fuzzy logic is not fuzzy. Basically, fuzzy logic is a precise logic of imprecision and approximate reasoning.”

-- LOTFI A. ZADEH [Zad08, p. 12]

Three classes of aggregation operators exist, namely *t-norms*, *averaging operators*, and *t-conorms* (or *s-norms*) [KY95]. These operators have not been specifically defined in

the scope of FST. Instead, they are accepted mathematical operators, which are also applicable to fuzzy sets. The class of t-norms, for example, was defined in 1942 by Menger as *triangular norm*, more than 20 years before fuzzy sets were first mentioned [Men42]. This class is also denoted by *fuzzy intersection*, denoting its similarity to the (standard) crisp set intersection. One prominent member of fuzzy t-norms is the min-operator. Its dual operator class is the class of fuzzy t-conorms or fuzzy s-norms, also called *fuzzy unions*. These operators behave on fuzzy sets similar to the union operator on crisp sets. The max-operator is the most prominent member of fuzzy t-conorms. A third class of operators filling the space in between t-norms and t-conorms is that of fuzzy averaging operators. These operators produce an averaged output on the basis of their inputs. One of the most prominent members of the averaging operator class is the arithmetic mean, but there are also more flexible operators. YAGER introduced the family of *ordered weighted averaging* (OWA) operators [Yag88]. It is parameterisable to adjust its aggregation characteristics according to specific needs. This can be anything between (and including) the min and the max operators, thus OWA is able to implement the complete range of fuzzy averaging operators. The classification of fuzzy aggregation operators is depicted in Figure 2.4.

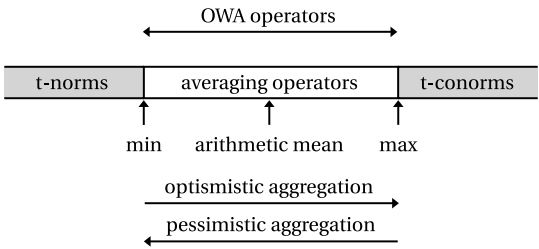


Figure 2.4: Classification of fuzzy aggregation operators (according to [Lar99, p. 740]).

The *implicative importance weighted ordered weighted averaging* (IIWOWA) operator [Lar99] is an extended version of OWA, which allows for weighting each element with respect to its importance in the current problem. It is the normalised version of the *importance weighted ordered weighted averaging* (IWOWA) to achieve value-equivalence instead of only order-equivalence to YAGER’s *weighted arithmetic mean* (WAM) operator [Lar99]. Other aggregation operators are presented in [Boc87; Lar02; DL07; HB09]. Basically, an aggregation operator with desired properties can be found or constructed.

Fuzzy models have successfully been applied in IFU problems in various application fields. HERBST and BOCKLISCH validate passwords entered by a person using a computer keyboard by evaluating the timing behaviour. Due to this, it is possible to determine whether the person is the permitted user, also if the password is mistyped [HB08]. Further advanced, this concept led to a time series prediction algorithm [HB10; Her11].

Researchers from the University of Göttingen and Siemens CERT presented a malware detection concept for Android mobile phones based on fuzzy pattern analysis [ASH+14]. The method denoted by DREBIN outperforms standard anti-virus scanners and is more resource-efficient.

Another diagnosis task is described in [AIK14], which deals with the monitoring

of electrical transformers. The authors concentrate especially on the insulation and present a fuzzy-based monitoring solution enhancing the devices' reliability.

ZADEH presented FST's foundations, but research on this theory is still a current research topic 50 years after its first publication. One branch, which arose from FST, is possibility theory introduced in the following section.

2.2.4 Possibility Theory Fusion Approaches

SHACKLE, a British economist, introduced the basic concepts for a theory of possibility. He considers uncertainty in economics in his work [Sha61] and provides a view on it as possibility, seen as degree of surprise. In addition, an axiomatic description of *possibility theory* (PosT) is provided.

Nevertheless, few publications reference SHACKLE's work when it comes to PosT's roots. ZADEH's elaboration on 'Fuzzy sets as a basis for a theory of possibility' is rather regarded as the pioneering work on PosT [Zad78]. Instead of being a distinct framework capable of handling uncertainty, it is regarded as a unifying theory involving concepts from ProbT, DST, and FST as well as providing links between them [Wol98]. This characteristic is underlined by PosT's ability to model epistemic as well as aleatory uncertainty [Dub06].

PosT operates on fuzzy sets, each characterised by its membership function, which acts as *possibility distribution function* in the scope of PosT [Zad78]. It is value-equivalent to the membership function and thus immediately related to fuzzy sets, but interpreted differently. On the one hand, fuzzy memberships are assigned to every element of the universal set and indicate the degree of membership to a certain, unsharp set. On the other hand, possibility distributions model crisp sets and express the evidence that an element belongs to this set [Zad78; KY95].

Since PosT has its roots in FST, the elaborations presented in Section 2.2.3 are also valid for PosT, except from the way of interpretation (fuzzy membership vs. possibility distribution function). All methods and tools which can be applied to FST are also applicable in PosT.

DUBOIS and PRADE are the main contributors to PosT after its introduction in 1978. They further developed the theory based on ZADEH's work [DP88; DP00; Dub06]. As possibilistic is transferable to fuzzy information, mappings from DST and ProbT to PosT also exist [DP93; Wol98]. These are bijective mappings, which allow the transformation of the information from one theoretical framework to PosT and also backwards or into another framework. This finding is exploited in this dissertation to transfer information between the information models (cf. work topic WT 3). It is important that these transformations preserve the information content and as such the information's inherent uncertainty [DP93; Wol98; DFM+04]. The relations between the information models is depicted in Figure 2.5, expressing the unifying character of PosT visually.

Besides the interrelation between FST and PosT, a prominent one also exists between ProbT and PosT: under certain constraints, a probability density function can be transformed into a possibility distribution function [DP93; MLF00; LMF00; DFM+04]. The methods belonging to the class of *probability-possibility transforms* facilitate applications as in the above mentioned random fuzzy variables [FPS14] or sensor reliability

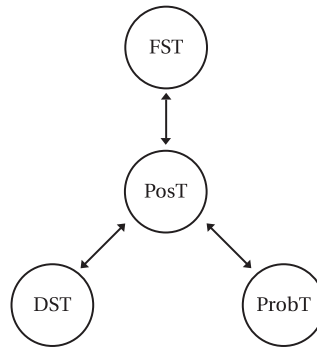


Figure 2.5: Interrelationships between *probability theory* (ProbT), *Dempster-Shafer theory of evidence* (DST), *fuzzy set theory* (FST), and *possibility theory* (PosT).

monitoring [LVG11]. Another application in the scope of reliability assessment of a technical system is presented by WOLKENHAUER, where the applied possibility distribution functions are designed based on measurement data [Wol98].

2.2.5 Hybrid Information Fusion Approaches

Each of the aforementioned frameworks have its specific advantages and disadvantages. In order to profit from advantages of an approach with attenuated disadvantages, research on *hybrid approaches* is found in the literature. These approaches cherry-pick concepts among one or more of the established approaches and bring these together. Such practice is valid, as information models are mutually connected and transferable (cf. Section 2.2.4). Recent examples of hybrid models are given below.

Due to DRC's deficiencies in summary, researchers have also been motivated to search for alternative theories, which are based on or at least inspired by DST. PARK et al. work on hidden Markov models, which they have extended such that the applied probabilities are replaced by DST's basic belief assignments [PCJ+14]. MAO et al. provide a tool for intelligent agents to reason about the planned intentions of others under certain preconditions. Here, the *maximum expected utility principle* [Hal05] is applied on observed series of actions an agent has taken with respect to a knowledge base consisting of several possible plans. In a benchmark experiment assessed by four human experts, their approach has been more accurate than a Bayesian network approach in predicting terror attacks after several observations [MGL12]. Other recent work focus on the transformation of DST basic belief assignments to pdfs for further processing in the framework of probability theory [SS14; SWL+14a; HDD15].

A DST generalisation approach has been proposed by YEN, which puts DST in the framework of fuzzy set theory (cf. Section 2.2.3). Its aim is to preserve as much as possible from DST, but let fuzzy sets serve as its inputs [Yen08]. An additional fuzzy approach, the combination of a certain type of fuzzy sets (interval-valued intuitionistic fuzzy sets) with DST, is presented in [DS14]. This results in the belief and plausibility functions having upper and lower bounds instead of being single-valued.

Hybrid approaches exploiting the advantages of one or more other theoretical frameworks in the scope of fuzzy set theory are also prominent in the literature. The concept of RFVs by FERRERO and SALICONE incorporates ProbT in the context of FST's fuzzy sets of type 2, which also relate to DST [FS06]. HEMPEL proposed an approach applying learning procedures from support-vector machines (cf., e.g., [SS02]) to construct non-convex fuzzy sets [Hem11]. Electrical drive diagnosis using fuzzy artificial neural networks is described in [JJ13]. STRASZECKA describes the advantageous application of a fuzzified DST approach to support diagnosis in a medical context. It is more robust than an evaluated ProbT-based approach in an environment dealing with overlapping focal elements [Str15].

Further information models not yet mentioned are presented in the following section.

2.2.6 Further Information Models

Research on theoretical frameworks to represent and handle incomplete information is vivid and not limited to the most prominent and promising approaches which have been described in the Sections 2.2.1–2.2.4. The following briefly presents a number of additional frameworks in order to give an impression of the present diversity.

Each of the above mentioned interpretations of probability theory has its specific advantages and disadvantages when compared to one another. Consequently, none can be applied universally and the appropriate concept must carefully be chosen for each application. This motivated JAYNES to research and introduce a more general approach, which is denoted by *probability theory as extended logic*. It is a logic concept based on reasoning principles (such as deductive reasoning) and Boolean algebra. This interpretation can be considered as a generalisation of the previously mentioned probability theory interpretations: their axioms, methods, and tools are also found in JAYNES' approach. Detailed information is found in [Jay03].

The *transferable belief model* (TBM) by SMETS is a distinct interpretation of DST, but is not necessarily linked to it or any other probability-based model. It incorporates two levels, on which belief is modelled. On the lower/earlier *credal level*, subjective or personal belief about a proposition is expressed. The belief on this level is not necessarily based on probabilities, which is the key difference to DST. Beliefs are nevertheless updated ("conditioned" in SMETS' nomenclature) with new information by applying Dempster's rule of combination, but without normalisation. The *pignistic level* (from Latin *pignus*: to bet) is only active when decisions are to be made. Credal belief functions are therefore transferred to pignistic probability functions (in the ProbT sense), forming the base on which decision-making is carried out [Sme90; SK94; Sme07].

A theoretical framework considered as generalisation of DST was introduced by DEZERT and SMARANDACHE and is referred to as *Dezert-Smarandache theory of paradoxical reasoning* (DSmT). It is based on TBM, but applies distinct combination rules. The foundations of DSmT have been published in [Dez02], while current research is underway [SD06; TD12; SD15].

PAWLAK's *rough set theory* deals with incomplete information by approximation of crisp sets. Each set is represented by a tuple of sets, of which one is the lower and one

the upper approximation. The lower approximation contains all elements, which are definitely members of the set, while the upper approximation contains elements which possibly belong to the set. Fusion is carried out by classic set operations as conjunction and disjunction [Paw82; Paw91].

Until now, a number of information models have been compiled. The information fusion approach proposed in this dissertation brings the pieces of information together to derive a single conclusion. The next section presents findings on research on how humans make decisions.

2.3 Human Group Decision-Making

It has been quite successful to adapt concepts from other areas of research or living systems for the creation of a new theoretical or technical solution. Prominent examples of the latter are *evolutionary algorithms* in the area of machine learning, which (as their name implies) orientate themselves along the evolutionary learning processes of animate beings [Fog06]. Another successful example is the *particle swarm optimisation* algorithm applying swarm intelligence concepts on nonlinear optimisation problems [KE95].

Therefore, it is reasonable for information fusion approaches to learn from successful decision-making concepts from psychology and adopt them appropriately. With respect to information fusion, the assignment is comparable to creating a consensus decision in a group of animate beings, of which each has its own information and belief. Such situations appear on a daily basis in human life, in which mechanisms operate subconsciously in an effective way. The findings of this section additionally influence the way how conflict is handled in this dissertation (cf. WT 4).

In order to understand and abstract these mechanisms, psychologic research is carried out in the area of *naturalistic decision-making* (NDM). It deals with studying the behaviour of people to understand and deduce tools, methods, and advices for decision-making in a structured manner. This discipline originates from a conference, which was held on this topic in 1989. It is regarded as a promising paradigm in psychologic research, which interconnects it to real-world problems in cognitive sciences [LKO+01].

LIPSHITZ et al. have summarised and categorised the first decade of research in the scope of NDM in [LKO+01]. GIGERENZER, for example, elaborates human's individual *intuition* and describes in which situations it is advantageous to follow intuition [Gig08] (translated from its English original [Gig07]). This concept is inapplicable for IFU since intuition is dependent on a person's mood, general attitude, and in addition a decision-making principle without rationales.

A promising group decision-making prerequisite is described by ORASANU: *team situation-awareness*. This is absolutely necessary for effective decision-making in groups and is achieved when collected information is exchanged amongst the group's members and planning is carried out at an early stage. She deduced her findings from an analysis of a number of flight crew decision-making processes [Ora94]. *Teamwork* additionally facilitates effective decision-making. It is based on certain principles, of

which one is “clear and concise communication” [SBC00, p. 347]. LIPSHITZ et al. denote teamwork as “process by which team members seek, exchange, and synchronize information in order to decide” [LKO+01, p. 342]. Their studies also reveal that all pieces of information are taken into account in decision-making processes, weighed according to the pros and cons. As such, the resulting decision is adjusted according to the currently processed piece of information [LKO+01].

In the work of AHLAWAT, auditor decision-making of accounting companies has been evaluated [Ahl99]. Here, studies have been conducted in which decisions were made both individually and in groups. AHLAWAT concludes that there are more prevailing effects in individual decision-making than when decision-making is carried out in a group. It was recency in this case, i. e., recent information is higher weighed and has more effect on adjusting the result than information, which has earlier been acquired. In other words, *group decisions are more robust against undesired external effects and thus more stable* [Ahl99].

LIPSHITZ et al. point out:

“Decision making has been traditionally studied at three levels: individual, group and organizational.”

-- RAANAN LIPSHITZ et al. [LKO+01, p. 341]

Hence, decision is to be made at three layers, the individual level, group level, and organisational level. In addition, conflict is unavoidable and has to be considered and solved in all of these levels. Appropriate information exchange between individuals is necessary in order to decide effectively on group level.

2.4 Scientific Gap

The previous sections appraised the scientific state of the art in fields of research relevant to information fusion. These findings are assessed in the following with respect to information fusion of physical signals acquired by technical sensors, which are prone to imprecision and uncertainty, and might be in conflict.

According to the work topics formulated in Section 1.1, necessary properties and requirements are derived, which should be fulfilled by the IFU approach proposed in this dissertation. These characteristics are listed and assessed with respect to probability theory, Dempster-Shafer theory of evidence, and fuzzy set theory in Table 2.6. Possibility theory as the theoretical framework unifying the three evaluated information models is omitted, as each of them is transferable to PostT. The assessment is carried out exemplarily for a standard IFU algorithm working within each information model. Nevertheless, the findings are also generally valid for other algorithms in the context of the respective model.

The assessment reveals that the fuzzy set theory-based fusion approach is the most beneficial one. It nevertheless does not support all properties and requirements favourably. Especially conflict handling is handled better by DST-based information fusion, which on the other hand lacks the output of intuitive results (cf. Example 3).

Table 2.6: Main properties and requirements of information fusion approaches and their assessments with respect to the considered information models. The qualitative assessments have been derived from typical representatives of each information model: Bayes' theorem (ProbT), DRC (DST), OWA (FST). *Source independence* denotes statistical independence (iid). For DST, *training data set size* is not applicable as the information model is generated manually. Full requirement support and favourable properties are marked grey.

<i>Information Model</i>	ProbT	DST	FST	
<i>Input Heterogeneity</i>	+	+	+	
<i>Source Independence</i>	– (required)	– (required)	+	(not required)
<i>Uncertainty Type</i>	– (aleatory)	+	+	(epistemic)
<i>Information Model Generation</i>	+	–	+	(automatic)
<i>Training Data Set Size</i>	– (ideally infinite)	n/a	+	(small)
<i>Result Intuitivity</i>	–	–	+	–
<i>Conflict Handling</i>	–	+	–	
<i>Computational Complexity</i>	– ($\mathcal{O}\left(c^n\right)$)	– ($\mathcal{O}\left(c^n\right)$)	+	($\mathcal{O}\left(n\right)$)
<i>Fusion Architecture</i>	– (single layer)	– (single layer)	– (single layer)	

Legend: +: full support/favourable property; +/-: partial support/property neither un-, nor favourable; –: no support/unfavourable property

None of the evaluated approaches contribute to work topic WT 1 considering the fusion system's structure to represent the actual structure of the monitored physical system. These approaches serve nevertheless as a benchmark for the approach proposed in this dissertation.

Probability theory-based approaches are not considered in this dissertation. These can only model aleatory uncertainties (cf. Table 2.6), whereas epistemic uncertainties are prevailing in the considered fields of application.

The research presented in this dissertation proposes and elaborates

- an IFU algorithm in the theoretical framework of DST,
 - which orients itself along human decision-making in groups to handle conflict,
 - which produces intuitive results in the scope of monitoring systems from machine and plant engineering,
- a method to derive basic belief assignments from fuzzy sets,

- a fusion system structure, which represents the structure of the monitored physical system.

The proposed solution improves the prevailing situation depicted in Table 2.6. That is, the solution supports said properties and requirements at least as good as the state-of-the-art solutions.

2.5 Chapter Summary

This chapter analysed the state of the art with respect to research and applications in the scope of information fusion for the monitoring of physical systems. It was shown that IFU serves as a concept to generate information of higher density and quality compared to each of the several input information. The constraints and challenges, under which IFU is carried out, were described. All of the frameworks to model and process the information have their individual right to exist and applicative justification, if chosen appropriately. Human decision-making was analysed from a psychological point of view.

The scientific gap was identified based on the previous analysis. This gap is closed by the approach denoted by *multilayer attribute-based conflict-reducing observation* (MACRO), which is proposed in this dissertation. It is capable of incorporating and reducing the effects of conflict between input information. Based on the amount of conflict, it provides a measure representing the information's credibility. Finally, the obtained results are in the same mathematical space as the fusion inputs, which makes the results traceable for human operators during every processing step. Before MACRO is elaborated, the next chapter compiles the necessary methods and tools.

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2017, XIX, 240 p. 58 illus., 35 illus. in color., Softcover

ISBN: 978-3-662-53751-0